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Moving towards sustainable development: exploring the impact of land-use policies on land green utilization efficiency

Edited by
Shikuan Zhao, Cunyi Yang, Lingli Qing and Chengqi Wang

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Moving towards sustainable development: exploring the impact of land-use policies on land green utilization efficiency

Topic editors

Shikuan Zhao — Zhejiang University of Technology, China
Cunyi Yang — Sun Yat-sen University, China
Lingli Qing — Guangzhou College of Commerce, China
Chengqi Wang — University of Nottingham, United Kingdom

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EDITED AND REVIEWED BY
Riccardo Buccolieri,
University of Salento, Italy

*CORRESPONDENCE
Shikuan Zhao,
zskcqu0801@163.com

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Editorial: Moving towards sustainable development: exploring the impact of land-use policies on land green utilization efficiency

Shikuan Zhao[1]*, Lingli Qing[2] and Chengqi Wang[3]

[1]School of Public Administration, Zhejiang University of Technology, Hangzhou, China, [2]School of Accounting, Guangzhou College of Commerce, Guangzhou, China, [3]Nottingham University Business School, University of Nottingham, Nottingham, United Kingdom

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Editorial on the Research Topic
Moving towards sustainable development: exploring the impact of land-use policies on land green utilization efficiency

Introduction

In the face of persistent sustainable development challenges, such as accelerated urban-rural integration, continued population growth, and mounting urban land scarcity, the efficient utilization of land resources has become paramount. A central inquiry for governments and academic researchers globally is how macro- and micro-level land policies can transform land-use practices, optimize territorial spatial structures, and thereby enhance land green utilization efficiency (LGUE). This Research Topic, entitled "*Moving Towards Sustainable Development: Exploring the Impact of Land-Use Policies on Land Green Utilization Efficiency*", compiles 24 articles that rigorously investigate the influence of land policies on utilization efficiency.

Research on land-use policies and LGUE has surged in recent years, yet several research gaps and unresolved issues remain. First, most studies focus on examining the impact of individual land-use policies, lacking analysis of the synergistic effects of policy combinations. This results in relatively one-sided research conclusions. Second, despite repeated discussions on the measurement, spatiotemporal evolution, and impacts of LGUE, the field still lacks a unified, multidimensional evaluation framework that considers long-term ecological resilience and social equity. Finally, a systemic disconnect exists between land-use policies and the behavioral responses of micro-level stakeholders, leaving internal transmission mechanisms unclear. Identifying these open questions is crucial for shifting from static policy evaluation toward a more dynamic and forward-looking understanding of sustainable land governance.

Responding directly to contemporary development themes and policy evolution demands, the Research Topic contributions employ a combination of qualitative and quantitative scientific methods. They examine the effects of land policies, fiscal land dependence, land property rights, and market-oriented land factor reforms on various critical dimensions, including utilization efficiency, ecological efficiency, and environmental risk. From a methodological perspective, the papers utilize frontier techniques to precisely measure the regional disparities in land utilization efficiency and analyze its spatio-temporal dynamics and evolution. This Research Topic features studies that assess how the development of the digital economy and related policies influence green utilization efficiency and resource allocation efficiency, reflecting the needs of the current era and the digital economy's emergence as a major pillar of macroeconomic development. In summation, this Research Topic offers valuable insights for researchers, policymakers, and relevant practitioners into land-use research, sustainable policy formulation, and practical implementation strategies.

The relationship between land use and green efficiency under urbanization

The acceleration of urbanization necessitates an evolution in urban spatial structures, marked by phenomena such as polycentric development, urban-scale expansion, and heightened population density. Against this backdrop, researchers have rigorously investigated the impact of these urbanizing processes on land utilization efficiency and regional landscape ecological risk. The core objective of this line of inquiry is to clarify the coordination mechanisms required to achieve a secure equilibrium between efficient land utilization and environmental sustainability.

Guo et al. (Paper 16), utilizing city-level panel data from 2000 to 2020, investigated the impact of urbanization on regional landscape ecological risk (LER) in the lower reaches of the Yangtze River, highlighting inherent human-land conflicts. Their findings show that the LER in cities along the lower and middle Yangtze River went up from 0.2508 in 2000 to 0.2573 in 2020, and that medium-risk cities always made up more than 30% of the total. Only Wuxi, Suzhou, and Changzhou were able to completely separate economic growth from LER. These cities are examples of how to balance urbanization and ecological security in the area.

Furthermore, other scholars have sought to disentangle the mechanisms and phased characteristics through which urbanization affects land green utilization efficiency (LGUE). Yang et al. (Paper 18), employing a multi-perspective analysis that includes mechanism, threshold, and heterogeneity on panel data from 30 Chinese provinces, found that urbanization promotes LGUE through industrial agglomeration and structural optimization. They further established a threshold effect: the positive contribution of economic development to LGUE intensifies as the urbanization process deepens. However, they found that this beneficial effect was more pronounced in eastern China.

Addressing the heterogeneous nature of urban development, Wang et al. (Paper 20) documented a significant paradox in Northeast China: simultaneous population shrinkage and land spatial expansion. They discovered a negative correlation between changes in population and land utilization intensity at the county level. The matching degree between population and land use was strong only in regional central cities, decreasing progressively toward surrounding areas. Complementing this, Jiang et al. (Paper 22) analyzed the effect of urban polycentricity and scale expansion on urban economic efficiency (UEE) from the perspective of urban and spatial economics. Empirical evidence indicates that polycentricity substantially enhances UEE, especially in economically advanced and densely populated urban areas, by optimizing resource allocation, augmenting innovation capacity, and upgrading industrial structures, whereas scale expansion demonstrates a detrimental effect. These findings collectively advocate for shifting policy focus from merely emphasizing scale expansion to strategically prioritizing spatial optimization and the moderate guidance of polycentric development to ensure sustainable land utilization.

The impact of land finance dependence and resource misallocation on land green utilization

China's rapid urbanization and industrialization have been characterized by an excessive reliance on land finance, a policy leveraging revenue from land sales, which has consequently led to structural flaws in the land factor market, most notably land resource misallocation. Against this backdrop, it is crucial to investigate the effects and underlying mechanisms of land finance, land resource misallocation, and factor distortion on overall land utilization efficiency. The conclusions drawn from such research are vital, offering critical reference points for policymakers seeking to advance land management institutional reforms, optimize land-use structure, and introduce novel land policies for sustainable development.

Guo (Paper 2) analyzes the impact of China's policy reliance on land finance on UGEE using city-level panel data. The findings indicate that land finance dependence significantly inhibits UGEE, with this negative effect being particularly pronounced in non-resource-based cities and those designated as key environmental protection areas. Mechanism analysis suggests that the land finance dependence indirectly affects UGEE by weakening environmental regulation stringency and exacerbating local government debt risks.

Given China's ambitious commitments to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, land-use optimization plays a pivotal role. Wen et al. (Paper 4), using data from 274 Chinese cities spanning 2010 to 2022, investigates the impact of land resource misallocation on regional carbon emission performance. Empirical analysis confirms that land resource misallocation is a critical structural impediment to enhancing carbon emission efficiency. This barrier operates through two primary channels: hindering industrial structure upgrading and suppressing green technology innovation. The heterogeneity analysis reveals that the adverse effect of misallocation on carbon efficiency is more pronounced in the central and western regions, small and medium-sized cities, and non-resource-based cities. These findings provide a solid basis for implementing differentiated land-use and carbon reduction policies.

Land property rights reform and rural land utilization efficiency

The dual structure of China's rural land system and the persistent ambiguities in property rights remain significant impediments to the free flow of land factors and the enhancement of land utilization efficiency. Relevant studies in this Research Topic follow policies like collective forestland tenure reform, urban-rural integration, and the digital economy. They aim to investigate how deepening property rights security, fostering the land transfer market, and facilitating the bidirectional flow of labor and capital factors between urban and rural areas can optimize rural land resource allocation. The ultimate goal is to achieve notable improvements in both forestry and agricultural production efficiency. These studies provide institutional and practical pathways for constructing a unified urban-rural factor market, realizing rural revitalization, and advancing agricultural modernization.

Wei et al. (Paper 6), utilizing micro-level panel data from 13,536 households across 18 counties in 9 Chinese provinces, examined the impact of the collective forestland tenure reform on household forestry production efficiency. The research established that the reform significantly enhanced farmers' efficiency. Mechanism analysis revealed that this improvement was channeled through three factors: increased production inputs, expanded operating scale, and improved credit availability. Finally, the efficiency-enhancing effect of the reform showed considerable heterogeneity across households with different livelihood strategies and forest types.

Liu and Liu (Paper 15) constructed a provincial-level index for urban-rural integration in China and explored its effect on rural land utilization efficiency (RLUE). They confirmed the study demonstrated that the reform markedly improved farmers' efficiency was mediated by two key mechanisms: an elevated land transfer rate and enhanced labor mobility between urban and rural areas. While the efficiency gains were more pronounced in the Eastern and Western regions of China, the study identified an issue of "central collapse", where the effect was less significant in the central provinces.

Xu et al. (Paper 23) investigated the direct boosting effect of Land Transfer (LT), a key market-oriented factor policy, on Food Security (FS) and its underlying complex mechanisms. Their major contribution is the empirical confirmation of the positive link between LT and FS, alongside the validation of the dual mediating roles played by environmental regulation and green technology innovation in this causal chain. This means that LT is not just about concentrating land; it also ensures the quality and long-term viability of grain production by improving and standardizing environmental management through larger operations. Furthermore, the study revealed that the FS-enhancing effect of LT is stronger in major grain-producing areas. Policy implications emphasize the necessity for the government to continue deepening rural land system reforms, accelerate the construction of the land transfer market, and strengthen the policy synergy between environmental regulation and agricultural technology innovation to ensure LT effectively serves national food security and sustainable development goals.

The critical role of land policy in ecological security and functional coordination

Ecological security and food security have been elevated to strategic planning priorities for China's future development. Consequently, the effective implementation of land-use policies is particularly crucial in ecologically vulnerable zones, protected areas, and water conservation regions. In practice, various land protection and ecological compensation policies, such as the ecological protection red line policy and the grassland ecological compensation policy, are being rolled out in batches. Investigating the impact and mechanisms of these policies on economic development and ecological function is therefore a question of paramount practical significance. The conclusions drawn from these studies offer scientific evidence and policy recommendations for perfecting the land governance system and achieving national ecological and food security objectives.

Facing mounting pressures on national food security due to land degradation and ecological constraints, the ecological protection red line policy (ERP) provides a crucial institutional guarantee for safeguarding grain production capacity. Xu (Paper 7) analyzed the promoting effect of the ERP on food security, discovering that this positive impact is strengthened through the mechanisms of land transfer and land reclamation. The policy implications of this work suggest that the government should strictly adhere to the ERP, establish a resilient cultivated land security system, and enhance the synergy between land transfer and reclamation to improve cultivated land quality and production capacity.

Ouyang et al. (Paper 12), using survey data from 542 herdsmen in Inner Mongolia, applied a difference-in-differences model to analyze the effect of the grassland ecological compensation policy on grassland ecosystems. Their findings indicate that the policy either had a negative stimulus or was ineffective in controlling overgrazing behavior among full-time and low-level part-time herdsmen, but it exerted a significant inhibitory effect on high-level part-time herdsmen. They confirmed that non-pastoral employment serves as a key moderating variable in enhancing policy effectiveness. The authors recommend that the government optimize subsidy standards and formats, adopt differentiated incentive measures, and actively develop the labor transfer market in pastoral areas to leverage non-pastoral employment in mitigating overgrazing.

Land use profoundly influences the production-living-ecological space (PLES), making the study of land development's impact on regional sustainable development relevant. Liu et al. (Paper 19) selected Duolun County, Inner Mongolia, as their case study and, based on meteorological and soil data from 2000 to 2020, investigated the spatio-temporal evolution of PLES development suitability and spatial conflicts. They found that the comprehensive PLES suitability in the study area exhibits a spatial pattern of high in the southwest and low in the northeast. Furthermore, the incoordination of PLES suitability is the main constraint limiting the county's territorial spatial development, with the current land use pattern being the critical factor affecting the PLES coupling coordination degree.

Water and land resource scarcity and environmental pollution pose major global challenges for karst regions, severely threatening

their sustainable development. Zhang et al. (Paper 21), using panel data from 54 counties in typical karst areas of China from 2010 to 2020, applied the DPSIR-SDGs model and a coupling coordination model to evaluate the sustainable development level of water and land resources. The study concluded that water and land resource sustainability in China's karst regions is in a state of medium coupling but insufficient coordination, with urbanization processes and industrial structure optimization identified as the primary driving factors.

Regional disparity, dynamic evolution, and policy adaptability of land utilization efficiency

Given the vast territory of China, significant heterogeneity exists across different regions in terms of economic foundations, industrial structure, resource endowments, and policy implementation effectiveness. Consequently, investigating the spatio-temporal differentiation, regional disparities, spatial agglomeration, and dynamic convergence of land utilization efficiency within specific geographical areas carries substantial theoretical and practical significance. Scholars have employed advanced spatial econometrics and statistical analysis methods to uncover the drivers and evolutionary patterns of efficiency gaps, thereby assessing the adaptability and efficacy of policies across diverse regional contexts.

Wang et al. (Paper 1) examined the spatio-temporal evolution characteristics and driving factors of interprovincial industrial green efficiency (INGE) in China from 2005 to 2022. By constructing a comprehensive evaluation system encompassing seven dimensions and 36 indicators, including land resources, they utilized the Geodetector method to identify that industrial governance is the dominant driver of INGE. The study confirmed a trend of INGE first rising and then slightly declining, affirmed the significant East-West regional disparity, and found a positive spatial correlation. Policy implications emphasize that the government should optimize industrial structure according to regional differences and intensify institutional investments, such as industrial governance and green finance, to boost the land and resource utilization efficiency of the industrial sector.

Wang et al. (Paper 14) analyzed the regional disparities and dynamic convergence characteristics of land use efficiency (LUE) in the Yangtze river economic belt (YREB) urban agglomerations under the goal of carbon neutrality. This study innovatively integrated carbon sequestration capacity into the LUE evaluation framework. Using the Dagum Gini coefficient and a spatial convergence model, they analyzed the sources and evolution trends of regional disparities. The results reveal significant spatial heterogeneity and a U-shaped temporal trend in LUE, with inter-regional disparity and hyper-variation intensity being the main contributing conflicts. Policy recommendations stress that efforts to enhance LUE in the YREB must be tailored to the specific regional contexts of different city clusters (YRD, MRYR, and Chengdu-Chongqing), considering factors like economic development, industrial structure, and fiscal capacity, to formulate differentiated yet collaborative land policies.

Fan and Zhao (Paper 17) investigated the impact of land use policies on the green utilization efficiency of 14 border cities in Northeast China. Their work reveals pronounced spatial heterogeneity in the land use patterns of border cities and establishes that the cities' functional orientation (industrial, port, or ecological) dictates their level of green efficiency. Mechanism analysis demonstrates that energy intensity and industrial structure are critical factors suppressing efficiency. Policy implications strongly advocate for implementing differentiated and adaptive land policies based on city types: for instance, industrial cities must leverage digital transformation to drive technological upgrading, while ecological cities should prioritize protection-oriented intelligent development to achieve regional collaborative carbon reduction goals.

Digital policy-driven land green efficiency and resource allocation

The application of digital technologies, encompassing the digital economy, digital finance, and digital rural construction, is acting as a new core factor of production and a national strategy, profoundly reshaping conventional patterns of land utilization. Scholars contributing to this Research Topic primarily investigate how digital policies serve as essential tools for achieving a green and highly efficient transformation of land utilization. These studies reveal the inherent driving logic of digital technology regarding the efficiency of land allocation and agricultural green productivity. The conclusions drawn from this research provide new institutional and technological pathways for policymakers to achieve the integration of digital technology with the real economy, overcome limitations of traditional development models, and consequently realize agricultural modernization and the sustainability of the ecological environment.

Jiang et al. (Paper 3) investigated the promoting effect and mechanism of the digital economy and 5G infrastructure on urban land green utilization efficiency (ULGUE). This study positions the digital economy as a general-purpose technology, confirming its significant boosting effect on ULGUE. Mechanism analysis explicitly identifies green technology innovation and resource utilization efficiency as its two major intermediary channels. Furthermore, the study found that the impact of the digital economy exhibits significant spatial spillover effects and regional heterogeneity, with the strongest effects observed in the eastern regions and early pilot cities. Policy implications recommend that governments should implement regionally differentiated green strategies and deploy digital infrastructure in a targeted manner to achieve sustainable urban transition.

Wang (Paper 9) examined how rural digital development activates agricultural land transfer from the dual perspectives of resource mismatch and labor mobility. The study's contribution lies in empirically confirming the significant and sustainable promoting effect of rural digital development on agricultural land transfer. Mechanism analysis reveals a dual transmission path: first, by alleviating the triple mismatch of labor, land, and capital to optimize resource allocation; second, by accelerating labor mobility to increase the supply of transferable land. Moreover, the study points out that digital development possesses a

"latecomer advantage" in less-developed regions, such as the central and western areas, capable of effectively balancing regional inequalities. Policy implications suggest that governments should leverage the advantages of digital technology, prioritize support for less-developed regions, and thus optimize the market-based allocation of agricultural land factors.

Li and Qu (Paper 10) investigated the direct impact, intermediary mechanisms, and threshold effect of digital economy development on agricultural land production efficiency. The study's contribution is confirming the significant promoting effect of the digital economy on agricultural production efficiency, and clarifying that its primary mechanism is realized by facilitating agricultural labor transfer. Concurrently, the study found that the digital economy's influence exhibits an increasing threshold effect (measured by the level of digital economy development), and the effect is stronger in major grain-producing areas. Policy implications suggest that governments should increase investment in rural digital infrastructure, particularly targeting less-developed Western regions, and construct a regionally differentiated development system to continuously enhance agricultural land utilization efficiency.

Zhang et al. (Paper 11) utilized the Digital Rural Construction (DRC) pilot policy as a quasi-natural experiment to study its causal effect and mechanism on Agricultural Green Total Factor Productivity (AGTFP). The study contributes by empirically confirming that DRC has a significant boosting effect on AGTFP. The core mechanism analysis, for the first time, integrates land factors and technical factors: DRC enhances AGTFP through three pathways—improving land finance, mitigating land resource misallocation, and promoting agricultural technology innovation. The study found that the effect of DRC is stronger in the Central and Western regions, non-major grain-producing areas, and regions with low land transfer efficiency. Policy implications suggest that the government should direct more resources towards less-developed regions and utilize DRC to primarily address the structural inefficiency issues of land resources.

Li et al. (Paper 13) investigated how digital finance (DF) regulates and enhances the positive impact of Intensive urban land utilization (IUUL) on Urban Ecological Resilience, thereby unlocking the ecological value of land. The study's contribution lies in the first-time construction of the "IUUL × DF" interaction model, confirming that DF can significantly boost the ecological benefits of IUUL. Mechanism analysis reveals a triple intermediary role: DF strengthens the promoting effect of IUUL on green innovation, rationalization of industrial structure, and overall upgrading. Policy implications emphasize that at the macro level, synergy between intensive land utilization and DF should be strengthened; at the micro level, financial institutions should develop green financial products to support firms in accelerating green innovation and industrial structure optimization through digital technology.

Conclusion and future directions

The twenty-four articles compiled in this Research Topic provide systematic evidence that the improvement of LGUE hinges upon the synergistic interplay among institutional design, technological innovation, and factor marketization. While the empirical findings are primarily rooted in the Chinese experience, the underlying mechanisms offer a transferable framework applicable to global sustainability debates. Digital policies in particular serve as critical enabling tools to mitigate resource misallocation by providing a strategic blueprint for other emerging economies striving to balance urban resilience with agricultural productivity. Furthermore, the identification of institutional impediments such as excessive reliance on land-based finance and administratively driven distortions offers a vital warning for developing regions aiming to bypass carbon-intensive growth trajectories. Ultimately, the emphasis on policy adaptability and land property rights reform establishes a fundamental cornerstone for food security and ecological governance that extends well beyond national borders. These findings collectively underscore that sustainable land governance is not merely a localized challenge but a global imperative necessitating synchronized institutional and technological responses.

To advance cutting-edge research on sustainable land governance, future academic exploration should priorities several directions. Firstly, there is an urgent need for comprehensive cross-regional and transnational comparisons to distinguish universal patterns of land use from outcomes shaped by specific institutional contexts. Scholars should also turn to long-term longitudinal assessments to accurately capture the common lag effects and non-linear trajectories inherent in land reforms. Furthermore, examining interactions across different spatial scales is crucial for revealing how macro-level national land planning ultimately influences micro-level plot utilization. The integration of emerging digital technologies and big data presents a pivotal opportunity to refine land use efficiency metrics and support real-time policy adjustments. Ultimately, these research endeavors should catalyze innovative reforms in fiscal and land policies. Such reforms are essential for establishing sustainable local governance systems capable of internalizing environmental costs and promoting green investment, thereby modernizing land use practices and ensuring fundamental ecological and environmental improvements.

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Wang Zhang,
Northwest University, China
Xianhong Cheng,
Changzhou University, China

*CORRESPONDENCE
Fenghua Guo,
120120017@aufe.edu.cn

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Digital rural construction, resource mismatch, and rural land use efficiency

Zhiguo Fan[1], Fenghua Guo[2]* and Chen Bian[1]

[1]School of Economics and Management, Weifang University of Science and Technology, Weifang, Shandong, China, [2]School of Accounting, Anhui University of Finance and Economics, Bengbu, China

Introduction: With the acceleration of the allocation of agricultural resource elements in agricultural development, the relationship between digital rural construction and rural land use efficiency has become increasingly close.

Methods: In order to explore the impact and underlying mechanism of digital rural construction on rural land use efficiency, this paper constructs an evaluation system index for China's digital rural construction and uses the SBM-GML model to measure rural land use efficiency. Based on this, data from 30 provinces in China from 2010 to 2022 are used to test it using fixed effects and mediation effects models.

Results: (1) The construction of digital rural areas can directly promote the improvement of rural land use efficiency. This conclusion still holds true after endogeneity and robustness tests. (2) Mechanism analysis shows that digital rural construction can alleviate the mismatch of land resources, capital resources, and labor resources, thereby indirectly promoting the improvement of rural land use efficiency. (3) Heterogeneity analysis shows that the construction of digital rural areas has a more significant driving effect on the efficiency of rural land use in eastern and southern regions of China, as well as in major grain producing and selling areas.

Discussion: This article suggests continuing to promote the development strategy of digital rural construction, improving the problem of resource mismatch, and paying attention to the regional imbalance of digital rural construction. It is necessary to maintain the leading position of "first mover advantage" areas and also pay attention to filling the gaps in "later mover advantage" areas, in order to comprehensively promote the further improvement of rural land use efficiency.

KEYWORDS

digital village construction, rural land use efficiency, land resource mismatch, capital resource mismatch, labor resource mismatch

1 Introduction

China's agricultural development has achieved remarkable success in the global economic landscape, not only becoming a new engine driving China's economic growth, but also demonstrating strong competitiveness and resilience on the international stage. However, the achievement of this result has long relied mainly on intensive investment in traditional factor resources. With the increasing depletion of these traditional resources, Chinese agriculture is entering a critical period of urgent

transformation. Guo and Liu (2023) pointed out that solving the problem of resource mismatch and exploring and utilizing modern production factors have become the key to promoting the sustainable and healthy development of Chinese agriculture. Against the backdrop of China's economy entering a new stage of development, the rapid rise of the tertiary industry has brought profound changes to the rural economic structure. However, this change has also brought many challenges, such as the massive loss of rural labor, the continuous decline in the quality of arable land, the decreasing efficiency of land use, and the generally low return on agricultural capital. These issues not only severely constrain the efficiency and benefits of agricultural production, but also pose a serious threat to the livelihoods of farmers and the sustainable use of rural land. In the face of this severe situation, we must take prompt action to explore new sources of driving force for improving rural land use efficiency and promoting high-quality agricultural development. Land, as the most fundamental and important resource element in agricultural production, its effective utilization and rational allocation are of great significance for improving agricultural production efficiency, safeguarding farmers' land rights, alleviating human land conflicts, and promoting sustainable agricultural development. However, under the existing non market mechanism land transaction model in China, there is a serious waste of land resources, and the problem of low efficiency in rural land use is particularly prominent. This not only leads to the damage of farmers' land and property rights, but also exacerbates the tension of the human land conflict. Therefore, further deepening the market-oriented reform of rural land factors in China and establishing a more fair, transparent, and efficient land trading market has become an urgent task to ensure the sustainable development of agriculture. In this process, we also need to pay close attention to the impact of agricultural resource allocation efficiency on rural land use efficiency. The mismatch of resources, especially the mismatch of capital factors, has become an important bottleneck restricting the development of agricultural economy. Hsieh and Klenow (2009) found that compared to optimal resource allocation, misallocation of resources can lead to reverse flow of resources, severely constraining the development of agricultural economy. Sun et al. (2021) further pointed out that the mismatch of capital factors has a significant negative impact on China's economic growth, and the income gap in regions where there is no mismatch of capital factors is smaller. This discovery reveals the intrinsic connection between resource misallocation and income inequality, and provides important reference for us to formulate more scientific and reasonable agricultural policies. Therefore, in order to promote the high-quality development of Chinese agriculture, we must start from multiple levels, including deepening the market-oriented reform of rural land factors and improving land use efficiency; We need to optimize the allocation of agricultural resources and reduce the mismatch of resource elements; At the same time, it is necessary to strengthen agricultural technological innovation and talent cultivation, and improve the total factor productivity of agriculture. Only in this way can we ensure that China's agriculture maintains a leading position in global economic competition, create better living conditions for farmers, and inject stronger impetus into China's economic and social development.

The construction of digital villages, as an inevitable product of the informatization of economic and social development in agriculture and rural areas and the enhancement of farmers' information skills, marks an important process of modernization and transformation of agriculture and rural areas (Silijuan, 2024). The construction of digital rural areas, as an important component of the rural revitalization strategy in the new era, is leading China's rural areas towards an unprecedented new stage of intelligent and information-based development. In 2019, the Outline of the Strategy for the Development of Digital Villages, jointly issued by the General Office of the Communist Party of China (CPC) Central Committee and the State Council, explicitly puts the "construction of a smart and green countryside" as one of the key tasks, requiring the deployment of the promotion of green production methods in agriculture, promoting the reduction of the use of chemical fertilizers and pesticides, and the development of green agriculture. Since then, the Ministry of Agriculture and Rural Affairs and other relevant departments have issued the "Digital Agricultural and Rural Development Plan (2019–2025)," the "Key Points of the Work on the Development of Digital Countryside for the Year 2020," as well as the "Notice on the Implementation of the National Digital Countryside Notice on Pilot Work" and other policy documents, which provide an important guide for further in-depth implementation of the digital rural development action and promote the greening and modernization of agriculture and rural areas. Through the construction of digital rural areas, we hope to create a smart, green, and harmonious new rural landscape, allowing farmers to enjoy more convenient, efficient, and intelligent production and living services, and making rural areas a beautiful home for living and working. This is not only a positive response to the aspirations of farmers for a better life, but also a powerful support for the country's modernization process, and a positive contribution to the global sustainable development goals. Therefore, in the era of digital economy, in-depth exploration of the potential relationship between digital village construction and rural land use efficiency from both theoretical and empirical perspectives can provide certain empirical evidence to promote the transformation of China's farmers' production, and accelerate the realization of comprehensive transformation and upgrading of agriculture. Specifically, this paper focuses on the following questions: first, does digital village construction have an impact on rural land use efficiency? Does it produce heterogeneous impacts under different locational conditions? Second, from the perspective of mismatch of resource, i.e., mismatch of land resource factors, mismatch of capital resource factors, and mismatch of labor resource factors, what is the intermediary role played by the mismatch of resource in the relationship between digital countryside construction and agricultural land use efficiency? Answering the above questions will help to further promote the real-time digital village construction policy, improve the efficiency of rural land utilization and put forward corresponding measures to solve the problem, thus empowering the synergistic and high-quality development of China's agriculture.

The existing literature has built a basic framework for the study of digital village construction as well as rural land use efficiency, but there are still the following shortcomings. First, the evaluation system of digital village construction is not perfect enough and is in the exploratory stage. Second, the existing literature on the study

of digital village construction on rural land use efficiency is relatively lacking, and the causal relationship between the two is not yet clear. Third, the transmission mechanism of digital village construction on rural land use efficiency is not yet clear, ignoring the impact of resource mismatch. Compared with the existing studies, the possible marginal contributions of this paper are: first, constructing indicators of digital village construction. On the basis of existing research, this paper constructs digital village construction indicators from three major dimensions: digital infrastructure, agricultural digitization, and rural digitization, to further improve the evaluation system of China's digital village construction, and to provide a more scientific and standard evaluation support for China's digital village construction evaluation system. Second, from the existing literature, there is a lack of research on the utilization efficiency of rural land by digital rural construction, which leads to a biased assessment of the accuracy of rural land utilization efficiency. In order to explore the possible impact of digital village construction on rural land use efficiency, this paper uses data from 30 Chinese provinces in China for the period 2020–2022 to empirically test and confirm the reliability of this paper's conclusions through a variety of methods, including instrumental variables and robustness tests, to provide important references for China's agricultural development as well as the improvement of land use efficiency. Thirdly, due to the relatively short period of time that digital village construction is proposed, the transmission mechanism on rural land use efficiency is still unclear, and from the existing studies, no literature has been conducted from the channel of resource mismatch, which may lead to an overestimation of the positive effect of digital village construction on rural land use efficiency. This paper clarifies the transmission mechanism of digital village construction on rural land use efficiency from the three dimensions of land resource factor mismatch, capital resource factor mismatch and labor resource factor mismatch.

The remainder of the paper is organized as follows: the second part is a literature review and theoretical hypotheses; the third part is the research design, which introduces the data sources, variables, and models; the fourth part is the benchmark regression, endogeneity test, robustness test, heterogeneity analysis, and the role of renewable energy sources, and the fifth part is a further study to test the roles of government environmental protection expenditures and government environmental protection taxation; and lastly, the research conclusions and policy recommendations.

2 Literature review

2.1 Research on the measurement and influencing factors of rural land use efficiency

In previous studies, some scholars have used principal component analysis and analytic hierarchy process to measure land use efficiency. However, the drawback of these two methods is that they have subjectivity in the selection of indicator weights and assignment values. More scholars will use data envelopment analysis to measure land use efficiency, thereby eliminating the interference of subjective factors and ensuring the objectivity of evaluation results (Zhang et al., 2019). For example, Lin and Ma (2004) used data envelopment analysis to measure the land use efficiency of urban agglomerations in China in the years 2000, 2006, and 2011. The study found that the land use efficiency of urban agglomerations in China was relatively low and exhibited significant heterogeneity. In terms of indicator selection, scholars pay more attention to the economic benefits brought by land use efficiency. For example, Rongzeng et al. (2021) used the SBM model to measure the efficiency of urban and rural land use in China from land input, capital input, labor input, and other aspects. However, Wu et al. (2011) found that the efficiency of urban land use in China is the result of multiple factors working together, and the evaluation system needs to be based on natural, economic, and social perspectives. In addition to considering the economic benefits of land use, social and environmental benefits should also be taken into account.

Long et al. (2007) studied the impact of socio-economic factors on land use efficiency in the Yangtze River Delta region of China. Liao et al. (2010) empirically analyzed the impact of urbanization rate on land use efficiency in the Changsha Zhuzhou Xiangtan region of China. The study found that in the short term, an increase in urbanization level would reduce land use efficiency, but in the long run, urbanization level would improve land use efficiency. Yang et al. (2010) found that rural population, urbanization rate, proportion of primary industry, Engel coefficient, and urban-rural *per capita* income ratio are all influencing factors of rural land use.

2.2 Research on the economic effects of digital rural construction

The research closely related to this article includes the economic and social effects of digital rural construction. Firstly, the scientific construction of an evaluation index system for digital rural areas is a prerequisite for studying their economic and social effects. Existing scholars often combine digital rural policy documents and select indicators such as digital infrastructure conditions, digital rural governance, digital capital investment, digital industry development, and digital service level to evaluate the construction of digital rural areas (Lin et al., 2023; Zhu and Chen, 2022). Other scholars use the Digital Rural County Development Index to refine digital rural construction into aspects such as infrastructure digitization, rural economic digitization, rural governance digitization, and rural life digitization (Jiajia et al., 2023). Specifically, in terms of the economic and social effects of digital rural construction, at the macro level, digital rural construction can significantly promote the improvement of industrial prosperity (Benqing et al., 2022), reduce the proportion of the primary industry in the county economy, optimize the non-agricultural industry structure, increase the proportion of the service industry, promote the transformation of the county economy to the tertiary industry (Tao et al., 2022), and help enhance the resilience of the food system (Aimin and Tan, 2022), and promote the improvement of agricultural green total factor productivity (Du et al., 2022); At the micro level, the development of digital rural areas can achieve the upgrading of rural household consumption by promoting the increase of total consumption and optimizing consumption structure (Wan and Wang, 2024), and significantly increase the probability of non-

agricultural employment and entrepreneurship in rural households (Yin et al., 2024), and improve the income level of farmers (Qi et al., 2021). The above-mentioned experts and scholars have conducted rich research on digital rural areas, laying the research foundation for this article. However, it is not difficult to find that existing studies have mostly constructed indicator systems from a macro level when evaluating the level of digital rural construction, with little refinement or quantification to a specific administrative village, and little research has focused on the potential relationship between digital rural construction and land use efficiency.

2.3 Related research on resource mismatch problem

Classical economic theory holds that in a state of perfect competition, the required resource factors are regulated by the market, and the factors can flow freely between regions, achieving effective allocation of factors. The academic community has conducted in-depth research and discussion on the issue of element configuration. Based on existing literature, the discussion mainly focuses on the reasons, impacts, and improvement behaviors.

The first reason is the mismatch of elements. There are two main explanations for the formation reasons. One reason is the "endogenous allocation distortion" caused by imperfect market competition, mainly due to market segmentation leading to inefficient allocation of resource factors (Kong and Zhou, 2020). Chen and Wang (2020) found that due to the "siphon effect" in cities, they compete with rural markets, leading to a decrease in the ability of rural markets to attract resource elements and further scarcity of agricultural resources.

Secondly, external factors outside the factor market, such as unreasonable institutional arrangements and excessive government intervention, can lead to problems in the allocation ratio of resource factors, resulting in misallocation of factor resources (Hengzhou et al., 2011). Zhou et al. (2022) found that although the implementation of the "urban bias" development policy has brought rapid development to cities and industrial sectors, it also leads to urban-rural segmentation and further widening of the economic gap, which is the key reason for the mismatch. Secondly, the impact of mismatched elements. Yuan and Dongdong (2011) found that labor mismatch in China leads to a 20% loss in economic output efficiency. Peiwen and Yang (2019) found that labor mismatch further widens income inequality, leading to uneven economic development and forming a vicious cycle. Some scholars have also found that the rural market in China has poor circulation of factors and insufficient activation of resources. If the flow of labor and capital in the rural market can be facilitated, the mismatch of factors between regions can be improved, and China's total productivity level can be increased by up to 51% (Jing et al., 2012). The above research conclusions indicate that the reasons for factor mismatch are diverse, and the impact of factor mismatch on the economy is negative, which will greatly affect the development of the Chinese economy.

Thirdly, improve the mismatch of elements. If it is in a closed market environment, Restuccia and Rogerson (2012) found that optimizing the flow of labor and capital factors can improve factor allocation. In the current situation of rapid development of digital technology, it is necessary to use the products of the new era to improve the current factor allocation (Wang and Zhang, 2021). Zhou et al. (2022) found from the perspective of resource mismatch that the digital economy has narrowed the urban-rural gap. However, Han and Zhang (2019) found that digital technology represented by the Internet has a threshold effect on the improvement of factor mismatch, and only when the Internet penetration reaches a certain level can the labor force mismatch be reduced.

2.4 Research on the impact of digital rural construction on agricultural land use efficiency

Firstly, the construction of digital rural areas is achieved through the superposition, diffusion, and penetration of rural infrastructure, data elements, and resource allocation, as well as digital technology. This results in the formation of superposition, diffusion, and penetration effects on rural agricultural production, thereby reducing resource misallocation and production costs, and improving agricultural scale production (Wang and Yongxiu, 2022). Wen and Chen (2020) believe that the integration of digital economy development with rural agricultural production can effectively alleviate the information asymmetry in traditional agricultural production, optimize agricultural resource allocation, and achieve goals such as reducing transaction costs and increasing agricultural scale production. In this context, studying the relationship between digital rural construction and rural land use efficiency has become a hot topic of academic concern. Currently, the academic community has a relatively consistent view on the impact of digital economy and digital rural areas on rural development. Firstly, the digital economy can provide platform technology for agriculture, improve agricultural production and land use efficiency, transform traditional extensive production methods, and influence agricultural development (Brody et al., 2006; Camarinha-Matos et al., 2009; Attour and Barbaroux, 2021).

Secondly, the construction of digital rural areas empowers agricultural production through multidimensional digital technology, becoming a new type of productive force for the development of the agricultural industry (Shen and Ye, 2021). Digital technology is conducive to optimizing resource allocation, creating disruptive innovation and creative destruction to traditional agricultural production models (Yin et al., 2020), and contributing to the construction of green, efficient, and intensive modern agriculture. Thirdly, the construction of digital rural areas can generate strong resource spillover effects on agricultural entities (Chen, 2021), help optimize factor allocation, reduce production costs, alleviate information asymmetry, further optimize labor structure, land use efficiency, transform agricultural production models (Shen and Ye, 2021), enhance agricultural production enthusiasm, stimulate internal motivation, and thus generate a multiplier effect on agricultural modernization. Fourthly, the construction of digital countryside can also reduce the cost of farmers obtaining information, including commodity and market information (Mary George et al., 2016), improve farmers' ability to directly connect with the market and human capital level, and

promote the transformation and upgrading of the agricultural industry (Song et al., 2020).

In summary, in the new era of digital rural construction, digital rural construction plays an important role in the development of China's rural economy and also has a significant impact on improving the efficiency of rural land use. However, existing literature on this topic is relatively scarce. Therefore, this article first analyzes the mechanism of digital rural construction on rural land use efficiency from a theoretical perspective, and uses panel data from 30 provinces in China from 2010 to 2022 to measure the evaluation system of China's land use efficiency and digital rural construction. Further, an empirical model is constructed to test the impact and mechanism of digital rural construction on rural land use efficiency.

3 Theoretical analysis and research hypothesis

The Outline of the Digital Rural Development Strategy states that digital rural construction is the application of networking, informatization and digitization to the economic and social development of rural agriculture, and the improvement of farmers' modern information skills, as well as the scaling up of agricultural production. Therefore, digital rural construction to improve agricultural economic efficiency, to a large extent, need to improve the efficiency of resource allocation, land as an important resource endowment, the utilization of efficiency can help agriculture to achieve transformation and upgrading. The connotation of digital rural construction is to further extend agricultural informatization by relying on the development of the digital economy, using modern information technology such as artificial intelligence as a driving force, and using platform technology as a carrier to reshape rural economic development as a means and process. The main feature of digital rural construction is to utilize the concept of digital economic development, drive the improvement of agricultural land use efficiency through technological innovation, realize efficiency change, power change and quality change, promote the precision, intelligence and greening of rural construction, and promote the comprehensive upgrading of agriculture and the comprehensive progress of rural areas (Wang et al., 2021). The following will comprehensively explain the impact of digital rural construction on rural land use efficiency and its mechanism of action.

3.1 Digital village construction and rural land use efficiency

First, agricultural technology transformation and upgrading and the optimal allocation of agricultural resources are key factors in the improvement of land use efficiency. Based on the theory of induced technological change, the key source of motivation for agricultural technology transformation and upgrading is the endowment of technological resource factors, and the application of technology and the relative price of factors determine the way of resource factor allocation. With the policy advancement of digital village construction, the pace of digital application in agriculture has accelerated, and the improvement of information collection, transmission and processing capacity is conducive to the flow of land resources, agricultural costs continue to decline, and land use efficiency has been improved. Digital village construction can provide channels for agricultural business entities to apply digital technology, and provide a meritocratic path for optimizing resource allocation, improving land use efficiency, and reducing agricultural pollution and carbon emissions. Therefore, digital village construction has changed the original traditional mode of rough operation, improved the development of agricultural industrialization, and land use efficiency is bound to be improved under large-scale operation.

Second, from the perspective of the land transfer side, the development of rural e-commerce and Taobao villages improves employment opportunities for the rural population, which leads to a decrease in the opportunity cost of land transfer and increases the probability of transferring the right to use land (Zhang and Zhang, 2020), which is conducive to the formation of large-scale development of agriculture and the improvement of the efficiency of land use. Therefore, if farmers originally engaged in agricultural production receive higher income from non-farm industries, farmers will be more willing to transfer land and thus invest in the non-farm sector (Shen et al., 2017). From the perspective of both sides of land transfer, digital village construction can provide an information platform for agricultural development, break the obstacles of time and space, provide timely information for both sides of land transfer (Coelli and Rao, 2004), and improve the efficiency of land transfer. Therefore, digital village construction can accelerate land transfer and improve land utilization efficiency. Since individual farmers lack access to information, they need to complete the collection of transfer information, contract negotiation and signing by themselves, which requires high costs. However, the information platform provided by digital village construction can help farmers obtain efficient land supply and demand information and reduce transaction costs. In short, agricultural production and management activities rely on digital village construction to increase land transfer, improve land allocation efficiency, and meet the large-scale operation of agricultural production.

Finally, the construction of digital villages can accelerate the flow of agricultural information and break down information barriers. First, Pereira et al. (2019) found that the application of digital technology can obtain timely information on production technology, market demand, government transmission, etc., which is beneficial to the rational allocation of resources, timely adjustment of industrial structure, and increased land utilization efficiency. Relying on digital technology can further break through the market information barriers between urban and rural areas and regions, reduce the cost of obtaining information, and increase the probability of successful transactions. Secondly, digital rural construction helps to improve the agricultural industry chain, and through the realization of the data sharing system between farmers and research institutes, it can accurately match the situation needed for scientific research and agriculture, thus improving the efficiency of the use of chemical fertilizers and pesticides, and promoting the effectiveness of the use of agricultural production resources. Thirdly, the construction of digital countryside helps to build a system to promote agricultural science and technology, form scale development, reduce the cost of agricultural learning, and drive

the improvement of land use efficiency. Based on this, the following hypotheses are proposed.

Hypothesis 1. The construction of digital villages can contribute to the efficiency of rural land use.

3.2 Digital village construction, resource mismatch and rural land use efficiency

Resource mismatch will lead to a decline in agricultural production efficiency, and the improvement of the allocation efficiency of resource is an important source of improving land utilization efficiency. Digital village construction, as an organic combination of digital economy and traditional agriculture and rural areas, can largely improve the allocation efficiency of resource elements according to the penetration effect, substitution effect and synergistic effect of digital technology, inhibit the degree of mismatch of resource to a certain extent, and promote the improvement of the efficiency of rural land use. In the process of digital village construction, the penetration effect refers to the initial stage of data elements used in rural areas, driving the flow of resource elements between urban and rural areas. The substitution effect refers to the substitution of data elements for the original traditional elements and the improvement of the utilization efficiency of traditional elements. Synergistic effect refers to the synergistic evolution of industrial digitization and digitized industries, which jointly promote the efficiency of factor allocation. Based on the ternary theory of agricultural production factors, this paper will analyze the role played by resource mismatch between digital village construction and rural land use efficiency from the three dimensions of land resource mismatch, capital resource mismatch, and labor mismatch.

First, in terms of land resource mismatch. All along, land elements have been evenly distributed based on the size of the family, so the differences in land utilization efficiency between different families have been ignored, resulting in the mismatch of land resources caused by the mismatch between scale and efficiency. In addition, the lack of digital technology leads to greater information asymmetry, increasing the opportunity cost of land scale transfer, and the existence of the above factors leads to a greater degree of land resource mismatch. The construction of digital villages can help realize the digitization of the whole process of land management, promote the new business model of land transfer, accelerate the process of land transfer, and to a certain extent can inhibit the degree of land mismatch. Firstly, the construction of digital rural areas can promote the establishment of land resource information platforms, achieve digitalization and visualization of land resources, and further improve the transparency of land resource information. Secondly, the construction of digital rural areas utilizes technologies such as artificial intelligence and big data to accurately analyze land resources.

Hypothesis 2. Digital rural construction can alleviate the mismatch of land elements and improve the efficiency of rural land use.

Second, in terms of capital resource mismatch. Due to the development of industrialization, the proportion of secondary and tertiary industries has gradually increased, and at the same time, the development of the urban-rural dual structure has led to a high degree of concentration of capital in the cities, resulting in a greater flow of capital to the cities and the emergence of a mismatch of capital in rural areas. According to Soto capitalization theory, capital can only be capitalized in the market. Digital village construction through digital technology in agriculture and rural areas continue to penetrate, gradually break the market space constraints, promote the integration of digital technology and rural economic development, stimulate the potential of rural idle assets, to the direction of capitalization, to a certain extent, can inhibit the degree of capital mismatch. At the same time, relying on digital finance and other forms of technology can further make capital flow back to rural agriculture, and further improve the capital mismatch situation.

Hypothesis 3. The construction of digital villages can alleviate capital factor mismatch and improve the efficiency of rural land use.

Finally, in terms of labor resource mismatch. Digital village construction can break the barrier of two-way flow of factors between urban and rural areas and reduce the degree of labor mismatch. Compared with cities, rural areas are more backward in terms of infrastructure, transportation facilities, etc., and have a single form of industry, mainly based on agricultural production, which makes the labor force with a higher level of skills unable to return to the rural areas for development, and one-way flow to the towns. At the same time, rural laborers with single skills and low educational level will encounter problems such as market system segmentation and structural employment in the urban market, which makes it impossible for rural laborers to integrate well into the urban market, and the efficiency of agricultural production is also not high. Through the transformation of rural infrastructure, the integration of factor endowments, and industrial digitalization, digital village construction can improve the quality of the rural workforce, improve the structure of the agricultural industry chain, and promote the development of the overall agricultural industry, which is conducive to the improvement of the efficiency of land use. At the same time, the construction of digital villages can drive mass entrepreneurship and innovation, provide more laborers with entrepreneurial and employment positions, attract the return of laborers, and further improve the efficiency of rural land use. Based on this, the following hypotheses are proposed.

Hypothesis 4. The construction of digital villages can alleviate labor mismatch and improve the efficiency of rural land use.

4 Research design

4.1 Initiative variable definition

4.1.1 Explained variable: rural land use efficiency (lue)

In 1978, Charnes and other scholars firstly proposed the Data Envelopment Analysis (DEA) method for measuring multiple-input multiple-output decision units, and this method has been

TABLE 1 Inputs and outputs of rural land use efficiency.

Level 1 indicators	Secondary indicators	Tertiary indicators	Meaning of the indicator	Unit (of measure)
Rural land-use efficiency	Input indicators	Land input	Area of rural arable land	Thousands of hm^2
		Labor input	Number of employees in the primary sector	All the people
		Fertilizer inputs	Fertilizer use	Tons
	Expected outputs	Economic benefit	Primary industry output	Billions
		Social benefit	Grain production	Tons
	Non-expected outputs	Sewers	Agricultural wastewater discharge	Tons
		Atmospheric pollution	Agricultural ammonia emissions	Tons

widely used in efficiency evaluation and other aspects. However, the traditional DEA model cannot realize the efficiency evaluation of non-expected outputs, and the model also suffers from the problem of input-output variable slackness, in this regard, Tone (2002) proposed the SBM-Undesirable model and the super-efficient SBM-Undesirable model, thus effectively solved the problem of input-output variable slack. The scientific validity of using SBM Undesirable model and super efficiency SBM Undesirable model to measure rural land use efficiency mainly lies in the following aspects: firstly, considering the influence of slack variables. It considers the slack variables of input and output, namely, the situation of input surplus and output deficit. This consideration enables the SBM model to more comprehensively evaluate the efficiency of decision units (DMUs), avoiding result bias caused by radial and angular selection issues. Secondly, it can effectively distinguish decision-making units. In the evaluation of rural land use efficiency, there may be situations where the efficiency values of multiple regions or farmers are high and close to 1. The use of the super efficient SBM model can more finely distinguish the efficiency differences between these efficient regions or farmers, providing a basis for formulating more accurate improvement strategies. Thirdly, consider cross period dynamic changes. The SBM-GML model can clearly demonstrate the changes in rural land use efficiency over different periods, as well as the driving factors behind efficiency changes. This helps policymakers understand the development trends of land use efficiency and formulate more forward-looking policies. To this end, this paper uses the super-efficient SBM-Undesirable model that considers non-desired outputs under the input perspective and constant fixed scale payoffs to measure the rural land use efficiency, and also uses the agricultural land use efficiency measured by the SBM-Undesirable model as a replacement of the explanatory variables for robustness Test.

Assuming that there are n production decision-making units (DMUs, n = 1, 2, 3, N), and each DMU contains cast desired outputs, non-desired outputs, the number of which are m, l, and h, respectively, the formula for measuring the efficiency of agricultural land use is as follows (Equation 1):

$$\min\theta = \frac{1+\frac{1}{m}\sum_{m=1}^{M}\left(\frac{S_m^x}{S_{jm}^t}\right)}{1-\frac{1}{l+h}\left(\sum_{l=1}^{L}\left(\frac{S_l^y}{y_{jl}^t}\right)+\sum_{h=1}^{H}\frac{S_h^b}{b_{jh}^t}\right)}$$

$$\begin{aligned} \text{s.t. } x_{jm}^t &\geq \sum_{j=1,j\neq 0}^{n}\lambda_j^t x_{jm}^t + S_m^x \\ y_{jl}^t &\geq \sum_{j=1,j\neq k}^{n}\lambda_j^t y_{jl}^t - S_l^y \\ b_{jh}^t &\geq \sum_{j=1,j\neq k}^{n}\lambda_j^t b_{jh}^t + S_h^b \\ \lambda_j^t \geq 0, S_m^x \geq 0 S_l^y \geq 0 \text{j} &= 1, \ldots\ldots, \text{n} \end{aligned} \quad (1)$$

Among them, θ is the rural land use efficiency; x_j^t , y_j^t , b_j^t denote the input, desired output, and non-desired output values, respectively; S_m^x , S_l^y , S_h^b denote the slack variables of inputs, desired outputs, and non-desired outputs, respectively; and λ denotes the weight variables.

Table 1 shows the inputs and outputs of rural land use efficiency.

4.1.2 Explanatory variables: digital village construction

In this paper, digital village construction is based on the Digital Village Development Strategy Outline issued by China as the policy basis, referring to the research of Zhu and Chen (2022), following the principles of data availability, scientificity and comprehensiveness, and constructing evaluation indicators for digital village construction from three dimensions: digital basic environment, agricultural digitization, and rural digitization.

First, the digital infrastructure environment provides the preconstruction foundation for digital village construction. This dimension is mainly measured by the construction of rural circulation facilities, the number of 5G base stations, rural electricity consumption, and the level of digital base construction, in which the number of 5G base stations indicates the current digital construction infrastructure situation, which is the core element of digital village construction. The construction of rural distribution facilities is mainly the number of rural express stations set up and delivery routes, which can reflect the level of digital technology application. Rural electricity consumption at a certain level can indicate the development of rural digital economy, the higher the level of digital economy, the higher the electricity consumption, the level of rural digital economy construction is an important supporting force for the construction of digital villages. The level of digital base construction is measured by the ratio of rural Taobao villages to administrative villages, and the use of e-commerce data can well reflect the level of digital base construction.

TABLE 2 Digital village construction measurement index system.

Level 1 indicators	Secondary indicators	Tertiary indicators	Definition of indicators	Unit (of measure)	Causality
Digital Rural Development	Digital infrastructure	Number of 5G base stations	Number of 5G base stations	Classifier for individual things or people, general, catch-all classifier	+
		Construction of rural distribution facilities	Length of rural delivery routes	Kilometers	+
		Agricultural electricity consumption	Rural electricity consumption/number of rural inhabitants	kWh/person	+
		Digital base level	Percentage of Taobao villages among administrative villages	%	+
	Digitization of agriculture	Digitalization of agricultural production	Number of enterprises utilizing Internet technologies for productive activities and adjusting the ratio of agricultural employment to total employment	Classifier for individual things or people, general, catch-all classifier	+
		Scale of digitization in agriculture	Online retail sales in primary sector/rural population	Million dollars per person	+
		Digital trade in agricultural products	E-commerce retail sales	Billions	+
		Level of digitalization of services in agriculture	Rural Financial Inclusion Index	%	+
	Rural digitization	Rural smartphone penetration	Year-end mobile telephones per million rural households	Troops	+
		Transportation and communication expenditures of rural residents	Transportation and communication expenditures *per capita*	Yuan/person	+
		Rural Internet penetration	Number of rural Internet broadband access subscribers	Ducal title meaning lord of 10,000 households	+
		Rural meteorological observatories	Number of rural weather station observations	Classifier for individual things or people, general, catch-all classifier	+

Second, the digitization of agriculture is the core content of digital village construction. This dimension is mainly measured by the degree of digitization used in the four links of agricultural production, distribution, sales, and service, thus measuring the penetration of digitization in the agricultural industry chain from different links. In particular, with reference to the study of Wang et al. (2023), the degree of digitization of agricultural production is measured by the number of enterprises engaged in production activities using Internet technology and by the ratio of the number of people employed in agriculture to the total number of people employed. The agricultural distribution, sales, and service segments are represented using the digitalized transactions of agricultural products, the scale of agricultural digitization, and the level of agricultural digitization services, respectively. The level of agricultural digitalization services is measured using the Digital Financial Inclusion Index compiled by Peking University.

Finally, rural digitization is a direct reflection of digital village construction. This dimension is mainly reflected through the degree of digitization of rural life, which is measured by the use of smartphones by the rural population, the rural Internet penetration rate, and the number of rural meteorological observation stations, respectively, from which the degree of digital upgrading of the countryside in terms of mobile communications, networks, and meteorological services is indicated. In addition, meteorological information such as wind speed, light, temperature, humidity, etc., can also be obtained through rural meteorological observation stations, thus providing first-hand meteorological information for agricultural digital production. The level of rural digital application is measured from the *per capita* transportation and communication expenditure of rural residents. Since the metrics of the indicators selected in this paper are not uniform, the entropy weight method is used to standardize the indicators. Specific indicators are shown in Table 2.

4.1.3 Mediating variable: resource mismatch

The research of this paper is resource mismatch, according to the characteristics of agricultural production, this paper divides resource mismatch into three dimensions: land resource mismatch (lan), capital resource mismatch (kap) and labor resource mismatch (lab). The resource factor mismatch index refers to the calculation method of Chen and Zhang (2022). The specific calculation formula is shown below (Equations 2–4):

TABLE 3 Descriptive statistics of variables.

Variable	Obs	Mean	Std. Dev.	Min	Max.
lue	390	15.648	8.277	0.650	60.193
dig	390	2.648	0.277	2.121	4.309
gdp	390	5.66	3.063	1.288	18.999
wag	390	0.596	0.181	0.065	0.952
dag	390	0.035	0.041	0	0.159
psi	390	0.113	0.069	0.002	0.348
med	390	0.649	0.239	0.25	1.387

$$lan = \left(\frac{lan_i}{lan}\right) \Big/ \left(\frac{s_i\beta_{ni}}{\beta_n}\right) \quad (2)$$

$$kap = \left(\frac{kap_i}{kap}\right) \Big/ \left(\frac{s_i\beta_{ki}}{\beta_k}\right) \quad (3)$$

$$lab = \left(\frac{lab_i}{lab}\right) \Big/ \left(\frac{s_i\beta_{li}}{\beta_l}\right) \quad (4)$$

Among them, $s_i\beta_{ni}$, $s_i\beta_{ki}$ and $s_i\beta_{li}$ denote the proportion of land, capital and labor resources used under efficient allocation, and s_i represents the proportion of agricultural GDP of province i to the national agricultural GDP, which is adjusted by the GDP deflator. β_{ni} The data of agricultural GDP are adjusted by the GDP deflator. β_{ki} and β_{li} denote the output elasticity of land, capital and labor respectively, and the three elasticities are measured by the C-D production function. $\frac{lan_i}{lan}$ $\frac{kap_i}{kap}$ and $\frac{lab_i}{lab}$ denote the shares of actual land, capital and labor use of province i in the national land, capital and labor use, respectively. Land, capital and labor are measured by the sown area of crops, agricultural capital stock and the number of people employed in agriculture, respectively. The agricultural capital stock is estimated using the perpetual inventory method (PIM).

4.1.4 Control variable

Gross domestic product (gdp) *per capita*, measured by the proportion of provincial gdp to total population; (2) rural population (rpo), measured by the proportion of rural population to year-end resident population; (3) water use in agriculture (wag), measured by the proportion of total water use in agriculture to total water use; (4) degree of agrarianization (dag), measured by the proportion of value added in agriculture to regional gdp; (5) machinery density (med), measured by the proportion of total power of agricultural machinery to the value added of agriculture; (6) the proportion of primary industry (psi), measured by the proportion of the value added of primary industry to the value added of secondary and tertiary industries. Descriptive statistics of the variables are shown in Table 3.

4.2 Model building

4.2.1 Baseline regression model

In order to test the impact of digital village construction on rural land use efficiency, this paper uses the "time-individual" two-way fixed-effects model for empirical testing. The use of a two-way fixed effects model is to simultaneously control for individual specific effects that do not change over time and the common utility that changes over time but affects all individuals. It can also avoid missing variables, reduce estimation bias, provide accurate estimation results, and avoid spurious regression. The model is shown below (Equation 5):

$$lue_{i,t} = \beta_1 dig_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t} \quad (5)$$

Where $lue_{i,t}$ denotes the rural land use efficiency of a province i in year t, $dig_{i,t}$ denotes the digital village construction of a province i in year t, $Z_{i,t}$ denotes the control variables, u_i denotes the individual fixed effects, ϱ_t denotes the time fixed effects, α denotes the constant term, and $\varepsilon_{i,t}$ denotes the randomized perturbation term.

TABLE 4 Regression results of the impact of digital village construction on rural land use efficiency.

Variables	(1)	(2)
	lue	lue
dig	0.139***	0.114**
	(2.604)	(2.138)
gdp		0.0172***
		(3.512)
dag		−0.0834
		(−0.414)
med		0.0603*
		(1.964)
psi		0.413**
		(2.230)
wag		−0.0136
		(−0.183)
Individual fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Constant	−0.800***	−0.926***
	(−61.82)	(−17.73)
Observations	390	390
R-squared	0.687	0.714

4.2.2 Mediation effects model

In order to test the mechanism of the role of digital village construction on the efficiency of rural land use, we use the mediating effect model to test. Referring to the research of Wen et al. (2004), it can be seen that there are many defects in a single test method, and on the basis of Baron, Sobel and other test methods, Use a new mediation effect test method. This method has obvious advantages, firstly, it has high statistical efficiency, and secondly, it can control the probability of the first and second types of errors. Secondly, better elucidate the intrinsic mechanisms among variables. The mediation effect model can help researchers reveal how

independent variables affect the dependent variable through mediation variables, thereby gaining a deeper understanding of the complex pathways and underlying mechanisms between variables. Thirdly, enhance the explanatory power of the model. By introducing mediator variables, the model can better explain the mechanism of the independent variable's influence on the dependent variable. The mediation effect model usually has higher explanatory power than models without mediation variables, and can provide more information to support research hypotheses. In this paper, we use the following model for the mechanism test (Equations 6, 7).

$$lan_{i,t}/kap_{i,t}/lab_{i,t} = \beta_1 dig_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t} \quad (6)$$

$$lue_{i,t} = \beta_1 dig_{i,t} + \sigma_1 lan_{i,t}/kap_{i,t}/lab_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t} \quad (7)$$

where $lan_{i,t}$、$kap_{i,t}$、$lab_{i,t}$ denotes land resource mismatch, capital resource mismatch, and labor resource mismatch, respectively. The remaining variables are consistent with the benchmark regression.

4.3 Data sources

Based on data availability, this paper selects the panel data of 30 provinces in China except Hong Kong, Macao, Taiwan and Tibet from 2010 to 2022. Among them, the data on the output value of agriculture, forestry, animal husbandry and fishery come from China Tertiary Industry Statistical Yearbook; the data on input-output variables and control variables come from China Statistical Yearbook and China Rural Statistical Yearbook, and the missing data are made up through the statistical yearbooks of each province and relevant statistical bulletins. In addition, the relevant data were deflated with 2010 as the base period and transformed into comparable variables in 2010.

5 Analysis of empirical results

5.1 Benchmark regression results

In order to test the impact of digital village construction on rural land use efficiency, the analysis is based on the baseline regression model constructed in this paper. Table 4, column (1) shows the regression results of digital village construction on rural land use efficiency when no control variables are added, and from the results, it can be seen that the coefficients of digital village construction are positive at 1% significance level, indicating that the digital village construction improves the efficiency of rural land use. After adding control variables in column (2), the coefficient of digital countryside construction is significantly positive at 5% significance level, and also digital countryside construction improves the efficiency of rural land use, and Hypothesis 1 of this paper can be verified.

The construction of digital countryside realizes the large-scale operation of agriculture by improving the rural land transfer, while the main body of large-scale operation prefers to use digital technology to obtain new agricultural technology and promote the improvement of agricultural production efficiency. In addition, the information platform established by the digital countryside can provide timely market information, which is conducive to the optimization of the agricultural industrial structure, so that the agricultural production division of labor refinement and specialization, which is conducive to the improvement of rural land efficiency. At the same time, the construction of digital villages can optimize the allocation of agricultural resources and factors and promote the improvement of land efficiency. In addition, farmers can also accurately control the process of agricultural breeding, irrigation, fertilization and other processes through the network information platform of digital rural construction, saving capital investment and reducing pollution and carbon emissions. Therefore, digital rural construction has improved rural land utilization efficiency in multiple dimensions.

5.2 Endogeneity test

In order to mitigate the possible endogeneity problem of digital village construction and rural land use efficiency, this paper includes control variables as much as possible to prevent the endogeneity problem caused by omitted variables. The results of the benchmark regression show that digital village construction can improve rural land use efficiency, and in turn, an increase in rural land use efficiency may lead to an increase in the level of digital village construction, thus leading to bidirectional causality. Therefore, this paper deals with the possible endogeneity problem by lagging the core explanatory variables by one period as well as the instrumental variables approach.

5.2.1 Lagging phase I digital village construction

Considering that the construction of digital rural areas requires a certain amount of time and may have a certain time delay, the construction of digital rural areas will be lagged by one period as an instrumental variable, and the system GMM method will be used for testing,and the results are shown in column (1) of Table 5, the AR (2) test results show that there is no second-order autocorrelation problem, the Sargan test results show that there is no over-identification problem, and the estimation results using the GMM model are reliable. From the empirical results, the coefficients are significantly positive at the 5% level after one period of lagging digital village construction, indicating that digital village construction with one period of lagging still has a positive promotion effect on rural land use efficiency.

5.2.2 Instrumental variables method

Digital village construction needs the support of Internet technology. To alleviate the endogeneity problem of the model, referring to Daleng and Peng (2023), the Internet penetration rate in each province is selected as an instrumental variable for digital village construction. On the one hand, digital village construction relies heavily on regional Internet penetration rates, and regions with better Internet penetration rates are more likely to carry out digital village construction; on the other hand, Internet penetration rates have a negligible effect on rural land use efficiency. Therefore, the selection of Internet penetration rate as an instrumental variable for digital village construction satisfies the requirements of relevance and

TABLE 5 Endogeneity test results.

Variables	(1)	(2)	(3)
	lue	internet	lue
	System GMM	IV-2SLS	
dig		0.0247***	0.853***
		(8.67)	(3.145)
L.dig	0.110**		
	(2.398)		
dtc			
gdp	0.0226***	0.0036	−0.0328***
	(8.368)	(0.77)	(−2.720)
dag	−0.255***	0.6527***	−1.270***
	(−2.790)	(2.70)	(−2.826)
med	0.00892	−0.1095	−0.0518
	(0.310)	(−1.19)	(−0.908)
psi	0.416**	−0.2297***	−1.078***
	(2.042)	(−6.63)	(−3.367)
wag	0.0288	−0.2410***	1.312***
	(0.383)	(−6.63)	(13.30)
Individual fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Constant	−0.725***	0.2452***	−1.312***
	(-9.688)	(6.10)	(−10.94)
AR (2)	0.276		
Sargan's test	32.189 [0.528]		
Kleibergen Paaprk LM		75.18 [0.000]	
Cragg-Donald Wald F		67.74 [16.38]	
Observations	360	390	390
R-squared	0.670	0.542	0.216

Note: Values in square brackets are p-values and values in curly brackets are critical values corresponding to the Stock Yogo test at the 10% level.

exogeneity. Table 5 columns (2) (3) show the regression results of instrumental variables. The first-stage regression results indicate that the coefficient of Internet penetration is significantly positive at the 1% level, indicating that Internet penetration is correlated with digital village construction, the value of Cragg-Donald Wald F-statistic is 67.74, which is much larger than 10, and the value of Kleibergen Paaprk LM-statistic is 75.18, with a p-value of 0.000, rejecting the weakly instrumental variables and the original hypothesis of unidentifiable variables, proving that the selected instrumental variables are valid. The results of the second stage regression indicate that the coefficient of digital village construction is significantly positive at the 1% level, which is consistent with the results of the benchmark regression.

5.3 Robustness tests

5.3.1 Replacement of explanatory variables

Considering that the evaluation system of digital village construction has different standards and there is no recognized and common evaluation system of digital village construction, in order to ensure the robustness of the digital village construction indexes constructed in this paper, this paper refers to the methodology of Han and Sun (2024), and reconstructs the evaluation indexes of digital village construction from the four dimensions of digital village environment, rural digitization, agricultural digitization, and farmers' wisdom, and uses entropy weight method to carry out the construction. The evaluation indexes

TABLE 6 Construction of evaluation system for digital village construction.

Level 1 indicators	Secondary indicators	Specific indicators	Causality	Unit (of measure)
Digital Rural Environment	Level of consumption of digital goods and services	Rural Engel coefficient	Negative direction	%
	Number of employees in the rural informatization industry	Number of employees in the information transmission, computer services and software industry	Forward	Man
Rural digitization	Internet penetration	Proportion of administrative villages with Internet broadband service	Forward	%
	Cable TV coverage	Cable TV coverage	Forward	%
Digitization of agriculture	Number and size of rural online payments	Digital Inclusive Finance Index	Forward	—
	Agricultural and Rural Digital Base	Number of Taobao villages	Forward	Classifier for individual things or people, general, catch-all classifier
Farmer Intelligence	Number of students in rural general secondary schools	Number of students in rural general secondary schools	Forward	Man
	Average years of schooling of rural residents	(Number of rural people without schooling × 1 + number of people with elementary school education × 6 + number of people with lower secondary school education × 9 + number of people with upper secondary and secondary school education × 12 + number of people with tertiary education and above × 12)/Total rural population aged 6 years and above	Forward	Surname Nian

are shown in Table 6. The constructed digital village construction index replaces the index in the benchmark regression, and the empirical results are shown in column (1) of Table 7. The coefficient of the digital village construction index is significantly positive at the 1% level, which is consistent with the results of the benchmark regression and proves that the conclusions of this paper are robust.

5.3.2 Replacement of explanatory variables

In this section, rural land use efficiency is measured using the results of the SBM-Undesirable model (xleu) instead of the results of the Ultra-Efficient BM-Undesirable model, and the effect of digital village construction on rural land use efficiency is re-examined, and the results are shown in column (2) of Table 7, the digital village construction coefficient remains significantly positive at the 1% level, indicating that the results of this paper are robust.

5.3.3 Excluding municipalities

Since the four municipalities of Beijing, Tianjin, Shanghai, and Chongqing are not clearly delineated between urban and rural boundaries, and the situation is quite different from that of other provinces, and the agricultural function is not focused on production, and the digital infrastructure is more complete and strong, the four municipalities are excluded from the test and re-tested, and the results of the test are as shown in column (3) of Table 8, and the coefficient of the digital countryside construction is still significantly positive at the 5% level, which suggests that the results of this paper are robust.

5.3.4 Mechanism analysis

The theoretical analysis shows that the digital village construction can alleviate the resource mismatch problem, but what role the resource mismatch problem can play between the digital village construction and the rural land use efficiency needs to be further tested. For this reason, the mediation effect model is used to test it, and the empirical results are shown in Table 8. Columns (1), (3) and (5) show the empirical results of digital village construction on land resource mismatch (lan), capital resource mismatch (kap) and labor resource mismatch (lab), respectively. The empirical results show that column (1) shows that the coefficient of the impact of digital village construction on land resource mismatch is significantly negative at the 5% level, and the regression coefficient of land resource mismatch on rural land use efficiency is also significantly negative in column (2), thus proving that the land resource mismatch has a mediating effect between the digital village construction and rural land use efficiency. Similarly, column (3) shows that the coefficient of the impact of digital village construction on capital resource mismatch is significantly negative at the 1% level and the regression coefficient of capital resource mismatch on rural land use efficiency is also significantly negative in column (4), thus proving that capital resource mismatch has a mediating effect between digital village construction and rural land use efficiency. Column (5) shows that the coefficient of the impact of digital village construction on labor resource mismatch is significantly negative at the 10% level, and the regression coefficient of labor resource mismatch on rural land use efficiency is also significantly negative in column (6), thus proving that labor resource mismatch has a mediating effect between digital village construction and rural land use efficiency. Meanwhile, the coefficients of digital village construction on rural land use efficiency are positive in columns (2) (4) (6).

Further, this paper conducts relevant tests on the mediation model, using Bootstrap method and Sobel method to test the

TABLE 7 Robustness test results.

Variables	(1)	(2)	(3)
	lue	xlue	lue
dif	0.580***		
	(3.070)		
dig		0.3050***	0.128**
		(2.616)	(2.209)
gdp	0.0110**	−1.706	0.0112*
	(2.068)	(−1.587)	(1.701)
dag	−0.110	−17.31	0.000803
	(−0.548)	(−0.392)	(0.00356)
med	0.0506*	−4.890	0.0403
	(1.652)	(−0.727)	(1.095)
psi	0.309	71.33*	0.334*
	(1.648)	(1.758)	(1.677)
wag	0.00991	10.86	0.0390
	(0.133)	(0.665)	(0.409)
Individual fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Constant	−1.159***	20.75*	−0.886***
	(−11.68)	(1.814)	(−13.57)
Observations	390	390	338
R-squared	0.718	0.255	0.682

robustness of the model. In the Bootstrap method test, the land resource mismatch, capital resource mismatch and labor resource mismatch do not cover 0 under the 95% confidence interval. Meanwhile, in the Sobel test, the land resource mismatch, capital resource mismatch and labor resource mismatch all pass the significance test. Tracing back the root cause, from the perspective of land resource mismatch, digital village construction with the help of digital technology can carry out real-time monitoring in the whole process of land planning, use, management, monitoring, etc., which reduces the degree of land resource mismatch, promotes the improvement of total factor productivity in agriculture, and then promotes the improvement of rural land utilization efficiency. From the perspective of capital resource mismatch, the construction of digital villages is conducive to the construction of rural digital infrastructure, thus breaking through the limitations of time and space, which can better break the boundaries between urban and rural areas, promote the integration of the digital economy and the real economy, activate the original idle assets in the countryside, and promote the transformation of rural capital into digital capital, for example, the immersive experience of the online digital rural tourism experience. From the perspective of labor resource mismatch, digital rural construction makes the digital literacy of farmers engaged in the main body of agricultural production improve, which in turn leads to the improvement of the level of human capitalization of the rural labor force. Due to the penetration and substitution effects of digital rural construction, mechanized production is brought into agricultural production, increasing labor productivity and forming a gravitational demand for highly skilled personnel, which in turn reduces the degree of labor resource mismatch and improves the efficiency of rural land use. To sum up, digital rural construction forms a "booster" effect on rural land use efficiency by reducing the degree of land resource mismatch, capital resource mismatch and labor resource mismatch, and Hypothesis 2, Hypothesis 3, and Hypothesis 4 can be verified.

5.3.5 Heterogeneity analysis

In the baseline regression, we empirically test the average effect of digital village construction on rural land use efficiency, but China is a vast country, with large differences in economic development between the east, middle and west, and large differences between the north and south in terms of resource endowment, agricultural infrastructure and development level. Based on this, this section analyzes heterogeneity based on location differences, geographic location differences, food functional areas, and mismatch degree differences.

TABLE 8 Mechanistic analysis test results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	lan	lue	kap	lue	lab	lue
dig	−0.267**	0.0628**	−0.353***	0.0104**	−0.0210*	0.0819*
	(−2.268)	(2.194)	(−2.820)	(2.303)	(−1.742)	(1.708)
lan		−0.165***				
		(−7.251)				
kap				−0.182***		
				(−8.712)		
lab						−0.180***
						(−9.074)
gdp	−0.0234**	0.0134***	−0.0377***	0.0497	−0.177	0.0135***
	(−2.153)	(2.904)	(−3.267)	(1.020)	(−1.356)	(3.039)
dag	0.606	0.0166	0.453	−0.00119	−0.0743	−0.0968
	(1.358)	(0.0883)	(0.956)	(−0.00650)	(−0.150)	(−0.534)
med	0.0152	0.0696	−0.0564	0.0501*	−0.0485	0.0516*
	(0.223)	(1.393)	(−0.782)	(1.798)	(−0.644)	(1.868)
psi	−1.193***	0.216	−0.745*	0.278	−0.502	0.323*
	(−2.913)	(1.235)	(−1.710)	(1.649)	(−1.105)	(1.935)
wag	−0.467***	−0.0908	−0.00337	−0.0143	−0.182	−0.0464
	(−2.832)	(−1.292)	(−0.0192)	(−0.211)	(−0.997)	(−0.692)
Constant	1.233***	−0.722***	1.024***	−0.740***	1.037***	−0.740***
	(10.67)	(−12.85)	(8.342)	(−14.26)	(8.091)	(−14.43)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	390	390	390	390	390	390
R-squared	0.351	0.752	0.360	0.766	0.314	0.770

5.3.5.1 Heterogeneity analysis of the eastern, central and western regions

Based on China's division into eastern, central, and western regions, we empirically test whether the construction of digital villages has a differential impact on rural land use efficiency in different regions. The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan provinces. The western region includes Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, Chongqing Municipality, Sichuan Province, Guizhou Province, Yunnan Province, Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, and Xinjiang Uygur Autonomous Region. The empirical results are shown in Table 9. Column (1) shows the regression results in the east, and the coefficient of digital village construction is significantly positive at the 5% level, while the coefficients of digital village construction in columns (2) and (3) are positive but non-significant, suggesting that digital village construction has a stronger role in promoting the efficiency of rural land use in the eastern region of China.

The construction of digital rural areas has had varying impacts on the efficiency of rural land use in different regions. We believe that there are three main reasons for the impact of regional differences. Firstly, there are differences in digital infrastructure. In the eastern region, the construction of digital infrastructure such as the Internet of Things and big data platforms is relatively complete. The improvement of these facilities provides efficient information processing capabilities for rural land use efficiency, which is conducive to the development of precision agriculture and smart agriculture. In the central and western regions, the construction of digital infrastructure is relatively lagging behind, which limits the speed of information transmission and processing, thereby affecting the intelligence level of rural land use efficiency. Secondly, there are differences in the degree of application of digital technology. In the eastern region, the use of digital technology in

TABLE 9 Heterogeneity test results for East, Central and West regions.

Variables	(1)	(2)	(3)
	The East	Central section	Western part
dig	0.452**	0.166	0.205
	(2.529)	(0.702)	(0.886)
gdp	−0.0103	−0.0438	0.0106
	(−0.728)	(−1.489)	(0.369)
dag	0.222	0.490	1.563**
	(0.287)	(0.698)	(2.036)
med	−0.0513	0.0284	−0.363*
	(−0.597)	(0.265)	(−1.675)
psi	−0.209	−0.430	−1.063
	(−0.217)	(−0.787)	(−1.111)
wag	−0.776***	0.308	−0.232
	(−3.203)	(0.649)	(−0.738)
Individual fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Constant	1.531***	0.528*	0.791***
	(6.600)	(1.898)	(3.447)
Observations	143	104	130
R-squared	0.443	0.433	0.317

agricultural production is becoming increasingly widespread, such as intelligent irrigation, drone detection, precision fertilization, and so on. The application of these digital technologies has improved agricultural production efficiency, reduced resource misallocation, further lowered costs, and increased the sustainability of rural land use. In the central and western regions, the application of digital technology in agricultural production is relatively limited, and traditional agricultural farming methods still dominate. This will result in lower land use efficiency in rural areas compared to the eastern region, making it difficult to meet the needs of modern agricultural development. Thirdly, there are differences in economic development level and policy support. In the eastern region, the level of economic development is relatively high, and there is also strong government policy support, which leads to significant investment and support for the construction of digital rural areas. This is conducive to the innovative development and further improvement of rural land use efficiency in the eastern region. In the central and western regions, the level of economic development is relatively low, and the government's financial pressure is high. The investment and support for digital rural construction are limited, which limits the promotion and application of digital technology in rural land use and affects the improvement of rural land use efficiency.

The construction of digital villages requires a good economic foundation and digital infrastructure environment, in comparison, the eastern region has obvious advantages in this regard, and the digital literacy of agricultural business farmers in the eastern region is higher, and the spillover effect is more obvious, and more colleges and universities and scientific research institutions are concentrated in the east, and the scientific research capacity is stronger, these conditions are favorable to the construction of the digital villages. Therefore, the construction of digital villages has a stronger effect on the eastern region and a relatively weaker effect on the central and western regions. However, on the other hand, the central and western regions can take advantage of the spillover and penetration effects of digital technology to obtain the "latecomer's advantage," gradually narrow the gap with the eastern region, and improve the efficiency of rural land use with the help of digital rural construction.

5.3.5.2 Heterogeneity between the south and the north

The previous empirical test shows that digital village construction has a heterogeneous impact on rural land use efficiency in east, central and west China, showing a certain degree of convergence. Then, the difference between the south and the north of China has become a new issue of regional unbalanced development, and the difference of regional economic development has become an important basic condition for the construction of digital villages. Therefore, this paper divides the south and the north into the south and the north according to the

TABLE 10 Heterogeneity test results for East and North-South.

Variables	(1)	(2)
	The Southern part of the country	The Northern part of the country
dig	0.401**	0.130
	(2.473)	(1.076)
gdp	−0.0646**	0.0138
	(−2.382)	(0.999)
dag	1.903	−0.130
	(1.539)	(−0.301)
med	0.106	0.0382
	(1.101)	(0.644)
psi	−0.354	0.726**
	(−0.358)	(2.344)
wag	0.242	−0.0889
	(0.552)	(−0.434)
Individual fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Constant	0.852***	−0.797***
	(5.688)	(−6.396)
Observations	195	195
R-squared	0.411	0.695

demarcation line of the south and the north "Qinling-Huaihe River." The southern region includes 15 provinces, including Jiangsu, Anhui, Hubei, Hunan, Sichuan, Chongqing, Yunnan, Guizhou, Guangdong, Guangxi Zhuang Autonomous Region, Fujian, Zhejiang, Shanghai, Jiangxi, and Hainan. The northern region includes Beijing, Tianjin, Hebei, Shaanxi, Shanxi, Inner Mongolia Autonomous Region, Heilongjiang, Inner Mongolia Autonomous Region, Jilin, Liaoning, Ningxia Hui Autonomous Region, Henan, Shandong, Gansu, Qinghai, and Xinjiang Uygur Autonomous Region, totaling 15 provinces.

The regression results are shown in Table 10. Columns (1) and (2) show the regression results of digital village construction on rural land use efficiency in the southern and northern regions, respectively. From the results, the promotion effect of digital village construction on the efficiency of rural land use in the southern region has already appeared, while the promotion effect on the efficiency of rural land use in the northern region has not yet appeared.

The construction of digital rural areas has had differential impacts on the efficiency of rural land use in the south and north. We believe that there are three main reasons for the impact of regional differences. Firstly, the level of economic development in the south is stronger than that in the north. The construction of digital rural areas predates that of the north, and in terms of speed, the development of digital rural areas in the south is also faster than that in the north. According to the "Research Report on Taobao Villages in China (2009–2010)," in 2013, only seven provinces in China, namely, Zhejiang, Guangdong, Jiangsu, Shandong, Hebei, Fujian, and Jiangxi, had Taobao villages. In terms of proportion, the number of Taobao villages in the southern region reached 70%. By 2014, this proportion had reached 80.2%. From 2015 to 2016, the proportion of Taobao villages in the southern region had reached 82.9%. Although this proportion has decreased since 2016, it still remained at 75.1% in 2020, indicating that the construction of digital villages in the southern region has a first mover advantage and has a significant promoting effect on rural land use efficiency. For the northern region, it is necessary to continue to work hard to tap into the potential of digital rural construction and help improve the efficiency of rural land use. Secondly, there are differences in natural resources and resource endowments. In the southern region, the climate is warm and humid, which is more suitable for the growth of crops. Abundant water resources are conducive to irrigation and agricultural water use, and can improve the efficiency of rural land use. In the northern region, the climate is cold and dry, the agricultural production cycle is long, and it is greatly affected by seasonality. The relative scarcity of water resources limits irrigation conditions, which may affect the improvement of land use efficiency. Thirdly, there are differences in talent reserves and training. In the southern region, the talent reserve is more abundant, and the ability in digital literacy and innovation is stronger. There are numerous universities and research institutions, which are conducive to the research and promotion of digital agricultural technology. The government and enterprises attach great importance to talent

TABLE 11 Results of the heterogeneity test for food functional areas.

Variables	(1)	(2)	(3)
	Major agricultural region	Major food marketing area	Food balance area
dig	0.341**	0.725**	0.227
	(2.218)	(3.323)	(1.622)
gdp	−0.0143	0.0228	0.00528
	(−0.743)	(0.712)	(0.323)
dag	0.0582	−2.410	−0.309
	(0.124)	(−1.705)	(−0.786)
med	−0.0602	−0.235	0.0397
	(−0.640)	(−1.704)	(0.575)
psi	−0.327	−2.075	1.087**
	(−0.961)	(−1.195)	(2.287)
wag	0.370**	−0.276	0.354**
	(2.281)	(−1.246)	(2.045)
Individual fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Constant	0.500***	1.181***	−1.039***
	(5.047)	(6.378)	(−7.994)
Observations	169	91	130
R-squared	0.374	0.475	0.622

cultivation and introduction, providing strong talent guarantee for the construction of digital countryside. In the northern region, talent reserves are relatively scarce, and digital literacy and innovation capabilities need to be improved. The number of universities and research institutions is relatively small, and the research and promotion capabilities of digital agriculture technology are limited. The government and enterprises do not attach enough importance to talent cultivation and introduction, which has affected the process of digital rural construction.

5.3.5.3 Heterogeneity of functional food areas

Guaranteeing food security is the primary task of the current modernization of agriculture and rural areas. Therefore, food functional zones have a pivotal position for China's agriculture. Therefore, whether digital village construction has a heterogeneous effect on rural land use efficiency in food functional areas deserves further study. According to the division criteria of the Ministry of Agriculture and Rural Affairs, the sample is divided into main grain producing areas, main marketing areas, and balance areas. The main grain producing areas include Hebei Province, Shandong Province, Jiangsu Province, Anhui Province, Liaoning Province, Jilin Province, Heilongjiang Province, Inner Mongolia Autonomous Region, Jiangxi Province, Henan Province, Hubei Province, Hunan Province, and Sichuan Province. The main grain marketing area includes Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong and Hainan provinces. The Grain Balancing Area includes Shanxi Province, Guangxi Zhuang Autonomous Region, Chongqing Municipality, Guizhou Province, Yunnan Province, Shaanxi Province, Gansu Province, Qinghai Province, Ningxia Hui Autonomous Region, and Xinjiang Uygur Autonomous Region.

The regression results are shown in Table 11. From the empirical results, the digital village construction has a significant promotion effect on the rural land use efficiency in the main grain production area and the main grain marketing area, while it has no significant effect on the rural land efficiency in the grain balance area. This shows that digital village construction has an unbalanced impact on grain functional areas, which also reflects the phenomenon of "digital divide" in China's grain functional areas, especially the obvious difference between grain balanced areas and grain main production areas and grain main marketing areas.

The construction of digital rural areas has had a differential impact on the efficiency of rural land use in food functional zones. We believe that the reasons for the impact of regional differences are: firstly, the division of the three major functional zones for grain is the result of the adjustment of the relationship between people and land in each region (Guo and Liu, 2023), which has led to practical problems such as "transporting grain from the north to the south." In this actual situation, it not only increases the environmental carrying capacity of the main grain producing areas in the north, but also poses certain challenges to the circulation efficiency and grain loss costs of the main grain selling areas. Due to the development of digital technology, the construction of digital rural areas can provide technical support for precise production, intelligent operation, and high-precision services of agricultural products, while improving the

efficiency of rural land use, expanding production, and reducing unnecessary costs. Secondly, there are differences in cooperation and sharing mechanisms between regions. The cooperation and sharing mechanisms between different food functional zones can also affect land use efficiency. A sound regional cooperation mechanism has been established in the main grain producing and main grain selling areas, realizing the sharing and promotion of digital agricultural technology. Areas lacking cooperation mechanisms in the grain balance zone may face problems such as technological isolation and resource waste. The construction of digital rural areas requires information sharing and collaborative management. A unified spatial information platform has been established in the main grain producing and main grain selling areas, achieving information sharing and collaborative management among multiple departments. Areas with lower levels of information sharing in the grain balance zone may face problems such as information silos and low management efficiency. Therefore, Hypothesis 1 in this article is once again confirmed.

6 Conclusion and policy recommendations

China's agricultural development has made rapid progress, and the total output of agricultural products as well as exports have been rising, but the food self-sufficiency rate has not been significantly increased, reflecting from the side that China's rural land-use efficiency has not been effectively utilized, and that the growth of output of cultivated land area needs to be urgently improved. Therefore, how to empower rural land use efficiency through digital village construction is an important issue to realize steady growth of agricultural economy and improvement of land use efficiency. Different from what previous scholars have studied, this paper provides a feasible interpretation for promoting rural utilization efficiency from the perspective of digital village construction. In order to explain the core logic, firstly, the impact of digital village construction on rural land use efficiency is empirically examined; secondly, the mediating effect model is used to examine the mechanism played by the mismatch of agricultural resource factors; and lastly, the heterogeneous impact of digital village construction on rural land use efficiency is systematically analyzed from the perspectives of regional differences, south-north differences, and food functional areas.

This paper selects data from 30 provinces in China from 2010 to 2022, and after empirical analysis using fixed-effects model and mediated-effects model, it is found that, firstly, digital countryside construction improves rural land use efficiency, and the results still hold after endogeneity and robustness test; secondly, mechanism analysis finds that digital countryside construction can alleviate land resource factor mismatch, capital resource factor mismatch, and labor factor mismatch, which in turn promotes the improvement of rural land use efficiency; third, heterogeneity analysis finds that at the zoning level, digital rural construction promotes rural land use efficiency more strongly in the eastern region. At the geographic location level, digital village construction has a stronger role in promoting rural land use efficiency in the southern region. At the level of food functional areas, digital village construction has a stronger effect on the promotion of rural land use efficiency in the main food production areas and the main food marketing areas.

Based on the above findings, this paper has the following policy implications:

First, the empirical results indicate that digital rural construction is beneficial for improving the efficiency of rural land use. Therefore, regions need to continue to promote the construction of digital villages and deeply consolidate digital village infrastructure. In future development, it is necessary to build new infrastructure, attract more investment to the rural market, expand the rural coverage of 5G networks, promote the coverage and upgrading of rural power grids through the government, accelerate the "information into villages and households," and improve the infrastructure of the digital countryside through a variety of ways. At the same time, according to the resource endowment of each region, we will create special agricultural products and establish a digital platform for production, processing and sales. Improving the efficiency of rural land use through digital technology can transform and upgrade agricultural development, improve total factor productivity, encourage the transfer of land resources in a variety of ways, promote the improvement of the efficiency of the scale of rural land, create a new form of agriculture, and improve the capacity of sustainable development for the construction of digital villages.

Second, the empirical results indicate that digital rural construction can further improve the efficiency of rural land use by alleviating resource misallocation. Therefore, in future development, it is necessary to deeply explore the mitigating effect of digital rural construction on the mismatch of resource and promote the improvement of rural land use efficiency. In terms of land elements, through digital technology to build up strength, actively improve the total amount of rural land resources, the proportion of agricultural cultivated area, the efficiency of rural land use and other deficiencies, to further improve the mechanism of rural land transfer, reduce the cost of land transactions, and make full use of rural idle land resources. In terms of capital elements, accelerate the integration and development of digital technology and idle rural resources, turn them to capitalization development, expand the coverage of digital rural construction in the agricultural industry chain, and rationally allocate agricultural resources. Open up the information channel between agricultural products and the agricultural market, shorten the realization cycle of agricultural capital stock as much as possible, introduce more capital into the rural market, alleviate the constraints of financing constraints on agricultural products, and optimize the efficiency of rural capital allocation. In terms of labor factors, through the digital information platform to increase the training of the rural labor force, efforts to improve the digital literacy of the rural labor force, with the help of digital technology to improve the ability of the labor force to use the land.

Third, the empirical results indicate that the construction of digital rural areas has heterogeneous effects on the efficiency of rural land use improve the non-equilibrium characteristics of digital rural construction caused by regions and differentiate the development of digital rural construction. In regions with first-mover advantages, such as eastern China, southern China, and the main grain-producing and main marketing areas, the dividends brought by digital technology should be steadily pushed forward, the layout of digital agricultural scenarios should be accelerated, the penetration effect of digital elements into the construction of the

countryside should be improved, and the digital virtual economy should be deeply integrated with the real economy of agriculture, so as to create a digital information center of agriculture centered on land resources, and to play a leading role in the digital countryside construction. Role due to the non-equilibrium capacity of digital rural construction, in the future development, it also focuses on strengthening regional cooperation and exchanges, and rapidly promotes the synergistic development of digital rural construction. The central and western regions, northern regions and food balance areas make full use of the "east counts and west counts," grasp the advantage of latecomers, and steadily promote and catch up with the regions with first-mover advantages, so as to make the digital village construction break the technological divide, promote the balanced development of various regions, build a cooperation platform between the regions with first-mover advantages and the regions with late-mover advantages, and narrow the digital divide between different regions. The digital divide between different regions will be narrowed. On the road of future agricultural construction, agriculture, processing industry and service industry will be connected, the cost of applying digital technology in villages will be reduced, and a new model of Chinese agriculture will be formed.

Finally, improve the regulatory system of digital village construction to reduce risks. A perfect regulatory system can reduce the unexpected risks in the construction of digital countryside, which is crucial for agricultural development and land use efficiency. The application of digital technology in accelerating the speed of information exchange and reducing information costs while distinguishing new features from traditional agricultural information, the need for targeted supervision based on the characteristics of digital rural construction, to ensure the efficiency of the application of digital technology and technical safety, and the establishment of data and information sharing mechanisms for digital rural technology. Rural land transactions have their own characteristics, and risks are very likely to occur when carrying out land transfers; therefore, it is necessary to establish an all-round supervision procedure for transactions before, during and after the event, in order to effectively improve the utilization efficiency of rural land.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZF: Conceptualization, Data curation, Formal analysis, Investigation, Software, Writing–original draft, Writing–review and editing. FG: Formal analysis, Funding acquisition, Methodology, Project administration, Validation, Writing–original draft, Writing–review and editing. CB: Data curation, Formal analysis, Supervision, Validation, Conceptualization, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Xiuyi Shi,
Southeast University, China
Tianshu Quan,
Nanjing Forestry University, China

*CORRESPONDENCE
Ming Xu,
b2023140200181@stu.swupl.edu.cn

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The impact of land transfer on food security: the mediating role of environmental regulation and green technology innovation

Ming Xu[1,2]*, Zhaoyang Lu[1], Xinyue Wang[3] and Guangwei Hou[4]

[1]School of Economics, Southwest University of Political Science and Law, Chongqing, China, [2]School of National Security, Southwest University of Political Science and Law, Chongqing, China, [3]Department of Economics and Management, Faculty of Management and Economics, Sultan Idris Education University (UPSI), Tanjong Malim, Malaysia, [4]Zheng Chengxin Law Firm, Shandong, China

Introduction: Food security is the lifeblood of national security and an important cornerstone for world 15 peace, stability, and development. In this context, the study of the impact of land transfer (TF) on food security (FS) provides a new perspective for land resource optimization.

Methods: Based on the empirical data of 30 provinces and regions in China from 2010 to 2022, this paper used the two-way fixed effect model to explore the causal relationship and the intermediary relationship between the two. Moreover, quantile regression is used to further explore the heterogeneity. In addition, the spatial Durbin model is used to analyze the spillover effect.

Results: First, land transfer has a significant promoting effect on food security. Secondly, land transfer has obvious heterogeneity to food security. Third, environmental regulation and green technology innovation play an intermediary role in land transfer to food security. Fourth, land transfer has a spatial spillover effect on food security.

Discussion: This paper not only enriches the theoretical research on the impact of land transfer on food security, but also provides empirical evidence. It provides an important reference for deepening China's land transfer policy system, optimizing land transfer resources and ensuring the safety of grain industry.

KEYWORDS

land transfer, food security, environmental regulation, green technology innovation, land resource optimization

1 Introduction

Food security, as a crucial aspect of daily life, is central to economic and social stability as well as sustainable development. As a typical agricultural country, China has played a prominent role in ensuring the supply of agricultural products and providing food and nutrition (Li et al., 2025). By 2023, China's grain output has remained above 1.3 trillion kilograms for nine consecutive years, and its *per capita* grain consumption has reached 493 kg, far higher than the internationally recognized food security line, providing important support for preventing hunger and stabilizing social development (Liu et al., 2025). However, it is undeniable that China is still a country that relies on food imports, which undoubtedly brings major hidden dangers to China's food security in the context of unstable international trade (Subramaniam et al., 2024). As an important factor of

production in the grain industry, land is not only an important resource to ensure social stability but also the core of food security. By the end of 2023, the transfer rate of contracted rural land management rights in China will be 36.73 percent, and the transfer area of farmland contracted by households will increase from 270 million mu to 565 million mu, accounting for 40 percent of the country's total farmland contracted by households from 22 percent. It is worth noting that although the scale of agricultural land transfer continues to expand, there are still problems such as cultivated land wastage, extensive use of cultivated land, reverse transfer, and low efficiency of agricultural land transfer (Pei et al., 2019). Although China's policy system of strengthening agriculture, benefiting farmers, and enriching farmers have been continuously improved, under the background of China's extensive agricultural economic model, the tight pattern of food supply and demand in China has not changed fundamentally (Li et al., 2023; Wei et al., 2024a). Therefore, studying the impact of land transfer on food security has important theoretical and practical value for formulating scientific land policy, optimizing land resource allocation, and promoting agricultural modernization.

At present, the research on land transfer mainly focuses on three aspects. First, from the perspective of farmers' income, promote rural labor transfer by exploring land transfer (Huo and Chen, 2021; Tian et al., 2021), Improving the education level of the rural labor force (Liu et al., 2023; Zhang, 2024), Improving land value (Wang et al., 2018), Promoting the transformation of Rural development (Qi and Yang, 2022; Li et al., 2023) and other ways to achieve farmers' income growth, and how to achieve agricultural modernization through these ways. Second, from the perspective of agricultural production efficiency, this paper analyzes how land transfer can be passed through the land policy system (Guo and Liu, 2021; Lv, 2023), Allocation of Agricultural Resources (Fei et al., 2021; Li et al., 2022), land asset structure (Kaletnik et al., 2020; Wang et al., 2020) and other methods to promote the comprehensive development of agriculture. Third, from the perspective of ecological environment impact, the green emission reduction through land transfer is analyzed (Song et al., 2021; Zhong et al., 2022), Green Technology Innovation and Progress (Lu et al., 2020; Lyu et al., 2022) Environmental Regulations (Li et al., 2022; Xu et al., 2022) and other methods to improve agricultural ecological efficiency, and how to achieve green and sustainable agricultural development by protecting the ecological environment.

Additionally, research on food security also emphasizes three key aspects: First, from the perspective of policy implementation, through environmental policy (Lang and Barling, 2012; Huang et al., 2024) Political Will (Prosekov and Ivanova, 2018), Land Policy (Cui and Shoemaker, 2018; Wu and Zhang, 2024) and other policy tools to ensure food security. Second, from the perspective of security risks, through the analysis of food quality risks (Umarjonovna and Gulomjonovna, 2022), food environmental risks (Gregory et al., 2005), food health risks (Havas and Salman, 2011) and other typical international food security risks, and respond to alleviate food security problems from the risk level. From the perspective of agricultural development, research on improving the level of food technology (Li et al., 2021; Zou and Mishra, 2024), food production and supply level (Barrett, 2010), economic development level (Lv, 2023), and other methods protect food security from achieving high-quality agricultural development.

While existing studies offer valuable insights into the relationship between land transfer and food security, few have directly investigated the direct impact of LT on FS. The effectiveness of land transfer is subject to external factors such as agricultural resource endowment conditions and grain production technology, so it is necessary to adopt local measures to improve land use efficiency. At the same time, from the perspective of top-level policy design and practical effects, grain production benefits and economic benefits are equally important, which serves as a crucial foundation for assessing the effectiveness of land transfer policies. However, most existing research is limited to theoretical research, not from the perspective of experience to explore, lacks broad representation, and the comprehensive evaluation effect is limited. Therefore, assessing the impact of LT on FS also requires careful consideration of a more scientific and broader perspective.

Due to the obvious differences in geographical conditions, resource endowment, ecological environment, and other aspects of different countries and regions, there are also differences in how to solve food security problems, especially in food production goals, food production capacity, and the adoption of new agricultural technologies (Gartaula et al., 2024). In this context, even with the implementation of the land transfer policy, regional topography can lead to variations in grain production efficiency and the sustainable development of the grain industry, landform, technology, ecology, and other problems, and thus the alleviation of food security problems will also show different levels. When the ecological environment and technological innovation in the region are consistent with the structure of grain production factors, the improvement of environmental benefits and the improvement of green technological innovation level will help grain enterprises make better use of the endowment advantages of the region and improve the production efficiency of grain enterprises. Redundancy of factor inputs can also be avoided (Robertson and Swinton, 2005). In addition, the implementation of environmental monitoring policies will make it easier to ensure land quality, help promote the implementation of land transfer policies, and further ensure that food production is not threatened by the environment. The introduction of advanced agricultural green technology not only improves the efficiency of land use, and reduces the cost of grain production, but also further improves the efficiency of grain output. In summary, environmental regulation and green technology innovation play a mediating role in the impact of LT on FS. Therefore, integrating environmental and technical factors into the food security research framework and exploring the mediating effects of different factors in land transfer policies is crucial for effectively ensuring food security.

As the most populous country in the world, China has a huge demand for food and plays a key role in ensuring food security in the international community. However, with resource constraints and changes in grain consumption structure, grain demand is still facing a situation of unbalanced supply. At the same time, China's agricultural resources are unevenly distributed, especially in backward areas, where there are problems such as poor land and limited ecological conditions, leading to huge challenges in grain production. For most developing countries, agricultural production relies heavily on the production level of the rural labor force. However, with the continuous advancement of urbanization, rural labor forces continue to transfer to cities and towns,

resulting in an increasingly high degree of arable land wastage, which in turn leads to a decrease in food output (Benton and Bailey, 2019). As the traditional agricultural development model becomes unsustainable, land transfer has become essential for enhancing the efficiency of rural labor and land in the process of agricultural modernization. In this context, although China implemented the land transfer policy relatively late, it has achieved significant improvement in land use, quality, transfer, and management, and its development momentum is obvious. In addition, by learning from the land and grain enterprises of developed countries, China constantly attaches importance to agricultural technology innovation, agricultural policy support, and agricultural professional personnel training, which not only effectively alleviates the domestic food security problem, but also provides reference experience for the development of the global food industry. Thus, using China as a case study, examining the impact of LT on FS can offer a scientific foundation for the high-quality, modern, and sustainable development of China's grain industry, while also providing valuable insights for other developing countries.

In summary, the marginal contribution of this paper to the existing literature is as follows: First, explore the impact of LT development on FS, and provide new empirical evidence for verifying the optimization of land resources from the perspective of food security. Second, considering the differences between different geographical and quantile, the heterogeneity analysis of LT on FS is deepened. Thirdly, by introducing environmental regulation and green technology innovation as intermediary variables, this paper systematically analyzes how LT acts on FS through these mechanisms, thereby enriching theoretical models and application practices in the field of land and food. By deepening the knowledge of the application of land circulation in the field of food, this paper provides ideas for optimizing the allocation of land resources, solving the problem of food security, and realizing the sustainable and modern development of agriculture.

2 Theoretical mechanism

2.1 Policy background

Promoting land transfer is an important measure for the government to vigorously develop agriculture, aiming at improving land use efficiency, improving agricultural productivity, ensuring food security, and promoting sustainable agricultural development. As previously stated, many developed countries have realized that to improve agricultural productivity and sustainable development, land transfer is indispensable. In China, agriculture and the food industry play a fundamental role in the national development process. However, for a long time, the traditional farming methods of crops in China have been inefficient, and the grain infrastructure has been relatively backward, leading to major challenges in grain production. Therefore, promoting land transfer and ensuring food security is not only of great significance but also has a distinct policy development trajectory.

For land transfer, in 1978, China introduced the household contract responsibility system, which created the foundation for land transfer. This reform separated land ownership from contracted management rights and laid the foundation for the reform of rural land management forms (Lin, 1991). In 1988, restrictions on the transfer of contracted rural land management rights were relaxed, providing a solid policy foundation for land transfer. In 2010, land transfer began to enter the stage of deepening development, further consolidating the basic rural management system, providing specific operations for rural land transfer, and greatly enhancing the rationality and standardization of the transfer market. In 2019, it was emphasized to strengthen the management and service of land management rights transfer, promote the optimal allocation of land resources, and provide a solid guarantee for agricultural efficiency, farmers' income increase, and rural revitalization. In addition, the fundamental principle that the land transfer system will be protected by law has been clarified, and relevant rules have been improved to promote the efficient and reasonable allocation of land resources (Zhou et al., 2020). By 2024, the land transfer policy further emphasizes the need to strengthen and improve the formation mechanism of land transfer prices, explore effective strategies, and prevent unreasonable increases in transfer costs.

In terms of food security, in 1974, the Food and Agriculture Organization of the United Nations defined the goal of food security as "everyone can get enough food for survival and health at any time", and obtaining enough food to meet the needs of food security is the only consideration (Chen and Kates, 1994). In 1983, the price factor was introduced, and food security was not only about food but also about affordability. In 1996, the goal of food security was further expanded, and the food obtained should meet the requirements of food hygiene, health standards, and nutritional balance (Maxwell, 1996). In 2001, the International Food and Agriculture Organization (FAO) revised its definition of food security. With the worsening of the ecological environment, the risks to future food security have significantly increased. Therefore, the International Food and Agriculture Organization (FAO) proposed that food security means that "all people in need of food have access to sufficient, safe and nutritious food at the physical, economic and social levels at any time." To further meet people's needs for a healthy diet and people's different food preferences (Lang and Barling, 2012; Liu et al., 2025). By 2024, FAO believes that ensuring food security requires eliminating hunger and malnutrition and providing adequate funding for food security and nutrition.

2.2 Influence mechanism of land transfer on food security

From a dynamic perspective, any policy and regulation introduced by the government aims to ensure the stable operation of society and meet the needs of the people. As a key policy, land transfer not only supports large-scale farming but also plays a vital role in ensuring the safety and growth of the food industry. From a practical perspective, it is the most fundamental logic in economics to expand the economic scale to maximize food income. As the key to achieving agricultural economic scale, land transfer policy provides the possibility to promote LT to ensure FS (Liu et al., 2018). First of all, land transfer has a factor allocation effect. Land and transfer facilitate the redistribution of agricultural land to those with higher production capacities, concentrating land

in the hands of those capable of achieving greater grain output, this helps align land with production capacity, optimize the allocation of land resources, and ultimately enhance land use efficiency and grain production. Secondly, land transfer has the effect of scale management. The land transfer makes agricultural land concentrate from the hands of small farmers with dispersed management to large-scale and specialized growers and agricultural enterprises, which is conducive to the realization of moderate-scale management of agriculture, which can not only reduce agricultural production costs and obtain economies of scale. Finally, land transfer has an output effect. By promoting the optimal allocation of factors and the appropriate scale operation of the grain industry, land transfer can not only improve the efficiency of grain production but also protect the interests of farmers and increase the total agricultural output, thereby ensuring the sustainable development of agriculture. Therefore, this paper proposes the first hypothesis:

Hypothesis 1: LT has a promoting effect on FS.

2.3 Impact mechanism of land transfer on food security

At present, food security is facing severe challenges. For a long time, the development of China's grain industry has been subject to the influence of the agricultural ecological environment, and the development of grain enterprises relies more on agricultural policy support and lacks innovation awareness. As an important part of ensuring stable output of the grain industry, land transfer needs to strengthen government environmental control and agricultural green technology innovation in order to give full play to the promoting role of LT on FS (Wani et al., 2023). The land transfer policy itself has environmental benefits. On the one hand, with the expansion of the land management scale, environmental regulation and control will ensure food security from the root of food production. Moderate environmental regulation can not only directly reduce agricultural non-point source pollution emissions, but also guide and encourage more grain enterprises to switch from diversified planting to more efficient specialized planting, thus ensuring food quality and health issues. On the other hand, expanding the scale of land management can also lower the per-unit cost of agricultural green technology, thereby encouraging farmers to adopt more sustainable agricultural practices. It helps break the fragmentation and decentralization of small farmers' land management. Further enhancing the efficiency of sustainable grain production. In addition, the expansion of the land management scale, is conducive to the implementation of environmental regulations and the improvement of the level of green technology innovation, reducing the green production cost of grain enterprises, thereby improving the grain output capacity and output efficiency, and achieving the green and sustainable development of the grain industry. Therefore, this paper proposes the second hypothesis:

Hypothesis 2: Environmental regulation and green technology innovation play a mediating role in the influence of LT on FS.

2.4 Regional heterogeneity of land transfer on food security

Due to regional variations in economic development, resource distribution, and the ecological environment, the importance of land transfer and food security differs across China. Therefore, the actual effect of LT on FS will be different in different regions and at different levels (Gartaula et al., 2024). First of all, in areas with developed economic conditions, government departments pay more attention to land transfer policies and food security issues, the implementation cost of land transfer policies is relatively low, and the implementation obstacles are relatively few, which can better improve the productivity of grain enterprises and help alleviate inter-regional food security problems. Secondly, in economically backward areas, due to external factors such as relatively backward agricultural technology and a relatively poor ecological environment, it is difficult to implement land transfer policies in backward areas, and the food security problem cannot be alleviated. However, in the long run, the economically backward areas may have a "learning effect", learn from the experiences of economically developed regions and their land transfer policies, and then apply these lessons to address food security challenges. Finally, in areas with a higher degree of implementation of the land transfer policy, the land use efficiency is higher, which can give full play to the advantages of different land cultivation, effectively reduce the cost of grain cultivation, promote the improvement of grain production capacity, and effectively alleviate the problem of food supply. Based on these considerations, the paper proposes a third hypothesis.

Hypothesis 3: The effect of LT on FS has regional heterogeneity.

2.5 Spatial spillover effect of land transfer on food security

In the grain industry, in addition to the government as a promoter of the grain market, the transfer of agricultural land is also a very important market participant. As the basic link of grain production and management activities, local grain enterprises are likely to mimic the land transfer practices of neighboring areas to maximize their benefits, leading to an "imitation effect." (Zhang et al., 2024a). On one hand, in the grain and land transfer market, neighboring enterprises observe and replicate each other's practices. Which not only ensures that technical exchanges are not affected by administrative boundaries, this also fosters the growth and expansion of both the land transfer and grain markets. On the other hand, the institutional guarantees and financial subsidies provided by government departments in the region will provide strong help to land transfer and grain market. Local governments will learn from their previous experience in implementing agricultural land transfer policies, and based on the learning effect between neighboring governments, learn and follow the behaviors of neighboring local governments in agricultural land transfer policies and food security policies. In addition, the spillover effect is one of the important characteristics of technological innovation (Jaffe, 1986). The research development and application of new agricultural technology in a region can have a demonstration effect on the land and grain market in neighboring areas, which helps the phenomenon of "free riding" in neighboring

areas and enables grain enterprises to better enjoy the dividends brought by the spillover of technological innovation. To better alleviate the problem of food security. Therefore, this paper proposes a fourth hypothesis.

Hypothesis 4: The spatial spillover effect of local LT on FS in adjacent areas.

3 Methods

3.1 Model setting

3.1.1 Benchmark model

Based on the above analysis, the bidirectional fixed effect model will be used in this study to verify the impact of land transfer on food security. The bidirectional fixed-effect model can accurately evaluate panel data, limit the source of bias to variables that change over time, and estimate the coefficient of the regression variable more accurately. The specific formula is as follows:

$$FS_{i,t} = \alpha + \beta_1 LT_{i,t} + \beta_2 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

In model (1), FS is the explained variable, representing food security, and LT is the core explanatory variable, representing land transfer; X is the set of control variables, i and t respectively represent the i province, the t period, μ_i represents the fixed effect of the region, λ_t represents the fixed effect of the year, and $\varepsilon_{i,t}$ represents the random disturbance term.

3.1.2 Mechanism model

In addition, investigate the possible mediating effect of land transfer on food security, we further added environmental regulation and green technology innovation into the benchmark model (1), and obtained model (2):

$$FS_{i,t} = \alpha + \beta_1 LT_{i,t} + \beta_2 Z_{i,t} + \beta_3 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

In model (2), $Z_{i,t}$ representative intermediate variable, environmental regulation and green technology innovation are the intermediate variables of this paper, and other symbols have the same meanings as in model (1).

3.1.3 Spatial model

To further examine the spatial spillover effect of land transfer on food security, model (1) is extended to spatial panel Durbin model (SDM):

$$FS_{i,t} = \alpha + \rho W FS_{i,t} + \beta_1 LT_{i,t} + \beta_2 X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

In model (3), ρ is the spatial autoregressive coefficient and W is the spatial weight matrix. The other symbols have the same meaning as model (1).

3.2 Variable selection

3.2.1 Explained variables

Food Security (FS). Food security is a key indicator of agriculture's sustainable development capacity, the goal is to safeguard the entire food chain from external threats at a lower cost during agricultural production. Specifically, FS is measured as follows.

(1) Index system. Referring to previous studies (Wang et al., 2024; Wei et al., 2024b), constructed an indicator system including "food supply security, food production security, food access security, and food sustainable security". These indicators form a comprehensive system for measuring food security. Unlike most studies, this research considers the entire food industry chain as a key measure of food security, and evaluates the possible threats to the safety of the food industry before, during, and after production, which not only helps to improve the environment of the food industry but also realizes the sustainable development of the food industry and promotes the sustainable development of agriculture. The specific measurement indicators of FS are shown in Table 1.

(2) Measurement model: The entropy method, known for its efficiency and accuracy, is widely used in academic research due to its scientific and practical advantages. This study also employs this method to measure FS.

Figure 1 illustrates the changes in food security levels in China from 2010 to 2022. As shown, there are significant differences in FS between different regions. Specifically, the FS level in the eastern and central regions is at the leading level compared with the western region, which may be due to the better grain production conditions, storage conditions, and technical conditions in the eastern and central regions, which also indicates that the western region still has greater room for progress in ensuring FS. On the whole, the development of food security in China shows positive progress, but there is still a need to further optimize agricultural resource allocation, improve resource utilization efficiency, and achieve sustainable food industry development to ensure long-term FS.

3.2.2 Explanatory variables

Land transfer (LT), refers to the process of transferring, leasing, or jointly managing rural household-contracted farmland for a specified period, aiming at improving the efficiency of land use, optimizing the allocation of agricultural resources, and ensuring the security of agricultural development. Refer to previous studies (Yang et al., 2021; Zhang et al., 2024b) determined the specific measurement index of land transfer as the ratio of the area of cultivated land under household contract to the total area of cultivated land under household contract. By calculating this ratio, the relationship between the area transferred and the total area of cultivated land under household contracts can be understood. A higher ratio indicates a greater degree of land transfer, while a lower ratio indicates a smaller degree of land transfer. This index not only reflects land use efficiency, farmers' operational scale, and land resource allocation but also provides a scientific basis for formulating and implementing rural land transfer policies. The LT results, shown in Figure 2, indicate a fluctuating yet upward trend from 2010 to 2022, highlighting China's increasing focus and efforts on LT.

TABLE 1 System of indicators of the level of food security.

Target level	Primary indicators	Secondary indicators	Tertiary indicators (units)	Weights	Quality
FS	Food supply security	Volatility of total food production	(Total food production in the current year - average of total food production in the last 5 years)/total food production in the current year (%)	0.012	-
		LT mobility	Cultivated LT *per capita* (mu/person)	0.047	+
		Grain reserves	Total grain production (tons)	0.054	+
		Resilience of crops to disasters	Area affected by crops/area sown with crops (%)	0.004	-
		Food supply stability	Grain purchases (tons)	0.102	+
		Food Circulation	Grain sales (tons)	0.064	+
	Food production security	Stability of food production	Grain sown area (millions of hectares)	0.050	+
		Agricultural financial support level	Grain sown area/Total sown area (%)	0.016	+
		Agricultural innovativeness	Total power of cropLT machinery (10,000 kW)	0.050	+
		Level of human capital	Qualified food workers (persons)	0.079	+
		Agricultural productivity	Gross agricultural output/primary sector employment (yuan/person)	0.296	+
		Infrastructure development	Number of agricultural water conservancy facilities constructed (units)	0.076	+
	Food access security	Rural Engel coefficient	Rural food consumption expenditure/total consumption expenditure (%)	0.005	-
		Food price volatility	(Current year food price index - previous year food price index)/Current year food price index (%)	0.004	-
		Food share	Total food production/resident population (tons/person)	0.044	+
		Road density	Length of transport routes (rail, road, waterway)/Urban area (km/sq km)	0.053	+
	Sustainable food security	Pesticide application rate	Pesticide application per unit of food sown area/Crop sown area (%)	0.004	-
		Fertilizer application rate	Fertilizer application per unit of food sown area Crop sown area (%)	0.008	-
		Agricultural film use	Agricultural film use per unit of food sown area/Crop sown area (%)	0.004	-
		Quality assurance	Effective irrigated area/crop sown area (%)	0.030	+

All indicators are calculated by the authors themselves.

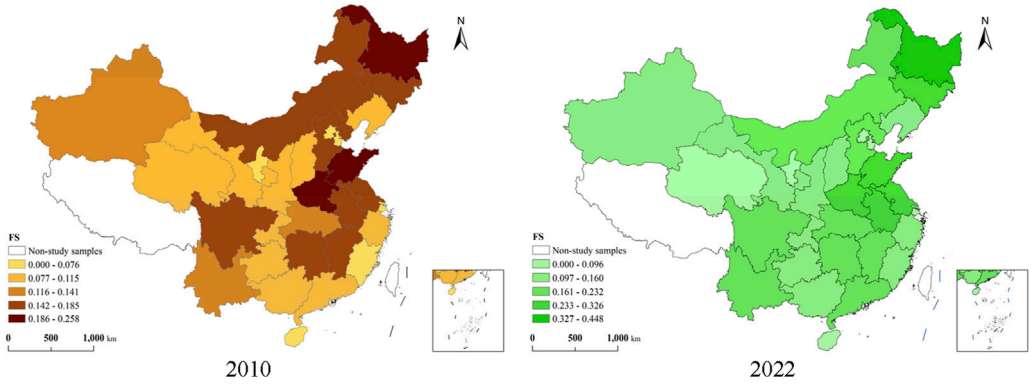


FIGURE 1
FS level.

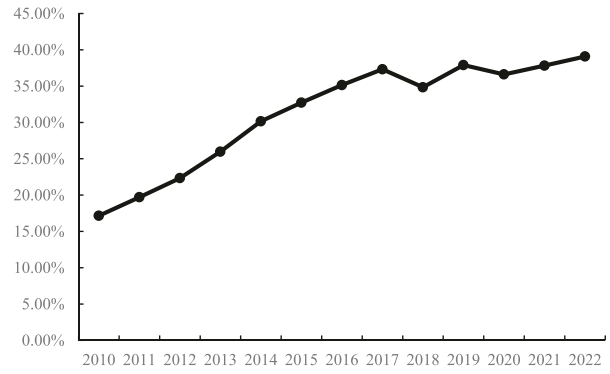


FIGURE 2
Land transfer level from 2010 to 2022.

3.2.3 Control variables

Considering that there are many factors affecting the level of food security, this paper refers to the published literature (Zhou et al., 2022; Wang et al., 2023). The following control variables are set in this paper, as shown in Table 2.

3.2.4 Mechanism variables

Environmental regulation. With the increasing emphasis on the environment in China, environmental regulation is an important means to affect land transfer and food security. Refer to the published literature (Zou and Wang, 2024; Zhou et al., 2021). First, this paper will choose the logarithmic form of the completed investment in industrial pollution control to measure environmental regulation (IPI). Secondly, the ratio of gross regional product to total energy consumption is used to measure environmental regulation (EG). Overall, industrial pollution control and energy consumption are important factors in China's environmental governance. Higher investment in pollution control and a greater share of green energy consumption reflects the effectiveness of government environmental regulations. Therefore, a higher ratio indicates a stronger environmental regulatory capacity.

Green technology innovation. Referring to previous studies (Xu and Lin, 2024; Yu et al., 2024) Two different ways are adopted to measure green technology innovation. First, the logarithmic form of the ratio of regional technology market turnover to GDP is selected as green technology innovation capability (TMT). Secondly, the ratio of R&D expenditure of regional industrial enterprises to GDP is used to measure green technology innovation capability (R&DE). Overall, regional technology turnover and industrial enterprise R&D funds are important inputs to promote green technology innovation. Technological innovation will reduce industrial production costs, and the reduction of production costs is the best reflection of green technology innovation. Therefore, the greater the ratio, the stronger the ability of green technology innovation in the industry.

3.3 Data sources

This paper is based on the reality of land transfer and food security in China, but there is a certain lack of statistical data in Xizang, Hong Kong, Macao, and Taiwan in China, to take into account the availability and operationalization of LT and FS data, and to obtain as much as possible a more complete data resource as well as to reflect the latest situation of LT and FS in China, this paper sets the time interval of the sample data as 2010–2022, and The sample cities are selected from 30 provinces in China. The sources of data are the China Land Statistics Yearbook, China Grain and Material Reserve Yearbook, China Statistical Yearbook, China Rural Statistics Yearbook, and provincial development work reports. In addition, for individual missing data problems, this paper will use linear interpolation to fill in the part. The results of the expressive statistical analysis are shown in Table 3.

4 Results

4.1 Baseline regression results

Before the baseline regression, the differential inflation factor was evaluated first. The results indicated that the average variance inflation factor (VIF) of the regression equation was 2.94, significantly lower than the critical value of 10, indicating that there was no obvious multicollinearity problem between the independent variables. This paper first investigated the regression results without introducing control variables, as shown in column (1) of Table 4. It was found that without adding control variables, the regression coefficient of land transfer (LT) was significantly positive, and LT had a positive impact on the improvement of the FS level. To

TABLE 2 Control variables.

Variable	Code	Definition	Unit
Industrial structure	IS	The proportion of the added value of the primary industry in the GDP of each province	%
Degree of agricultural mechanization	DAM	Logarithmic form of the total power of agricultural machinery in each province	Megawatt
Foreign direct investment	FDI	Logarithmic form of actual utilization of foreign direct investment by each province as a share of each province's GDP	%
Human capital	HC	Average years of schooling = (illiterate ×1+ number of primary school education ×6+ number of junior high school education ×9+ number of senior high school and secondary school education ×12+ number of college and bachelor's degree or above ×16)/total population over 6 years old	%
Urbanization rate	URBAN	The proportion of the urban population to the permanent population in each province	%

TABLE 3 Descriptive statistics of variables.

Variable	N	Average	SD	Min	Max
Food security	390	0.155	0.077	0.039	0.464
Land transfer	390	0.313	0.171	0.001	0.958
Industrial structure	390	0.098	0.053	0.002	0.258
Degree of agricultural mechanization	390	3417.614	2924.189	93.970	13,353.020
Foreign direct investment	390	11.935	59.559	0.770	833.705
Human capital	390	9.341	0.891	7.607	12.698
Urbanization rate	390	0.585	0.132	0.226	0.895
Industrial pollution investment	390	199,739.500	200,984.700	476	1416464
Proportion of energy consumption	390	0.105	0.071	0.030	0.409
Technology market turnover	390	0.017	0.028	0.001	0.192
R&D expenditure	390	0.110	0.060	0.017	0.324

TABLE 4 Baseline regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
LT	0.058*** (2.890)	0.060*** (3.080)	0.065*** (3.420)	0.062*** (3.270)	0.064*** (3.370)	0.053*** (2.680)
IS		0.497*** (4.500)	0.513*** (4.770)	0.509*** (4.75)	0.506*** (4.730)	0.476*** (4.400)
DAM			0.032*** (4.503)	0.033*** (4.710)	0.034*** (4.850)	0.038*** (5.150)
FDI				−0.005* (−1.700)	−0.005* (−1.780)	−0.005* (−1.81)
HC					0.106 (1.580)	0.110 (1.640)
URBAN						−0.114* (−1.730)
Year	Control	Control	Control	Control	Control	Control
Region	Control	Control	Control	Control	Control	Control
R^2	0.409	0.442	0.473	0.478	0.482	0.486
N	390	390	390	390	390	390

Note: The t statistic is in parentheses; *, **, *** are significant at the level of 10%, 5%, and 1% respectively, the following tables are the same.

further improve the accuracy and reliability of the study. In this paper, Model 1 is used to add different control variables to paragraphs (2) to (6) in order to carry out regression again, to more accurately capture the indirect impact of these potential influencing factors on the regression results. The results show that the coefficient of LT remains positive and significant at the 1% level, confirming that increased land transfer plays a crucial role in enhancing FS. It is important to note that the size of the LT coefficient remains largely unchanged with the inclusion of control variables, suggesting that the findings of this study are relatively robust, and further prove hypothesis H1.

4.2 Endogeneity test and robustness test

As demonstrated above, LT significantly promotes FS. To further validate the robustness of the baseline regression results, this paper will employ the following verification methods. In addition, in order to avoid endogeneity problems that may occur in regression, this paper will first conduct an endogeneity test and then conduct a robustness test. The specific methods are as follows:

First, is the instrumental variable method. Considering that the traditional bidirectional fixed effect evaluation model may have estimation bias and endogeneity problems, this paper chooses the stage lag of land transfer as the instrumental variable (Söderström and Stoica, 2002). The specific test results are shown in column (1) of Table 5. The value of the LM statistic is 298.823, which is far greater than the critical value of 10% significance level, indicating that there is no obvious problem of weak instrumental variables in the benchmark regression in this paper. In addition, the value of Wald F statistic is 1724.260, which is significant at a 1% level, rejecting the null hypothesis that the selected instrumental variables are not identifiable, which proves that the selection of instrumental variables is scientific and reasonable, and also proves that the baseline regression in this paper is robust.

Second, replace the model. Tobit regression model was adopted as an alternative model (Amemiya, 1984), and the results of Tobit regression were shown in column (2) of Table 5. The influence

TABLE 5 Robust regression of FS by LT.

Variable	(1)	(2)	(3)	(4)
LT	0.211*** (10.980)	0.083*** (4.440)	0.040* (1.940)	0.037* (1.870)
Control variable	Control	Control	Control	Control
Year	Control	Control	Control	Control
Region	Control	Control	Control	Control
LM statistic	298.823			
Wald F statistic	1724.260***			
N	360	390	360	390

coefficient of LT on FS remains significantly positive at the 1% level, further confirming the robustness of the baseline regression results in this paper.

Third, the control variable lags by one stage. According to Miao et al. (2024) research method, the robustness test selects the one-stage hysteretic method of control variables, this not only helps mitigate the endogeneity issue in estimating the benchmark model but also provides a scientific measure of its robustness The test results are shown in column (3) of Table 5. Although the significance level of the LT coefficient has slightly decreased, it remains significant, confirming the robustness of the baseline regression results in this paper.

Fourth, add a control variable. Economic development is an important factor affecting the level of local food security, which can not only provide the necessary capital input for agricultural production but also improve comprehensive agricultural efficiency (Bedasa and Deksisa, 2024). Therefore, this paper selects the logization of the GDP of each province as a measurement index to measure economic development and adds it to the benchmark regression model. The evaluation results in column (4) of Table 5 show that LT continues to have a significant positive effect on FS, further confirming the robustness of the baseline regression results.

4.3 Heterogeneity analysis

To further explore the effect of LT on FS, the study examines regional heterogeneity and uses quantile regression. This approach enhances the understanding of land transfer's impact and offers a more detailed perspective for policy formulation.

4.3.1 Geographical regional heterogeneity

Due to the significant differences in the level of economic development and soil type in different regions of China, the effect of LT may be affected to different degrees. Therefore, in order to better evaluate the performance of LT in different regions, we divided the sample into three regions: east, middle, and west. The results are shown in columns (1)–(3) of Table 6. The study found that LT had the most significant promoting effect on FS in the eastern region, and the influence coefficient was significantly positive at the 5% level. This is because the eastern region of China has a higher level of economic development and more advanced agricultural technology, making it easier to foster the high-quality development of the food industry. Additionally, the eastern region is primarily flat, and good ecological conditions can better promote LT to play its advantages in agricultural resource allocation. In contrast, the impact of LT on FS in the central and western regions is either insignificant or weak, highlighting the complex risks and challenges these regions face in implementing LT. For instance, the western region is predominantly characterized by hilly and mountainous terrain, and there are practical problems such as complex terrain and poor ecological conditions, and the economic development and agricultural frontier technology in the central and western regions are relatively backward. Therefore, the implementation cost of LT is high, and the improvement effect of grain production and acquisition efficiency is limited, which leads to the limited development of the grain industry.

TABLE 6 Regression of regional heterogeneity of FS by LT.

Variable	(1) Eastern	(2) Central	(3) Western
LT	0.037** (2.490)	−0.031 (−0.790)	−0.045 (−0.810)
Control variable	Control	Control	Control
Year	Control	Control	Control
Region	Control	Control	Control
N	143	104	143

4.3.2 Quantile regression

The advantage of quantile regression is that estimation conditions of different levels can be selected, and dependent variables can be captured through quantiles distributed under different conditions to more scientifically and accurately reflect the nonlinear relationship between LT and FS (Koenker and Hallock, 2001). Therefore, this paper selects nine quantiles, including 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%, to study the potential impact of LT on FS under different quantile conditions. The results are shown in Table 7. On the whole, LT has a statistically significant effect on FS, and its influence shows a steady upward trend from low score to high score, indicating that LT can produce significant improvement effects. In addition, it is worth noting that at the decimal point near 80%, the influence coefficient of LT shows a "decrease followed by an increase" trend. This finding reveals that during the implementation of LT, the marginal utility of LT is not a purely linear increase, but may briefly decrease when the

TABLE 7 Quantile regression.

Variable	FS	FS	FS	FS	FS	FS	FS	FS	FS
	P10	P20	P30	P40	P50	P60	P70	P80	P90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LT	0.093***	0.120***	0.125***	0.131***	0.138***	0.155***	0.173***	0.156***	0.210***
	(4.870)	(9.550)	(12.300)	(12.900)	(9.520)	(9.610)	(9.040)	(6.270)	(5.480)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	390	390	390	390	390	390	390	390	390

marginal effect reaches the critical point, and then increases again after the critical point. This finding is significant for governments in developing countries, suggesting that government agencies should actively support LT initiatives, continuously optimize the allocation of land resources, improve the efficiency of land use, and maximize the land benefit. In addition, as an important guarantee for the development of the food industry, the higher the degree of circulation of LT, the better to ensure that FS is not threatened by land elements, and the better to promote the sustainable development of agriculture.

4.4 Mediation effect

4.4.1 Environmental regulation

First of all, the conclusion above proves that environmental regulation has a mechanism function. Therefore, this paper chooses environmental regulation as the first intermediate variable based on Model 2 and selected the completed investment in industrial pollution control (IPI) and the proportion of GDP and energy consumption (EG) to characterize environmental regulation respectively, and added them to the model (2) as mechanism variables for evaluation. The experimental results are shown in columns (1) and (2) of Table 8. The conclusion indicates that the effect of LT on FS remains significantly positive at the 5% level even when IPI and, EG are included, with both IPI and, EG showing positive correlations at various levels. The results show that environmental regulation plays an obvious mediating role in the impact of land transfer on food security. By comparing the two measures, it is found that the coefficient and significance of investment in environmental governance are not as significant as the ratio of energy consumption, which shows that only strengthening investment in the environment is not enough, but should also focus on the actual environmental governance, and promote the green production of food with the green use of land, so as to better reflect food security. Hypothesis 2 is proven.

4.4.2 Green technology innovation

Secondly, according to the conclusions above, we choose green technology innovation as the second mediating variable in this paper. In addition, we selected the ratio of regional technology market turnover (TMT) and R&D expenditure (R&DE) to GDP respectively to measure green technology innovation capability and included it again as a mechanism variable in model (2) for regression. The test results are shown in Table 8 (3) and (4). The results showed that the coefficient of LT was positively significant at 1% and 5% levels, respectively, the coefficients of TMT and R&DE were also significantly positively correlated at the 1% level The results of the study verify that the use of green innovation technology can help to play the role of land transfer in promoting food security and prove the intermediary role of green technology innovation. By comparing the effect coefficients of the two types of technological innovation, it is found that R&D investment generates greater value, which directly indicates that in order to better guarantee food security, technological innovation has more far-reaching value in land transfer. Prove Hypothesis 2 again.

4.5 Space spillover effect

To further test the spatial spillover effect of land transfer on food security, this paper uses the spatial Durbin model (SDM) for spatial regression analysis of LT and FS, based on a geographic linkage matrix.

4.5.1 Moran index test

Before using a spatial model, it is necessary to verify the spatial correlation between explanatory variables and explained variables (Moran et al., 1994). In this paper, the Moran index test was conducted based on a geographic collar matrix, and the results are shown in Table 9. From 2010 to 2022, the global Moran index of LT and FS variables is significantly positive at 1% and 5% levels, respectively. From the perspective of the time dimension, the spatial correlation level of LT and FS in China presents an up-and-down amplitude, which may be due to the uneven development degree of LT and FS in different periods in China. Therefore, since both LT and FS have significant spatial autocorrelation, it means that the spatial correlation and spatial spillover can be further discussed in the regression analysis of LT to FS, which can prove that the use of spatial regression in this paper is scientific and reasonable.

TABLE 8 Mechanism test of FS by LT.

Variable	(1)	(2)	(3)	(4)
LT	0.052** (2.490)	0.044** (2.240)	0.045** (2.260)	0.056*** (2.830)
IPI	0.003* (1.820)			
EG		0.193*** (2.920)		
TMT			0.005** (2.260)	
R&DE				0.196*** (3.130)
Control variable	Control	Control	Control	Control
Year	Control	Control	Control	Control
Region	Control	Control	Control	Control
N	390	390	390	390

TABLE 9 Spatial correlation regression.

Year	LT	Z-value	FS	Z-value
	Moran's I		Moran's I	
2010	0.283***	2.742	0.189**	1.886
2011	0.287***	2.723	0.192**	1.915
2012	0.310***	2.899	0.217**	2.133
2013	0.333***	3.094	0.243***	2.371
2014	0.373***	3.439	0.264***	2.574
2015	0.349***	3.209	0.289***	2.885
2016	0.406***	3.685	0.306***	2.979
2017	0.420***	3.783	0.285***	2.803
2018	0.221**	2.324	0.295***	2.936
2019	0.430***	3.892	0.235**	2.342
2020	0.453***	4.120	0.216**	2.170
2021	0.416***	3.776	0.257***	2.565
2022	0.374***	3.392	0.207**	2.101

4.5.2 Spatial regression effect

Secondly, for the use of spatial models, after Wald, LM, Hausman, and other diagnostic tests, the optimal estimation method is the spatial-temporal dual fixed-effect SDM model, and the geographical connection and geographical distance are respectively adopted as the basic matrix, and the regression Model 3 is used to evaluate the results. The specific evaluation results are shown in Table 10. The results show that under various matrix conditions, the direct effect, spatial spillover effect, and total effect of LT on FS are all significantly positive, to varying degrees, which further proves hypothesis H4, which indicates that LT not only has a promoting effect on the development of FS in the local area but also has a significant promoting effect on neighboring areas. This indicates that LT has a regional spillover effect, promoting the positive development of FS within the region and also benefiting neighboring areas.

5 Discussion and policy implications

5.1 Conclusion

Through a detailed analysis of panel data from 30 provinces in China (excluding Xizang, Hong Kong, Macao, and Taiwan) from 2010 to 2022, this study deeply explores the impact of LT on FS, and draws the following four core conclusions:

First, the baseline regression results revealed a substantial and positive effect of LT on FS, a finding that persisted even after the inclusion of control variables. At the same time, robustness tests confirmed the reliability of these findings, and adjustments for various model specifications and control variables did not significantly change the conclusion that LT has a positive effect on FS. This conclusion highlights the critical role of increasing the frequency and efficiency of land use in protecting food security.

Second, the mediation effect test further revealed the specific mechanism of LT's influence on FS, in which environmental regulation and green technology innovation, as important intermediary variables, had a significant promoting effect on the improvement of FS. This indicates that LT can indirectly ensure food security and development by improving the intensity of environmental regulation and strengthening the development of green technology.

Thirdly, the results of heterogeneity analysis showed that there was heterogeneity of LT in different regions. LT significantly increased FS in eastern China, but had no significant effect on FS in central and western China. In addition, LT at higher points has a more obvious promoting effect on FS. This is due to the better economic conditions in eastern China, the higher comprehensive quality of the rural labor force, the higher degree of LT, and the higher degree of policy implementation, which can better promote the growth of FS.

Fourth, the spatial regression results show that LT has a spatial spillover effect on FS. This indicates that LT will promote FS geographically and spatially. This also indicates that the development in the local region can drive the development of FS in neighboring areas, which can have a learning effect and better promote the development of FS in the whole country.

To sum up, the practical contribution of this study is mainly reflected in that this study takes China as the experimental sample,

TABLE 10 Spatial spillover effect regression.

Geographical adjacency weight matrix	Geographic collar matrix			Geographic distance matrix		
	LR_Direct	LR_Indirect	LR_Total	LR_Direct	LR_Indirect	LR_Total
LT	0.035* (1.810)	0.185*** (3.850)	0.219*** (4.000)	0.059*** (3.070)	0.093** (2.230)	0.154*** (3.020)
Control variable	Control	Control	Control	Control	Control	Control
Area effects	Control	Control	Control	Control	Control	Control
Time effects	Control	Control	Control	Control	Control	Control
N	390	390	390	390	390	390

not only discusses the influence of LT on FS from the theoretical level but also verifies how LT affects FS from the empirical level, thus helping to enrich the research between LT and FS. On the one hand, it can provide ideas for China's land circulation and sustainable development in the future; On the other hand, it can also provide practical experience for other developing countries to further promote the high-quality development of the food industry by optimizing land resources, and provide important ideas for realizing the sustainable development of global land.

5.2 Discussion

In this paper, the influence of LT in China on FS was discussed, and the conclusion showed that LT had a significant promoting effect on FS, which verified hypothesis H1 in this paper, which was consistent with the results of existing literature (Alamirew et al., 2015). This indicates that in China's current grain production and management activities, the allocation of land resources is insufficient, the emphasis on land circulation is insufficient, and the construction level of agricultural infrastructure is not good, so it is necessary to strengthen the use of land resources to achieve FS. Environmental regulation and green technology innovation have mediating effects on the influence of LT on FS, which verifies hypothesis H2 and is consistent with the results of Pei et al. (2024). On the one hand, the implementation of government environmental control can better strengthen farmers' awareness of ecological environmental protection in grain production. On the other hand, the application of green technology can promote the improvement of production efficiency and the reduction of production costs of grain enterprises. In the eastern region with more developed economic development and the region with higher LT levels, LT has a significant positive impact on FS, especially in the region with higher LT levels, which proves that hypothesis H3 is consistent with the research results of Peng et al. (2021). This indicates that in areas with sufficient funds and high management levels, land transfer and utilization should be increased to ensure land use efficiency, while in relatively backward areas, more advanced agricultural technologies can be introduced to optimize land resource allocation to improve food security. From a spatial perspective, this paper proves that LT has a spatial spillover effect on FS, which is consistent with the conclusion of hypothesis H4 and the results of existing literature (Petrescu-Mag et al., 2019). China should increase the situation of land in different regions, and give full play to the advantages of regional land and geography, better allocate agricultural land resources, reduce waste in the production process, accurately control grain planting and sales, and better improve the efficiency of land use. In addition, we should also pay attention to inter-regional technical exchanges and achieve cross-regional technical support to better ensure the development of the food industry. For other developing countries, exchanges and support between different regions should be strengthened to achieve better development of FS through inter-regional driving and learning effects.

5.3 Policy recommendations

First, we will strengthen the infrastructure of the grain industry. Perfect basic hardware facilities are an important guarantee to promote the efficiency of land transfer and the high-quality development of grain industry. Therefore, government departments should increase investment in infrastructure, improve the level of grain industry infrastructure construction, give play to the guiding role of land policies, implement and implement the implementation of land regulations in various regions, and build a complete land transfer and supervision system. In addition, it is necessary to give full play to the government's capital investment in the field of land and food, promote the deep integration of production, university and research led by land and food enterprises, take market demand as the guidance, and constantly promote the rational distribution of land resources, which not only provides the core driving force for the stable development of the food industry, but also provides an important idea for optimizing land resources.

Second, promote the deep integration of government environmental regulations and agricultural green technology innovation. Environmental regulations and agricultural green technology innovation are the key factors to optimize land resources and ensure food security. It is suggested that the government strengthen the ecological environment control of the food industry and investment in agricultural scientific research funds, and accelerate the improvement and implementation of agricultural ecological environment laws and regulations, which can not only better protect the ecological environment of agriculture and land resources, but also reduce pollution emissions in the process of food production, so that food quality can be guaranteed. At the same time, through the development and

application of cutting-edge agricultural green technologies, promote the application of cutting-edge technologies such as smart agriculture and artificial intelligence in the land and food industry. While improving the efficiency of rural land use, it can also improve grain production capacity, help land resources be fully utilized, and further promote the sustainable development of the food industry.

Third, optimize the allocation of rural human capital and deepen the reform of the agricultural policy system. The comprehensive quality of the rural labor force is an important factor affecting the implementation and application of land transfer policy. It is suggested that the government strengthen the training of the comprehensive quality and comprehensive ability of the rural labor force, strengthen the learning of land use knowledge through reasonable guidance to farmers, cultivate agricultural land planting talents with professional skills, give full play to the advantages of land transfer, and optimize the utilization of land resources. On the other hand, the government should strengthen the implementation of agricultural policies, establish a sound land use and supervision system, reduce the cost of land use in the process of food production, improve farmers' land use efficiency, and give full play to the advantages of different land resources according to different land conditions, choose food planting methods according to local conditions, so as to ensure a steady increase in food output and better guarantee food security.

6 Research deficiencies and prospects

As a whole, this paper studies the impact of LT on FS from a provincial perspective, and confirms that LT plays an important role in promoting FS. However, it is undeniable that there are still shortcomings, and future research can be in-depth from the following three levels:

First, expanding the sample data. The data samples used in this study are at the provincial level, which can provide us with macro-level analysis, but more detailed and in-depth discussion of the impact of LT on FS in deeper geographical areas, future studies can refine the granularity of LT and FS data, and further expand the samples to prefecture-level and even county-level data. This will help us more accurately show the differences between LT in different geographical, and economic backgrounds and resource endowment conditions.

Second, deepen the evaluation of the effect of land policy implementation. Although the relationship between LT and FS is evaluated using a bidirectional fixed-effect model, the consideration of land policy application and implementation is still missing. Future studies should introduce land policy as an evaluation indicator and use a more comprehensive evaluation model to explore the long-term effects and potential impacts of LT on FS.

Third, take developed countries as research objects. Although this study takes China as an experience sample, it can provide some experimental basis for developing countries, but it can better show the advantages of LT policies in developed countries and the experience of land resource optimization in developed countries. Future research can choose developed countries as research objects, use developed countries' index data for evaluation and analysis, explore the development experience of developed countries' land and food industry, and put forward substantive suggestions for developing countries to optimize land resources and ensure high-quality development of the food industry.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

MX: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Writing–original draft, Writing–review and editing. ZL: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing–review and editing. XW: Supervision, Validation, Visualization, Software, Writing–review and editing. GH: Writing–review and editing, Supervision, Validation, Resources, Visualization.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Chante Jian Ding,
University of Malaya, Malaysia
Bo Chen,
Jinan University, China
Xianneng Ai,
Peking University, China

*CORRESPONDENCE
Xinyang Jiang,
jiangxy@bit.edu.cn

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The impact of urban polycentralization and scale expansion on economic efficiency: evidence from Chinese cities

Xinyang Jiang*, Siyi Wei, Chen Yi, Siyu Liu, Bo Yang and Yao Wu

School of Management, Beijing Institute of Technology, Beijing, China

Introduction: This study investigates the effects of urban polycentricity and city size on total factor productivity (TFP) in Chinese cities.

Methods: Using high-resolution population distribution data from Landscan and applying instrumental variable (IV) estimation to address endogeneity concerns, we construct a novel measure of urban polycentricity.

Results: Our findings show that while expanding city size enhances TFP through increased economies of scale, greater urban polycentricity negatively affects productivity by weakening agglomeration economies and innovation spillovers.

Discussion: The analysis suggests that polycentricity reduces the concentration of economic activities, which hampers knowledge diffusion and innovation, leading to lower productivity. Additionally, we identify the optimal city size for maximizing TFP, where excessive urban growth beyond a certain point becomes counterproductive.

KEYWORDS

total factor productivity (TFP), polycentricity, agglomeration effect, City size, innovation spillover, China

1 Introduction

With the fast advancement of urbanization, changes in urban spatial structure have emerged as a key factor influencing urban economic growth and development (Anas et al., 1998; Liu et al., 2020; Dadashpoor and Malekzadeh, 2020). Urban spatial structure not only governs the distribution and layout of functional sectors inside a city, but it also has a significant impact on resource allocation (Zhu et al., 2018), industrial development (Liu et al., 2021), and manufacturing efficiency (Yu et al., 2019). In recent years, scientists have focused on the significance of urban agglomeration effects in fostering economic development, particularly total factor productivity (TFP), a key indicator of urban economic efficiency (Thisse, 2018; Liu et al., 2024a). As the world's largest developing country, China's complexity of urbanization and diversity of urban spatial organization make this issue especially pressing. Changes in urban spatial organization, especially polycentric growth trends, are likely to have significant impacts on regional economic productivity and therefore deserve further study.

In China's urbanization process, many scholars have begun to pay attention to the formation and development of urban polycentricity (Liu et al., 2018; Liu et al., 2016; Yue

et al., 2019). Traditional urban planning emphasizes centralized development, but as urban agglomerations expand, polycentric spatial forms have gained popularity. Existing research primarily focuses on the relationship between city size, agglomeration effects, and economic outcomes such as GDP growth and employment distribution. However, few studies have systematically explored the impact of urban polycentricity on total factor productivity (TFP), a comprehensive measure of economic efficiency. Moreover, the mechanisms through which polycentric structures influence TFP—such as knowledge spillovers, innovation, and resource allocation—remain underexplored. These gaps limit our understanding of the costs and benefits of polycentric urban development, particularly in the context of developing countries.

This study aims to address these gaps by examining the impact of urban polycentricity on TFP and uncovering the underlying mechanisms. We investigate whether polycentricity enhances or hinders TFP, how this relationship varies across cities with different characteristics (e.g., population density, geographic location), and what policy implications can be drawn for optimizing urban spatial structures. By integrating theoretical insights with empirical analysis, our research not only contributes to the academic debate on urban planning and economic efficiency but also provides practical guidance for policymakers in developing countries facing similar urbanization challenges.

The primary goal of this research is to investigate the impact of urban polycentricity on regional total factor productivity and its mechanism of action through the lens of urban spatial structure and scale. First, using the *Landscan* high precision population distribution database, this paper quantitatively examines the polycentricity distribution level of Chinese cities. This dataset can provide accurate and thorough population distribution statistics, allowing for a more scientific approach to analyzing urban spatial structure. Second, this research employs Chinese prefecture-level city data from 2010 to 2019 and a variety of econometric models to investigate the impact of urban spatial organization on regional total factor productivity. The relationship between urban spatial structure, city size, and total factor productivity is examined using several econometric frameworks, and the underlying mechanism of action is investigated.

This article's empirical result reveal that urban polycentric structure has a considerable negative impact on regional TFP, whereas city size growth promotes TFP improvement. Specifically, even after controlling for city and year fixed effects, the coefficient of urban polycentricity remains negative, indicating that the polycentric structure reduces the city's TFP, whereas increasing city size increases TFP. Further investigation revealed that when city size was introduced, the absolute value of the polycentric effect was marginally reduced, indicating that city size mitigated the detrimental impact of polycentricity to some extent. Both the robustness test and the heterogeneity analysis results show that polycentricity in coastal cities has a more significant negative impact on TFP, while urban scale expansion has a positive impact on TFP, especially in megacities. Furthermore, urban polycentricity limits the city's TFP growth by increasing the geographical distance between centers, reducing innovation output, and diminishing innovation spillover effects.

The marginal contributions of this paper are reflected in the following aspects:First, building on previous research, this paper provides a comprehensive theoretical and empirical analysis of the impact of urban spatial structure on total factor productivity (TFP). By exploring the mechanisms linking urban polycentricity and TFP—such as knowledge spillovers, innovation, and resource allocation—we offer new insights into how spatial organization influences economic efficiency. This contributes to the literature by addressing a critical gap in understanding the productivity implications of polycentric urban development.

Second, this paper employs high-precision data to scientifically measure population distribution and urban spatial structure. We introduce innovative metrics for quantifying polycentricity, which not only enhance the accuracy of spatial structure measurement but also improve the identification of its impact on regional TFP. This methodological advancement provides a robust foundation for future research in this field.

Third, while investigating the impact of urban polycentricity on TFP, this paper explicitly considers the urban scale effect and addresses potential endogeneity issues through rigorous econometric models. By conducting nationwide causal inference, we reduce estimation bias and provide more reliable empirical evidence. This approach overcomes the limitations of existing studies, which often overlook endogeneity and focus narrowly on the economic benefits of spatial structure, thereby offering policymakers a more nuanced and actionable understanding of urban planning strategies.

The remainder of this paper is organized as follows: Section 2 presents the theoretical analysis and research hypotheses. Section 3 primarily describes the main data and empirical model used in this study. Section 4 analyzes the empirical results, and Section 5 presents the conclusions of this paper.

2 Theoretical analysis and research hypothesis

2.1 Polycentralization and economic agglomeration effect

In recent years, academics have paid close attention to the relationship between urban spatial structure and economic construction results (Walker, 2018; Zhang et al., 2020; Long and Huang, 2019). Urban spatial structure typically refers to the spatial distribution of different functional areas within a city. This structure has significant implications for the city's economic development and productivity. Early research has shown that the shape of urban spatial structure is strongly related to economic growth, particularly in terms of resource allocation (Guo et al., 2020), labor market (Rosenthal and Strange, 2020), and industrial distribution (Xu and Jiao, 2021), all of which have a significant impact on productivity. For example, Chinitz (1961) observed that the diversity and agglomeration effect of urban space promote interaction and knowledge spillover between industries, thereby increasing overall productivity. Glaeser (2011) emphasized that cities' agglomeration effect can effectively promote innovation, resource flow, and labor market efficiency, all of which contribute to city economic growth. Duranton and Puga (2004) proposed that the urban space's division of labor effect is important at various stages of development. The alternation of the agglomeration and dispersion effects of cities will

have an impact on industrial structure and resource allocation, thereby influencing the quality and speed of economic growth.

Especially in China, the rapid advancement of urbanization has brought about large-scale urban expansion (Wei and Ye, 2014; Ding et al., 2024). In order to achieve short-term economic development goals, many cities have promoted GDP growth by expanding city size and building infrastructure, while ignoring production efficiency and technological progress. Overreliance on land and capital inputs for economic growth frequently results in a lag in total factor productivity, and may even exacerbate resource waste and environmental burden (Wolff, 1991; Isaksson, 2007; Li et al., 2021). As a result, relying solely on traditional economic indicators to measure urban development while ignoring total factor productivity may not accurately reflect the true nature of urban development. Improving total factor productivity, particularly in terms of spatial structure and city size expansion, is a critical issue in China's urban development (Liu et al., 2024b).

However, despite the importance of urban spatial structure in economic development, few people have noticed that the polycentric structure that emerges gradually during the urbanization process may have a negative impact on the improvement of total factor productivity. The polycentric spatial structure refers to the process by which originally concentrated urban functions and economic activities are dispersed across multiple regions or "sub-centers" as the city expands (Roca Cladera et al., 2009; Yu et al., 2022). Although this shift has alleviated the over-concentration of resources in urban centers to some extent, it may also bring a series of negative consequences, especially challenges to productivity improvement (Derudder et al., 2021; Wang et al., 2019).

The effect of urban polycentricity on agglomeration and TFP is complex and multifaceted. First, urban polycentricity frequently results in decentralized resource allocation, which weakens the city's agglomeration effect (Dadashpoor and Yousefi, 2018; Chen et al., 2021). The agglomeration effect is a significant advantage of urban spatial structure because it promotes interaction between industries, technological innovation, and knowledge spillover, ultimately improving TFP. However, a polycentric structure frequently results in relative isolation between multiple functional areas, affecting resource allocation efficiency and technology diffusion. Ellison et al. (2010), for example, noted that an overly dispersed spatial structure can stifle industrial agglomeration and innovation activities, resulting in a decrease in overall productivity. It is difficult for resources and knowledge to flow fully across polycentricity, undermining the mechanism of technology spillover and preventing the city's innovation potential from being realized. This is in stark contrast to the centralized urban structure, which achieves efficient resource utilization and technology diffusion through agglomeration effects, resulting in increased productivity (Duranton and Puga, 2004).

Second, polycentricity can raise the cost of infrastructure construction and disrupt regional coordination (Escaleras and Calcagno, 2018; Frank and Martínez-Vázquez, 2015). In a single-center city, the concentration of economic activities usually reduces the duplication of infrastructure construction and transportation costs, whereas in a polycentric city, the cost of infrastructure construction and operation often rises dramatically (David and Kilani, 2022; Sweet et al., 2017). Furthermore, poor transportation and information exchange between the city's various centers may result in inefficient organization of overall economic activities, affecting productivity improvement. Henderson (2000) proposed that the polycentric structure would result in duplicate resource allocation and increased coordination and management costs, affecting the city's overall productivity. Specifically, the independent development of each sub-center may result in redundancy in infrastructure construction, increasing the fiscal burden and decreasing the city's overall operational efficiency.

With China's rapid urbanization, many large cities have gradually implemented a multi-center strategy, attempting to relieve pressure on the central city by decentralizing urban functions. However, this transformation process may present numerous challenges. Although multi-center can alleviate traffic congestion and overexploitation of land resources in the short term, a lack of effective policy coordination and infrastructure construction may prevent it from effectively promoting technological innovation and industrial upgrading, resulting in a decrease in productivity (Short and Kopp, 2005; Koppenjan and Enserink, 2009). For example, Su et al. (2017) discovered that in many large Chinese cities, despite the implementation of a multi-center strategy, a lack of effective spatial planning and regional coordination has resulted in inefficient productivity improvement and insufficient innovation capabilities. The multi-center structure may lead to the break of the industrial chain between different regions, reduce the synergy effect, and thus affect the total factor productivity of the city (Ding et al., 2022).

Polycentricity, particularly in small and medium-sized cities, can exacerbate spatial fragmentation and result in inefficient integration of economic activities (Dadashpoor and Yousefi, 2018). The relative independence of multiple economic functional areas prevents cities from forming a strong economic agglomeration effect similar to a monocentric structure, which not only affects technological innovation but also reduces labor and capital flow efficiency (Fujita et al., 1999). In these cities, an overly dispersed spatial layout may complicate industrial coordination, impeding productivity improvement and economic structure optimization (Ter Wal and Boschma, 2011).

Although the existing literature has explored the relationship between city size, spatial structure and innovation spillover effects, there are still several research gaps. First, the research on urban polycentricity and innovation spillover effects is relatively limited, especially the empirical research on Chinese cities is relatively scarce. Existing studies mostly focus on the economic effects of a single city center, and lack in-depth discussion on the specific mechanism of polycentricity and its inhibitory effect on innovation spillover effects. Second, the existing literature mainly stays at the theoretical level for the impact of city size on TFP, and most of the research focuses on cases in developed countries, lacking a systematic analysis of the impact of city size in the specific context of Chinese cities. In addition, although polycentricity can alleviate the congestion problem of large cities and optimize spatial layout, it may also bring about negative effects such as the dispersion of innovation resources, duplicate infrastructure construction and insufficient coordination between cities, thereby inhibiting the growth of urban productivity. Therefore, based on the goal of improving TFP, the polycentric transformation of urban spatial structure needs to be carefully considered. This study fills these gaps,

systematically explores the dual impact of polycentricity and city size on TFP in Chinese cities, and combines multiple case empirical analysis to deeply reveal the specific mechanism of spatial structure on innovation and productivity.

2.2 Research hypothesis

The agglomeration effect of urban spatial structure is widely regarded as a key mechanism to promote economic growth and improve total factor productivity (TFP). Duranton and Puga (2004) pointed out that urban agglomeration not only promotes the flow of labor and capital, but also enhances the spillover effect of knowledge and improves innovation capabilities, thereby promoting productivity growth. In a monocentric urban structure, all economic activities and resources are relatively concentrated, which can improve the overall production efficiency of the city through a high degree of resource integration, technology diffusion and industrial cooperation (Ning et al., 2016; Zhang et al., 2022; Liang and Lu, 2019). However, when the urban spatial structure turns to polycentricity, the dispersion of multiple functional areas often leads to inefficient resource allocation and limited knowledge spillover, which may inhibit technological innovation and productivity improvement (Ellison et al., 2010). Therefore, the polycentricity of urban space may reduce the agglomeration effect, thereby having an adverse impact on total factor productivity.

Based on the above theoretical analysis, when the urban spatial structure tends to be polycentric, the relative isolation between multiple regions and functional areas will lead to the obstruction of resource flow and the weakening of synergy (Deng et al., 2024). This spatial structural transformation may reduce the spillover effect of technological innovation and cooperation between industries, thereby inhibiting the improvement of total factor productivity. Therefore, this study proposes the hypothesis:

Hypothesis 1. The trend of polycentric urban spatial structure will have a negative impact on regional total factor productivity.

A large body of literature shows that there is generally a positive relationship between city size and TFP. Glaeser (1961) pointed out that the expansion of urban size helps to promote technological innovation, labor mobility and efficient allocation of capital, and these factors jointly promote productivity improvements. In larger cities, agglomeration effects are usually more significant, with more frequent flows of resources and information, which in turn promotes innovation and technological progress (Carlino and Kerr, 2015; De Groot et al., 2009). At the same time, the economic activities in larger cities tend to be more diversified and the synergy effects between industries are more significant, which creates favorable conditions for the improvement of total factor productivity (Duranton and Puga, 2004). However, although urban size expansion usually brings economic benefits and productivity improvements, in the context of polycentralization, over-dispersed spatial layout may inhibit some synergy effects, especially in cities with smaller population sizes, which may lead to inefficiencies loss. Therefore, larger cities may mitigate the negative impacts of polycentric structures to some extent, but will still experience some productivity losses overall.

Combining the impact of city size and polycentric structure, it can be hypothesized that in larger cities, the agglomeration effect brought by city size can alleviate the negative impact of polycentricity to a certain extent, especially in larger cities with larger populations. In large cities, the flow of resources and knowledge between polycentric nodes is relatively smooth, and the synergy effect is more significant. However, despite this, further dispersion of space may still bring some efficiency losses. Therefore, this study hypothesizes.

Hypothesis 2. As the size of a city increases, its regional TFP gradually increases. For cities with larger populations, the adverse impact of polycenters on urban TFP creation will be weakened, but overall it will still bring some efficiency losses.

Changes in urban spatial structure are not only reflected in spatial distribution, but also involve the physical distance between different regions and the intensity of economic activity connections. Fujita et al. (1999) pointed out that urban polycentricity may lead to the dispersion of economic activities between different regions of the city. This dispersion will not only increase the transportation and information transmission costs between regions, but also weaken the innovation benefit spillover between regions. As the distance from the center increases, the effects of innovation and technological spillover will gradually weaken, and the cooperation and synergy between regions will also be affected (Henderson, 2000). Therefore, in theory, with the polycentricity of urban spatial structure, the increase in the distance between centers will lead to a decline in the spillover effect of knowledge and technology, thereby affecting the improvement of regional total factor productivity (Li and Du, 2022; Ahlfeldt and Wendland, 2013; Zambon et al., 2017).

By increasing the physical distance between centers and decreasing the spillover effect of innovation benefits, the polycentricity of urban spatial structure will impede technological advancement and productivity improvement, according to the theoretical analysis presented above. The growth of total factor productivity will be impacted by the limited spillover effect of innovation, particularly when there is a lack of cooperation and information flow amongst several sub-centers. Thus, this study makes the following hypothesis:

Hypothesis 3. Urban polycentricity may have a negative impact on regional TFP by reducing the spillover of innovation benefits and extending the distance between centers.

3 Empirical model and data

3.1 Variable definition

3.1.1 Dependent variable

The core dependent variable in this study is the Total Factor Productivity (TFP) of the city in the given year. To achieve this, we employ multiple methods to calculate TFP, ensuring the accuracy and reliability of the results. Specifically, drawing on the methodologies of Levinsohn and Petrin (2003) and Olley and Pakes (1996), referred to hereafter as the LP method and the OP method, respectively, we primarily adopt the Data Envelopment Analysis (DEA) model. DEA is a widely used nonparametric

approach for TFP measurement that evaluates production efficiency without requiring the specification of a production function, thus allowing for precise TFP estimations.

In selecting input indicators, we incorporate data from multiple dimensions. These include the baseline capital stock, reflecting the level of capital investment in the city; electricity consumption, which serves as a proxy for industrial activity and economic vitality; railway freight volume, capturing the city's logistical capacity and economic interconnectivity; and urban employment, directly linked to the city's labor resources and economic scale. Together, these input indicators form the foundation for our TFP evaluation.

For output indicators, we account for both desirable and undesirable outputs. The desirable output includes the city's GDP for the year, representing its economic output over the specific period. The undesirable outputs encompass environmental pollutants, such as sulfur dioxide, industrial wastewater discharge, and smoke emissions. The inclusion of these indicators allows for a more comprehensive assessment of the environmental impacts of urban economic activities, thereby contributing insights into sustainable development. Additionally, all monetary variables are deflated to constant 2010 prices for consistency.

In the main regression model analysis, we prioritize results derived from the LP method due to its ability to effectively control for unobservable heterogeneity in panel data. For robustness checks, we supplement our analysis with results from the OP method, which considers changes in firm productivity and adjustment costs of production factors, thereby providing more robust TFP estimates.

3.1.2 Focus variables

(1) Urban polycentric spatial structure is one of the core explanatory variables. Typically, this metric describes the degree of even distribution in the "importance" of centers within a city, where "importance" can be quantified using factors related to urban form, such as labor force population size, regional GDP, or regional transportation (Meijers and Burger, 2010; Rossi-Hansberg and Wright, 2007; Burger and Meijers, 2012). In this paper, we define the degree of urban polycentricity as a quantitative representation of the distribution characteristics of multiple central nodes in the urban spatial structure and their functional intensity, reflecting the spatial dispersion and agglomeration of factors such as economic activities, population distribution, and public service facilities within the city.

So the polycentricity measure adopted in this paper is based on the distribution of population within the city, as population distribution directly reflects the internal spatial structure of the city and serves as a foundation for the distribution of urban production and consumption activities. Following the principle of data availability, this study employs *LandScan* population distribution data to capture the average 24-hour population distribution within the city. This dataset integrates various economic activities within the region, including employment, residence, and transportation, during the estimation process and allocates the population involved in economic activities to a grid cell scale of one square kilometer. This approach allows for a direct observation of population density across different grid cells within the city when analyzing urban sub-centers. Widely used in urban economics, this data effectively captures the spatial distribution of economic activity within cities.

Using the aforementioned techniques, this article identified a number of population centers in Chinese cities between 2010 and 2019 using the Landscan database. These centers included both main and secondary centers, and the population corresponding to each center was calculated by adding up the grids in each population center. This article measures the level of urban polycentricity using the ratio of each sub-center's population ($Pop_{subcenter,it}$) to all population centers ($Pop_{subcenter,it}$ + $Pop_{center,it}$), based on the viewpoint of morphological polycentricity. The significance of the city's secondary center in relation to its main center is represented by this indicator. The larger the indicator value, the higher the proportion of the secondary center population in the city, the more important the secondary center, and the more polycentric the city. The specific calculation can be expressed by Equation 1:

$$\boldsymbol{Poly_{it}} = \boldsymbol{Pop_{subcenter,it}} \Big/ \left(\boldsymbol{Pop_{subcenter,it}} + \boldsymbol{Pop_{center,it}}\right) \tag{1}$$

(2) City size is also the main explanatory factor in this research. Since a city's population size might fluctuate based on a number of variables, we mainly utilize the logarithm of the average permanent population of the city as a proxy variable for city size.

3.1.3 Control variables

In order to reduce estimation bias due to omitted variables, also refer to Combes et al. (2015)'s research results on urban and regional economics, we select control variables that may influence urban TFP. These control variables include the level of foreign direct investment (*FDI*), local human capital (*Hr*), research and development intensity (*R&D*), and *GDP per capita* (*Pgdp*). Specifically, foreign direct investment (*FDI*) represents the depth of capital flow and international cooperation; local human capital (*Hr*) reflects the region's educational and skill base; research and development intensity (*R&D*) measures the capacity for innovation and technological advancement; and GDP *per capita* (*Pgdp*) gauges the prosperity of the economy in terms of material wealth. By incorporating these variables, we aim to control for other factors that may affect total factor productivity, thereby enhancing the accuracy of the model's estimates. Table 1 provides the comprehensive definitions of these variables.

3.2 Empirical model

This study establishes a two-way fixed effect model (Equation 2) to investigate the relationship between polycentric structure, city size, and regional TFP:

$$\boldsymbol{TFP_{it}} = \boldsymbol{\alpha_0} + \boldsymbol{\alpha_1 Poly_{it}} + \boldsymbol{\alpha_2 Size_{it}} + \boldsymbol{\alpha_i Control_{it}} + \boldsymbol{Year_t} + \boldsymbol{Prefecture_i} + \boldsymbol{\varepsilon_{it}} \tag{2}$$

Among them, TFP_{it} represents the total factor productivity of the city, which is mainly calculated by the OP method and the LP method in this paper. $Poly_{it}$ represents the degree of polycentricity in the city, specifically measured by the even distribution of "importance" among the centers within the city. $Size_{it}$ represents the measurement of the city size, which includes the city population

TABLE 1 Variables definitions.

Variables type	Symbol	Definition
Dependent variable	TFP	TFP measured by the LP and OP method
Explanatory variable	Poly	Polycentric index
	Size	The logarithm of the average annual resident population
Control variables	FDI	Actual use of foreign capital for the year (US $, reduced to 2010)
	Hr	Human resources (population with tertiary education)
	R&D	Proportion of urban scientific undertakings expenditure in fiscal expenditure
	Pgdp	Gross regional product *per capita* (2010 deflated, 10k yuan)
	Area	Built-up area of the previous year (10,000 square meters)

size and built-up area in this paper. $Control_{it}$ represents the control variables of a series of sample cities introduced in Section 3.1, $Year_t$ and $Prefecture_i$ represent the time fixed effect and city fixed effect respectively, and ε_{it} represents the regression residual term.

3.2.1 Sources of bias and instrumental variable selection

(1) Endogeneity is a common issue in economic research, particularly in the field of urban economics, where it typically arises from the mutual influence and interdependence between variables. In the context of this study, a key source of endogeneity is the cause of urban polycentricity. The emergence of urban polycentricity is not only influenced by urban planning but is also profoundly constrained by natural geographic factors. In the early stages of urban development, elements such as rivers, mountains, and coastlines have already played a crucial role in the selection of urban locations, spatial layout, and subsequent urban expansion. The influence of the natural environment has, to some extent, shaped the spatial structure of cities and determined whether multiple development centers can emerge. Thus, urban polycentricity may not solely be driven by policies or human interventions; geographic factors also play a significant role. This endogenous relationship makes it difficult to eliminate the interference of external factors when analyzing the impact of polycentricity on urban Total Factor Productivity (TFP), potentially leading to biased estimation results.

To address the issue of endogeneity, a commonly used method is the Two-Stage Least Squares (2SLS) estimation. This method mitigates the bias caused by endogeneity by introducing instrumental variables to replace the endogenous variables. Instrumental variables must meet two essential requirements: first, they must be strongly correlated with the endogenous variable; second, they must be uncorrelated with the error term in the regression model, i.e., they must exhibit exogeneity. In this study, we select surface roughness (Rugg) as an instrumental variable for urban polycentricity. There are two main reasons for choosing surface roughness as an instrumental variable:

First, from the perspective of correlation, the flatness of the terrain directly influences the formation of urban spatial structure. Cities with flatter terrain are more conducive to the development of polycentric centers, as flat landscapes are better suited for large-scale urban expansion, infrastructure construction, and population concentration. In contrast, cities with more rugged terrain typically exhibit a monocentric spatial structure, as the uneven topography limits the available space for population agglomeration and urban expansion, while also increasing the costs of infrastructure construction and maintenance.

Second, from the perspective of exogeneity, although human activities may modify the terrain to some extent, such modifications are limited and the roughness of the terrain is unlikely to change significantly in the short term. Therefore, surface roughness can be considered an exogenous instrumental variable, meeting the requirements for the Two-Stage Least Squares (2SLS) method. By using this instrumental variable, we can effectively address the estimation bias caused by the endogenous relationship between urban polycentricity and natural geographic factors, thus obtaining more accurate and reliable regression results.

(2) In addition to the potential endogeneity between urban polycentricity and TFP, there may also be an endogeneity relationship between city size and TFP. Specifically, the endogeneity between city size and TFP could stem from the interaction between urban economic development and population mobility. The expansion of city size is often a result of urban economic growth, while a larger city size may also stimulate more investment and innovation, thereby further boosting TFP. On the other hand, improvements in TFP may attract more businesses and labor, leading to the expansion of city size. Therefore, the mutual influence between city size and TFP could create a bidirectional causal relationship, resulting in endogeneity issues.

To address this issue, we also apply the Two-Stage Least Squares (2SLS) method and select the built-up area of the city in the previous year (Area) as an instrumental variable for city size. There are two main reasons for choosing built-up area as the instrumental variable: First, from the perspective of correlation, the built-up area of a city is highly correlated with its population size. A larger built-up area means more space to accommodate a larger population and provide more residential, commercial, and public service areas. Therefore, the size of the built-up area is closely related to the city's population size, which in turn influences the expansion of city size.

Second, from the perspective of exogeneity, the built-up area is determined by historical urban expansion and land development patterns. While human activities may influence the expansion of the built-up area to some extent, these effects are typically lagged, and changes in built-up area are not directly affected by the current level of TFP. Therefore, the built-up area can be regarded as an exogenous instrumental variable that satisfies the exogeneity requirement for instrumental variables in the Two-Stage Least Squares (2SLS) method. In other words, although city size may be subject to feedback effects from TFP levels, the built-up area as an instrumental variable is largely unaffected by TFP, thus avoiding the interference of endogeneity on the estimation results.

(3) Model Specification for 2SLS: In the first stage, we regress the endogenous variables (such as urban polycentricity or city size) as the dependent variable, using the instrumental variables (such as surface roughness or the built-up area from the previous year) as the independent variables. We develop the following regression models for the first stage, mathematically formulated in Equations 3, 4 respectively:

$$\boldsymbol{Poly_{it} = \beta_0 + \beta_1 Rugg_{it} + \beta_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \quad (3)$$

$$\boldsymbol{Size_{it} = \beta_0 + \beta_1 Area_{it-1} + \beta_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \quad (4)$$

where, $Poly_{it}$ (or $Size_{it}$) represents the urban polycentricity index and city size for city i in year t, and $Rugg_{it}$ and $Area_{it-1}$ represent surface roughness and the built-up area from the previous year, respectively. The other variables are the same as in model (2). The second-stage model remains as Equation 2, but the results from the first-stage regression are incorporated into the main model.

3.2.2 Mechanism Modelling

The above theoretical explanation and analysis of the impact mechanism of multicenter and city size on urban TFP have been verified based on the results of empirical analysis. The following needs to carefully examine the mechanism by which urban spatial structure affects centralization and knowledge spillover. To examine the possible mechanisms, this paper adapts the Jiang (2022) mediation effect analysis framework, establishing the following two models mathematically formulated in Equations 5, 6 respectively:

$$\boldsymbol{M_{it} = \alpha_0 + \alpha_1 Poly_{it} + \alpha_2 Size_{it} + \alpha_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \quad (5)$$

$$\boldsymbol{TFP_{it} = \theta_0 + \theta_1 M_{it} + \theta_i Control_{it} + Year_t + Prefecture_i + \varepsilon_{it}} \quad (6)$$

where, M_{it} represents the potential mechanism variable, while the remaining variables in the equation are consistent with the baseline regression.

3.3 Data source

The urban polycentric index, the study's primary explanatory variable, comes from the *LandScan* Global Population Distribution Dataset, which was created by the U.S. Department of Energy's Oak Ridge National Laboratory (ORNL). The extended time series and great resolution of this dataset are well known. We make use of the 1 km resolution of the dataset, which yields accurate urban population density estimates that represent the average population distribution over a 24-h period.

The statistics for Total Factor Productivity (TFP) and other city control variables are sourced from the China Urban Statistical Yearbook, China Urban Construction Statistical Yearbook, China Transport Statistical Yearbook, and China Energy Statistical Yearbook. The study's first research sample consists of Chinese cities at the prefecture level between 2010 and 2019. Data from the China National Geographic Conditions Monitoring Cloud Platform's Digital Elevation Model and city level terrain slope data obtained from the National Intellectual Property Administration's patent authorization and citation data are also used in this study to perform endogeneity and mechanism tests.

We use the following criteria for sample selection in order to guarantee the reliability and consistency of the results. We take into account city mergers and divisions and eliminate cities with obvious administrative boundary changes during the study period, samples with large data gaps, and the top and bottom 1% of cities in terms of sample size. Ultimately, we are left with 276 cities out of 2,710 samples.

TABLE 2 Descriptive statistics of variables (observations = 2,710).

Variable	Mean	Std. Dev	Min	Max
TFP (OP)	1.0106	0.0627	0.5713	1.763
TFP (LP)	1.0084	0.0623	0.5047	1.9979
Poly	0.0234	0.0434	0.0052	0.0836
Size	15.1377	0.6587	12.6105	17.3466
Fdi	10.0176	1.9068	1.3863	14.9413
Hr	10.4594	1.348	0.3221	13.7814
Rd	9.4896	1.7592	3.8067	15.5293
Pgdp	6.4926	1.1545	3.2813	10.5495
Area	7.0556	0.937	3.9703	9.6884

4 Empirical results and analysis

4.1 Descriptive statistics

For the variables included in this paper, descriptive statistics are provided in this section. Table 2 displays the results. The OP technique yielded an average TFP of 1.01 for the main variables, with a standard deviation of 0.063 and a range of 0.571–1.763. These values demonstrate the significant variations in production efficiency among the various cities. Regarding urban area, the mean population size of Chinese cities included in the sample is approximately 3.72 million (é15.13), with notable variations in size across the various cities.

4.2 Main results

The baseline regression results of the effect of polycentricity and city size on TFP are shown in Table 3.

TABLE 3 Effect of polycentricity and city size on TFP (Total Factor Productivity).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	TFP(OP)	TFP(OP)	TFP(OP)	TFP(OP)	TFP(OP)	TFP(OP)
Poly	−0.2022***	−0.2013***	−0.2038***	−0.2032***	−0.1996***	−0.1892***
	(0.0275)	(0.0275)	(0.0274)	(0.0274)	(0.0270)	(0.0270)
Size		0.0050***		0.0058**		0.0044*
		(0.0018)		(0.0024)		(0.0023)
Observations	2,710	2,710	2,710	2,710	2,710	2,710
Controls	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes
City FE	No	No	No	No	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Columns (1–2) control for any fixed effects, columns (3–4) add city-related control variables, and columns (5–6) add year and city fixed effects.

Table 3's columns (1–2) show the regression findings for models that simply use the urban polycentricity index and models that use both polycentricity and city size, without any fixed effects or control variables. When no other factors are present, urban polycentricity significantly reduces Total Factor Productivity (TFP), as shown by column (1)'s negative and statistically significant coefficient for urban polycentricity at the 1% level. Moreover, the coefficient for city size in column (2) is positive and significant at the 1% level, indicating that city size growth positively affects town productivity.

To capture other factors that can affect TFP, we include additional city-level characteristics in the regression analysis shown in columns (3–4). The findings show that the coefficients for urban polycentricity and city size essentially stay the same even after adjusting for these extra city-specific factors. This implies that our preliminary results are solid. In particular, the coefficient for city size stays positive and the coefficient for polycentricity stays negative, thereby reaffirming the positive influence of city size on TFP and the negative impact of urban polycentricity on TFP.

We adjust for time invariant city-specific characteristics and macroeconomic effects by controlling for both city and year fixed effects in the regression analysis shown in columns (5–6). In this instance, the city size coefficient is still significantly positive, but the urban polycentricity index coefficient is still significantly negative. According to this finding, the polycentric spatial structure still significantly reduces urban TFP even after controlling for time effects and unobservable city heterogeneity, but city size growth somewhat increases TFP. There is no doubt that hypothesis 1 is confirmed. Based on data from Asian countries, Bac (2024) found based on Vietnam's experience that excessive polycentricity will have a negative impact on the economic structure. At the same time, this phenomenon is not unique to developing countries. Caset et al. (2023) also found based on data from 34 European countries that areas with high levels of urban polycentricity usually have lower productivity levels.

An intriguing finding emerges from comparing the data in columns (5) and (6): the estimated effect of polycentricity may capture the influence of city size when city size is excluded. In particular, column (6) shows a tiny decrease in the absolute value of the urban polycentricity coefficient. Although this decrease is small, it indicates that the negative effects of polycentricity are somewhat offset by the growth of the city. This could suggest that the coordination costs and efficiency losses linked to a polycentric structure are somewhat mitigated by the expansion of the metropolis, which offers more market opportunities and economic activity.

4.3 Endogenous test results

We use the Two-Stage Least Squares (2SLS) method for regression analysis, and the results are presented in Table 4.

Based on the first-stage estimation results in columns (1–2) of Table 4, we can confirm that the instrumental variables are highly correlated with urban polycentricity and city size. Specifically, the regression coefficients for the instrumental variables (such as surface roughness and built-up area) with respect to urban polycentricity and city size are in the expected direction and show statistically significant correlations with the endogenous variables. To further validate the effectiveness of the instrumental variables, we examined the F-statistics in the regression models. The results indicate that the F-statistics are all greater than 10, suggesting a strong correlation of the instrumental variables (Stock and Yogo, 2002).

In the estimation results in columns (3–5) of Table 4, the coefficients for urban polycentricity and city size are generally consistent with the baseline regression results in Table 3, but their absolute values have noticeably increased. This change indicates that after applying the 2SLS method, the effects of urban polycentricity and city size on TFP have been amplified, and the estimation results are more accurate. In contrast, the OLS regression may underestimate these effects. Specifically, in column (5), for every 1% increase in urban polycentricity, city TFP decreases by 0.24%, while for every 1% increase in city size, city TFP increases by 0.87% (where $e^{0.0087}-1 \approx 0.0087$). This result suggests that, without considering endogeneity, OLS regression may underestimate the negative effect of urban polycentricity and the positive effect of city size on TFP.

By comparing the results with the OLS regression, we further validate the effectiveness of the 2SLS method in addressing the

TABLE 4 Effect of urban polycentricity and city size on TFP: Instrumental variable regression.

Variables	(1)	(2)	(3)	(4)	(5)
	First stage		Second stage		
	Poly	Size	TFP(OP)	TFP(OP)	TFP(OP)
Poly			−0.2449***	−0.2467***	−0.2480***
			(0.0538)	(0.0537)	(0.0538)
Size				0.0050***	0.0087**
				(0.0018)	(0.0042)
Rugg	−0.3285***				
	(0.0109)				
Area		0.0015***			
		(0.0001)			
Observations	2,710	2,710	2,710	2,710	2,710
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
KP F-statistic			913.6	914.1	293.7

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Column (4) includes only the instrumental variable for polycentricity, while column (5) includes both the instrumental variables for polycentricity and city size.

TABLE 5 Robustness test: Replace variables and lagged explanatory variable.

Variables	(1)	(2)	(3)	(4)	(5)
	Forward. TFP(OP)	TFP(LP)	TFP(OP)	TFP(OP) 2010–2014	TFP(OP) 2015–2019
Poly	−0.0739**	−0.1981***	−0.1988***	−0.2262***	−0.1740***
	(0.0305)	(0.0270)	(0.0270)	(0.0447)	(0.0314)
Size	0.0061***	0.0051***		0.0033	0.0065***
	(0.0016)	(0.0018)		(0.0029)	(0.0021)
Pop density			0.0606*		
			(0.0347)		
Observations	2,434	2,710	2,710	1,331	1,379
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Column (1) considers the impact of polycentricity and city size on the lagged TFP; column (2) uses the LP, method to measure TFP; column (3) replaces city size with population density; columns (4–5) divide the sample based on time.

endogeneity issue. While the OLS regression may underestimate the effects of polycentricity and city size due to endogeneity, the use of instrumental variables in the 2SLS method provides more accurate regression estimates, supporting the hypothesis in this paper regarding the impact of urban polycentricity and size on TFP. Therefore, these results not only align with our expectations regarding endogeneity but also offer valuable insights for urban planning and development policies, particularly when considering the impact of spatial structure and city size on economic efficiency.

4.4 Robustness checks

To ensure the reliability of the results, we conducted the following three robustness tests in Table 5.

(1) Consider urban polycentricity and hysteresis in scale expansion. The improvement of regional TFP cannot be achieved in the short term, and the urban spatial structure in this article reflects the long-term variation of urban

TABLE 6 Heterogeneity analysis: Whether it is a coastal city and the size of the city.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Non-coastal city	Coastal city	Population size			Population density	
			< 2 million	2~5 million	>5 million	> 500/km^2	< 500/km^2
Poly	−0.1263***	−0.1976**	−0.2338***	−0.1405***	−0.0828***	−0.1933***	−0.0443
	(0.0280)	(0.0793)	(0.0797)	(0.0379)	(0.0046)	(0.0324)	(0.0380)
Size	0.0021	0.0052***	−0.0040	−0.0031	0.0128**	0.0012	0.0053*
	(0.0019)	(0.0016)	(0.0091)	(0.0072)	(0.0060)	(0.0025)	(0.0030)
Observations	2,190	520	450	1,243	1,011	1,671	1,039
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1. Columns (1–2) use whether the city is located on the coast as the classification standard, columns (3–5) use population size as the classification standard, and columns (6–7) use population density as the classification standard.

development. By replacing the explanatory variables with the second year, there is no significant difference in the estimation results.

(2) Considering the robustness of the explained variable and the explanatory variable, in column (2) we use the TFP calculated by the LP method instead of the TFP calculated by the OP method as the dependent variable, and in column (3) we use population density instead of population size as the independent variable, respectively, to eliminate the risk of indicator measurement bias.

(3) Finally, due to China's hukou system reform in 2014, which allowed a large number of people to obtain urban residency, we test the samples before and after 2014, yielding the results in columns (4–5). Overall, regardless of the method used, urban polycentricity has a negative impact on TFP, while the expansion of city size has a positive impact on regional TFP. Moreover, these effects are both significant and robust.

4.5 Heterogeneous effects

To explore the heterogeneity of urban location and size, this study conducts the following estimations, with results presented in Table 6. As shown in columns (1–2) of Table 6, we divide the sample data into non-coastal and coastal cities. It is evident that the negative impact of polycentricity on regional TFP is more significant in coastal cities, and the positive impact of city size expansion on TFP is only significant in the coastal city sample. columns (3–5) examine the heterogeneity among small and medium-sized cities, large cities, and super-large cities. The results show that the negative impact of polycentricity gradually weakens, while the positive impact of city size expansion follows the opposite trend, being significantly evident only in super-large cities with populations over 5 million. In this regard, based on the estimation results from columns (2) and (5), we hypothesize that this may be related to the specific industrial and population distribution in China. Most large cities and industries are located in the southeastern coastal areas of China, which also have more mountainous regions. Consequently, polycentric distribution is common in many cities, and the expansion of city size significantly enhances TFP in these regions.

Columns (6–7) examine the heterogeneity of cities with high and low population density using 500 people/km^2 as the limit. The results show that in high-density cities, the negative impact of urban polycentricity on TFP is statistically significant, and the absolute value of its coefficient is greater than the baseline regression result. In contrast, in low-density cities, the impact of urban polycentricity on TFP is not significant. Kwon and Seo (2018) found similar results based on urbanization data in South Korea, namely, that in high-density population areas, urban polycentricity is highly negatively correlated with labor productivity.

We further explored the optimal city size. City size expansion and TFP have been shown to positively and significantly correlate, but this does not imply that cities can grow indefinitely (Scott and Storper, 2015; Su et al., 2024). Figure 1 illustrates the outcomes of fitting the city size quadratic term to TFP. Our findings indicate that TFP will sharply decline above a certain city size threshold, indicating that urban development must balance size expansion with economic benefits. Hypothesis 2 is supported by the data.

Therefore, we further add the quadratic term of city size into model (1). The regression results are shown in Table 7, where we verify whether control variables are included and examine the optimal city size for coastal and inland cities. Without considering city related control variables, the optimal city size is approximately 2.36 million people. After incorporating control variables such as infrastructure pressure, environmental issues, and social services, this size decreases somewhat.

4.6 Mediating analysis

(1) Does urban polycentricity lead to an increase in the distance between centers?

Urban polycentricity may lead to an increase in the geographic distance between centers because a polycentric structure typically implies a dispersed layout of different functions and economic

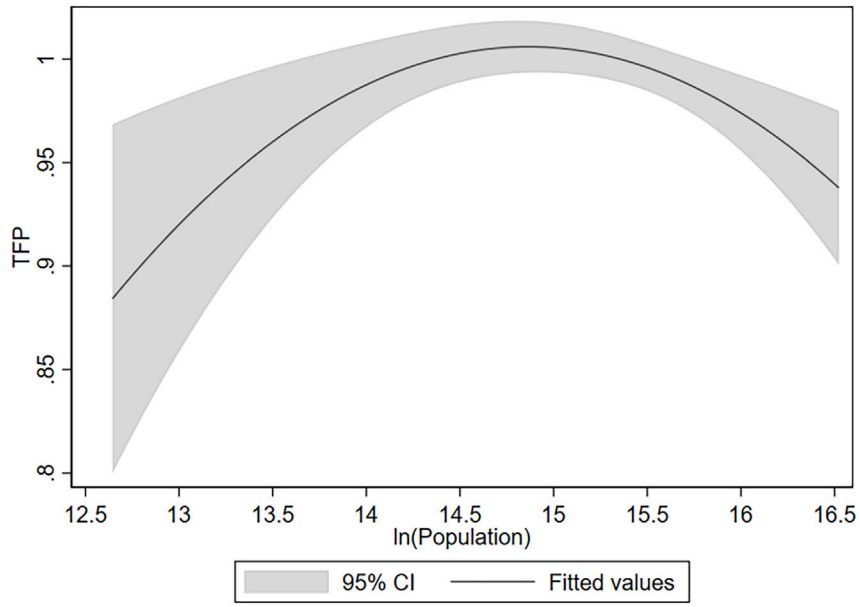


FIGURE 1
Quadratic fitting relationship between city size and TFP. (Optimal size threshold: 2.36 million people).

TABLE 7 Effect of the quadratic term of city size on total factor productivity.

Variables	(1)	(2)
	TFP(OP)	TFP(OP)
$(Size)^2$	−0.0043**	−0.0035*
	(0.0020)	(0.0021)
Size	0.1262**	0.1019*
	(0.0596)	(0.0618)
Optimal City Size (Million)	2.36 M	2.10 M
Observations	2,710	2,710
Controls	No	Yes
Year FE	Yes	Yes
City FE	Yes	Yes

Note: Optimal City size = EXP (-(Coefficient of Size)/(2*Coefficient of $(Size)^2$)). Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

activities, rather than a highly concentrated single-center model. In such a structure, the various centers within the city tend to be spatially separated, thereby increasing the physical distance between them. As the process of poly-centric development advances, the dispersion between centers intensifies, and the city's spatial layout becomes more complex and fragmented, further expanding the geographic distance between centers. To explore the impact of polycentricity on the internal spatial distribution of the city, we calculate the average distance between the sub-centers and the main center's centroid in terms of latitude and longitude (Central), using this as the dependent variable in model (5), and analyze whether polycentricity increases the geographic distance between centers.

Based on the regression results in columns (1–2) of Table 8, it is clear that the regression coefficient for urban polycentricity is significantly positive, indicating that the current polycentric development model in Chinese cities indeed exacerbates the expansion of distance between centers (i.e., the average distance between centers in-creases). The decentralization of centers not only leads to a more dispersed urban spatial layout but also significantly reduces the efficiency of collaboration and resource sharing as the distance between centers increases. This change in spatial distribution may hinder interaction between businesses, thus negatively impacting the city's TFP. Therefore, while urban polycentricity can facilitate spatial expansion, it may also reduce

TABLE 8 Effect of polycentricity and city size on TFP: Mediating affects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Central	TFP(OP)	Patents	TFP(OP)	Citations	TFP(OP)
Poly	0.6741***		−0.3557**		−0.8365***	
	(0.1599)		(0.1657)		(0.1710)	
Size	0.3479***		0.3393***		0.3863***	
	(0.0105)		(0.0109)		(0.0112)	
Central		−0.0048*				
		(0.0028)				
Patents				0.0050*		
				(0.0027)		
Citations						0.0084***
						(0.0026)
Observations	2,710	2,710	2,710	2,710	2,710	2,710
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

the city's productivity by increasing the geographic distance between centers.

(2) Does urban polycentricity suppress urban innovation performance?

Polycentricity may suppress urban innovation activities because a polycentric structure often leads to the decentralization of innovation efforts (Liu et al., 2023). When a city develops multiple independent economic and functional centers, innovation resources and activities tend to be scattered across these centers, reducing the concentration and collaboration opportunities for innovation. This spatial dispersion increases the cost of communication and cooperation between businesses and research institutions, thereby hindering the efficiency and effectiveness of innovation activities. Aritenang (2021), based on data from technology companies in Malaysia, also agreed that technological advancement is further driving economic agglomeration, and found that more spatially dispersed industries are conducive to the long-term development of technology companies.

To test this hypothesis, we selected the number of patents granted in the city as a mediator variable to measure innovation performance (Patents). The number of patents is an important indicator of innovation activities and reflects a region's capability in technological research and innovation. The results in columns (3–4) of Table 8 confirm our expectation: urban polycentricity indeed suppresses innovation performance by reducing the total number of patents granted. A decrease in the number of patents directly implies a decline in innovation output, and innovation is a key driver of regional TFP growth. Therefore, the polycentric structure of cities may suppress overall innovation capabilities by dispersing innovation activities, thereby negatively affecting the city's TFP growth.

(3) Does polycentricity suppress innovation spillover effects?

The urban polycentric structure may suppress innovation spillover effects because the technological and knowledge spillover effects often depend on close cooperation and frequent interaction between urban centers, which can be reflected in patent citations (Citations). Polycentricity typically means that innovation activities and technological collaborations within a city are spread across different centers, weakening technological exchange and knowledge sharing between centers. As the physical distance between urban centers increases, the flow of technology and knowledge is restricted, and the innovation spillover effect may therefore be suppressed. Existing studies show that the innovation spillover effect in urban clusters largely depends on the cooperation networks and knowledge transfer between cities, and the decentralization of such networks undoubtedly weakens their effectiveness. Based on data from Japan's manufacturing industry, Otsuka (2024) also found that enhancing regional network connections and improving high-quality transportation infrastructure can offset the negative externalities caused by urban polycentricity.

According to the estimation results in column (5) of Table 8, the urban polycentric structure indeed leads to a decrease in the total number of patent citations, indicating a significant suppression of innovation spillover effects between cities. Patent citations are an important indicator of innovation spillover, as the citations between patents often reflect the dissemination and diffusion of technology

and knowledge. Further analysis of the regression results in column (6) of Table 8 shows a significant positive correlation between patent citations and regional TFP, indicating that an increase in patent citations effectively promotes TFP growth. Therefore, the urban polycentric structure, by reducing patent citations, suppresses innovation spillovers, thereby negatively impacting the city's TFP growth. Obviously, the results of the mechanism test effectively prove that with the increase of the spillover effect of innovation and the multi-center distance of cities, it is possible to further lead to TFP loss, and hypothesis 3 is proved. Based on observations of the Barcelona metropolitan area, Masip Tresserra (2012) found that urban sub-centers have a positive impact on labor productivity and can alleviate the problem that the higher the expansion of the central urban area, the lower the labor productivity.

The inhibiting effect of polycentricity on innovation spillovers is clearly demonstrated in the case of the Barcelona metropolitan area. Research indicates that as urban spatial structures transition to polycentricity, the increased geographical distance and the dispersion of innovation resources significantly weaken the efficiency of cooperation between firms. This is reflected in the slowdown in patent application growth and the reduction in collaborative innovation projects between firms (Liu et al., 2023). This phenomenon is consistent with existing literature, which suggests that while polycentricity can alleviate the resource pressure on city centers, it may also lead to the fragmentation of innovation activities, thereby hindering the efficient flow of knowledge and technology (Derudder et al., 2021; Li and Du, 2022). Furthermore, Aritenang (2021), based on a study of technology firms in Malaysia, points out that spatially dispersed industrial layouts, while beneficial for the long-term development of firms, significantly increase the cost of innovation cooperation and weaken innovation spillovers within the region. Therefore, urban planning needs to enhance transportation links between centers and optimize the allocation of innovation resources in order to maintain the vitality of the innovation ecosystem and mitigate the negative impacts of polycentricity on innovation spillovers (Otsuka, 2024).

5 Conclusion and policy implications

5.1 Conclusion

In the current urbanization process, the impact of urban polycentricity and size expansion on regional total factor productivity is an important research topic, but its impact size and optimal city size have not yet been deeply explored. Based on this thinking, this paper takes urban spatial structure and scale as the main research perspective to examine the impact and mechanism of urban spatial structure on regional TFP. Specifically, based on the panel data of China's prefecture-level and above cities from 2010 to 2019, this article empirically analyzes the causal effects of urban poly-centers and size expansion on regional total factor productivity, and estimates the optimal city size for development.

The research results show that: first, urban polycentric spatial structure has a negative impact on regional TFP, and a series of robustness tests such as considering TFP time lag, replacing explained variables and explanatory variables, and exogenous household registration policy all support this A conclusion. The expansion of urban size has a significant positive impact on regional TFP. For every 1% increase in urban population, the marginal increase in total factor productivity is approximately 0.87%. This effect partly offsets the negative effect of polycentricity.

Second, in China, when many cities are developing into polycentric patterns, they will enlarge the geographical distance between urban centers and increase the geographical barriers between tacit knowledge flows. And as the distance between centers further expands, in fact, new special economic zones or scientific research centers in Chinese cities are often far away from old cities. The scale effect of each urban center will be eliminated, the center agglomeration trend will be destroyed, knowledge innovation within the city will be hindered, and multi-center It mainly suppresses urban TFP by destroying the externalities of innovation spillover within the city.

Third, from the perspective of location and city size, the polycentric spatial structure has a stronger inhibitory effect on TFP in coastal cities than inland cities. However, coastal cities can offset this negative impact within certain limits by expanding the city size and attracting population. Under the current productivity level, China's optimal city size is between 2.49 million and 2.84 million people. Excessively large city size may cause significant efficiency losses.

5.2 Policy implications

Our findings are of great reference value to governments in developing countries in terms of urban development planning policies. From a practical perspective, developing countries should avoid blindly pursuing polycentric development in urban planning, especially in areas with small cities or weak economic foundations. Although polycentric development can help alleviate traffic congestion and excessive resource concentration in monocentric cities, excessive dispersion may lead to reduced economic efficiency. It is recommended to reasonably balance the relationship between polycentric development and urban expansion according to the stage of urban development and population size. For cities with high population density, priority should be given to improving economic efficiency through moderate agglomeration rather than excessive dispersion of urban functions. At the same time, attention should be paid to offsetting the possible negative effects of polycentric development through the positive effects brought about by urban expansion (such as population growth and resource concentration). For example, economies of scale can be formed by guiding population and industry to concentrate in the core areas of cities, while secondary centers can be moderately developed in peripheral areas to achieve functional complementarity.

Given the heterogeneity analysis results, policymakers should tailor urban development strategies to specific city characteristics. For coastal cities, where polycentricity significantly hinders TFP, enhancing connectivity between urban centers through infrastructure investment is crucial. Meanwhile, coastal cities can leverage their economic advantages by moderately expanding city size to attract talent and boost innovation. For inland cities, where the negative impact of polycentricity is less severe, controlling city

size and promoting moderate agglomeration should be prioritized to improve economic efficiency. Additionally, for cities with high population density, where polycentricity has a more pronounced negative effect on TFP, enhancing inter-center connectivity and optimizing urban spatial layout are essential. In contrast, for low-density cities, the focus should be on developing secondary centers to complement the core areas and improve overall productivity.

Second, strengthen the connectivity between urban centers to promote knowledge flow and innovation. In the process of polycentric development, the expansion of geographical distance between urban centers may hinder knowledge flow and innovation spillover, which is particularly prominent in developing countries. The spread of tacit knowledge often relies on face-to-face communication and high-frequency interaction, while the expansion of geographical distance may weaken such interaction. It is recommended to reduce the negative impact of geographical barriers on economic activities by investing in transportation infrastructure (such as bus rapid transit systems, rail transit) and digital platform construction. For example, the rapid flow of people, information and resources can be promoted by building an efficient inter-city commuting network and smart city platform. At the same time, promote the functional complementarity and coordinated development between new and old urban areas to avoid weakening the overall innovation ability and economic vitality of the city due to excessive dispersion. This experience is of great reference significance for developing countries to optimize the internal spatial layout of cities, especially in the process of rapid urbanization, how to improve innovation ability and economic competitiveness through spatial planning is a common challenge.

Third, optimize the scale and functional layout of cities. Developing countries should formulate differentiated urban development strategies based on their own location conditions and development stages. For coastal or economically developed cities, while promoting multi-centerization, they should focus on improving economic efficiency by moderately expanding the scale of cities and attracting high-quality population. For inland or economically underdeveloped cities, they should give priority to controlling the scale of cities to avoid waste of resources and loss of efficiency caused by excessive expansion. In addition, countries should explore the optimal city size range that suits their national conditions to avoid efficiency losses caused by cities that are too large or too small. This experience has universal reference value for the global urbanization process.

5.3 Research limitations and prospects

This paper analyzes the relationship between urban polycentralization trend and urban size expansion and TFP in China, and gives corresponding countermeasures and suggestions according to the changes of sample cities' TFP. However, due to limitations such as time constraints and data availability, the paper exhibits certain limitations that could be addressed in future studies. First of all, this paper focuses on the annual average urban centralization level, and the impact of the dynamic flow of people on TFP cannot be observed. Future research should aim at systematically and comprehensively analyzing the changes of total factor productivity through more frequent data (such as quarterly or even monthly data). Second, the paper does not delve into the analysis of TFP changes, a limitation that provides an avenue for future research to explore the topic in greater depth and nuance, that is, to further decompose TFP for technological progress or efficiency optimization. Finally, the focus of this paper on the mechanism of TFP change focuses on agglomeration effect and innovation spillover, and subsequent research may involve the construction of corresponding causal inference models to accurately examine the influence of each factor on TFP change. This method will help to provide more targeted countermeasures and suggestions for promoting the development of urban economy.

Data availability statement

The Landscan Global Population dataset is available here: https://www.eastview.com/resources/e-collections/landscan/. Prefecture-level data are sourced from the China Urban Statistical Yearbook, China Urban Construction Statistical Yearbook, China Transport Statistical Yearbook, and China Energy Statistical Yearbook. Available at: https://data.cnki.net/and https://www.stats.gov.cn/sj/ndsj/.

Author contributions

XJ: Conceptualization, Formal Analysis, Funding acquisition, Project administration, Supervision, Writing–original draft, Writing–review and editing. SW: Formal Analysis, Investigation, Methodology, Writing–original draft, Writing–review and editing. CY: Data curation, Software, Visualization, Writing–original draft, Writing–review and editing. SL: Writing–original draft, Writing–review and editing. BY: Validation, Writing–original draft, Writing–review and editing. YW: Resources, Writing–original draft, Writing–review and editing.

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EDITED BY
Lingli Qing,
Guangzhou College of Commerce, China

REVIEWED BY
Tao Peng,
Guizhou Communication Polytechic University, China
Jintong Ren,
Guizhou University of Engineering Science, China

*CORRESPONDENCE
Jianzan Yang,
yangjzgyy@powerchina.cn

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Evaluation of water-land resources in karst regions within the framework of sustainable development goals

Hao Zhang[1,2], Qingping Zhou[1], Jianzan Yang[1]* and Huawei Xiang[1]

[1]Power China Guiyang Engineering Corporation Limited, Guiyang, China, [2]College of Urban and Environmental Sciences, Peking University, Beijing, China

Introduction: The shortage and irrational utilization of water-land resources (WLR) are the main obstacles to the sustainable development of karst regions.

Methods: In accordance with the principles of Sustainable Development Goals (SDGs), an evaluation system for WLR utilization was established. As a representative karst region in China, Guizhou Province was selected to analyze the spatio-temporal variation characteristics of the sustainable development level of WLR from 2000 to 2020, and then revealed the driving factors by using factor detector.

Results: The key findings are as follows: 1) There was a slight intensification in the bearing pressure of cultivated land and water resources, whereas the stress on construction land underwent a notable reduction, from 9.71 in 2000 to 2.02 in 2020, and the pressure on ecological land experienced a modest alleviation. 2) The matching degree of WLR increased significantly at the provincial and prefecture-level city scales, but the effectiveness of improvement at the county scale was limited. 3) The sustainable development level exhibited an upward trajectory, but the sustainable development potential index remained relatively low, consistently below 0.3. 4) Factors *urbanization rate* and *NDVI* exerted a pronounced influence on the spatial differentiation of sustainable development level, with the synergistic driving effect of factors sharing the same attribute significantly heightened.

Discussion: Recommendations include urbanization construction, strengthening the control of rocky desertification, improving water conservancy infrastructure, and establishing cross-regional cooperation mechanisms for cultivated land and ecological land protection to boost the overall sustainable resources utilization in karst regions.

KEYWORDS

water-land resources, karst, SDGs, evaluation, Guizhou Province

Highlights

- The evaluation indicator system of sustainable development level of water-land resources is innovatively proposed;
- From 2000 to 2020, the variation trend of the bearing pressure index of resources in the study area was different, but their spatial equilibrium had been improved;

- The sustainable development level index of water-land resources showed an overall upward trend, but the matching degree had not been effectively improved at the county scale;
- Reducing the area of rocky desertification through ecological restoration can improve the level of sustainable development in karst areas more effectively.

1 Introduction

Karst presents a global ecological and environmental challenge, posing a significant obstacle to regional sustainable development (Huang et al., 2022). As a distinct form of land desertification, karst landforms are characterized by their rugged terrain, widespread exposure of bedrock, and a pronounced decrease in soil fertility (Yu and Chi, 2020), thereby exhibiting landscape features akin to desertification (Pei et al., 2018). China's southwestern region lies at the core of the karst terrain in East Asia, characterized predominantly by mountainous and hilly landscapes (Han and Song, 2019). While rocky desertification has been observed in other karst regions worldwide, the karst in the mountainous area of southwest China stands out for its comprehensive types and vast scale (Zhang et al., 2023). The issue of rocky desertification is exacerbated by the combined pressures of population growth, a delicate ecological environment, and unsustainable economic activities (Gao et al., 2021). Nestled in the heart of the karst region in southwest China, Guizhou Province boasts 73% of its territory underlain by soluble carbonate rocks, with 95% of its counties displaying karst landforms (Peng et al., 2022a). The development of karst landforms, resulting in the shortage of available water resources and land resources, has surfaced as the foremost ecological challenge, hindering the region's path towards sustainable development (Meng et al., 2023).

As one of the most emblematic regions for karst landform evolution globally, Guizhou Province faces a scarcity of viable land resources (Liu Y., 2021), along with an uneven temporal and spatial distribution of water resources, and severe soil erosion, collectively contributing to a fragile ecological environment (Wang et al., 2020). Due to the strong geological tectonic movement, Guizhou Province has formed a special double-layer karst hydrogeological structure (Zhang et al., 2023). The water resources are mainly groundwater, which poses challenges in exploitation, leading to issues of engineering water scarcity (Liu L. Y., 2021). The rugged topography and slow soil formation in Guizhou Province result in impoverished soil, shallow soil layers, dispersed cultivated land resources, and notably, 61% of the total cultivated area being slope-cultivated land (Peng et al., 2022b; Chen et al., 2021). Irrational human activities, including planting crops on steep inclines, excessive grazing, and deforestation, exacerbate the risk of soil erosion even further (Peng et al., 2022a). In recent years, the issue of water resources and land resources misallocation has been alleviated to some degree via ecological initiatives such as converting farmland back to forests, controlling rocky desertification and building water conservancy facilities (Qiao et al., 2021). However, there is still a lack of long-term and multi-scale quantitative assessment of the comprehensive utilization of water resources and land resources in karst regions, and the impact mechanism of water resources and land resources utilization on regional development has not been clarified.

Water resources and land resources serve as the cornerstone for guaranteeing food security and fostering economic and social development (Qin et al., 2023). The way in which water resources are used determines the productivity of land resources (Duc et al., 2023), and conversely, the distribution of land resources imposes limitations on the exploitation and utilization of water resources as well (Liu et al., 2022). Especially for karst regions, water resources have emerged as the main limiting factor of land resource utilization (Field, 2021). In this context, scholars commenced focusing on the interplay between water resources and land resources, examining them collectively as an integrated system of natural resources, which in turn formed the basic definition of water-land resources (WLR) (Geris et al., 2022; Gedefaw et al., 2023). Additionally, research has delved into the coordinated relationship between water resources and land resources during the urbanization process, proposing corresponding strategies for optimal allocation and regulation of WLR (Zhou et al., 2020). The foundation for sustainable development within a region lies in its resource carrying capacity (Lane, 2010). Recent studies focusing on the bearing capacity of WLR has primarily concentrated on static evaluations (Swiader et al., 2020). This includes perspectives such as supply and demand (Ibarrola-Rivas et al., 2017), carbon footprint (Li et al., 2023), ecosystem services (Lilburne et al., 2020), and resources matching (Ying et al., 2023). However, these studies tend to prioritize the productivity of agricultural land, neglecting the bearing capacity of both ecological and construction land. There is also a notable gap in analyzing the impact of WLR utilization on regional sustainable development.

Human activities play a pivotal role in altering the evolution process of rocky desertification (Zhang et al., 2010), and reciprocally, rocky desertification influences regional development, with the two unfolding concurrently and interacting (Zhao et al., 2022). Excessive resources exploitation can lead to a detrimental cycle of poverty and rocky desertification (Gao et al., 2021). Conversely, the advancement of ecological industries proves effective in controlling rocky desertification and fostering regional sustainable development (Tian et al., 2017). To address the sustainable utilization of WLR in karst regions, researchers have proposed a restoration and reconstruction plan for the karst ecosystem to mitigate the issue of resources mismatch (Zhang et al., 2016). The structure of WLR is an important driving force for the change of ecosystem service value (Pacetti et al., 2020). Consequently, researchers have suggested strategies for the optimal allocation of WLR based on sustainable ecosystems (Shiferaw et al., 2019). The 2030 Agenda for Sustainable Development, introduced by the United Nations, encompasses 17 Sustainable Development Goals (SDGs), offering a new perspective for the evaluation of WLR (Lee et al., 2016; Safaei et al., 2023). Among the 17 SDGs, those directly related to WLR include *End Hunger* (SDG2), *Clean Water and Sanitation* (SDG6), *Sustainable Cities and Communities* (SDG11) and *Terrestrial Ecosystems* (SDG15). In recent years, researchers have developed indicator systems centered around the SDGs framework, employing them to conduct sustainable development evaluations across diverse regions and sectors (Leal Filho et al., 2023; De Francesco et al., 2023). Therefore, based on the challenges faced by karst regions such as ecological fragility, rocky desertification threat and backward

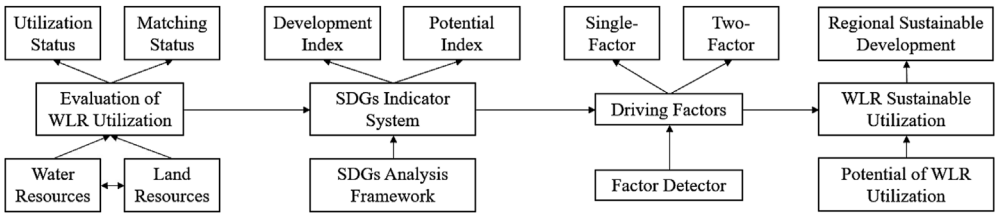


FIGURE 1
Research framework and steps.

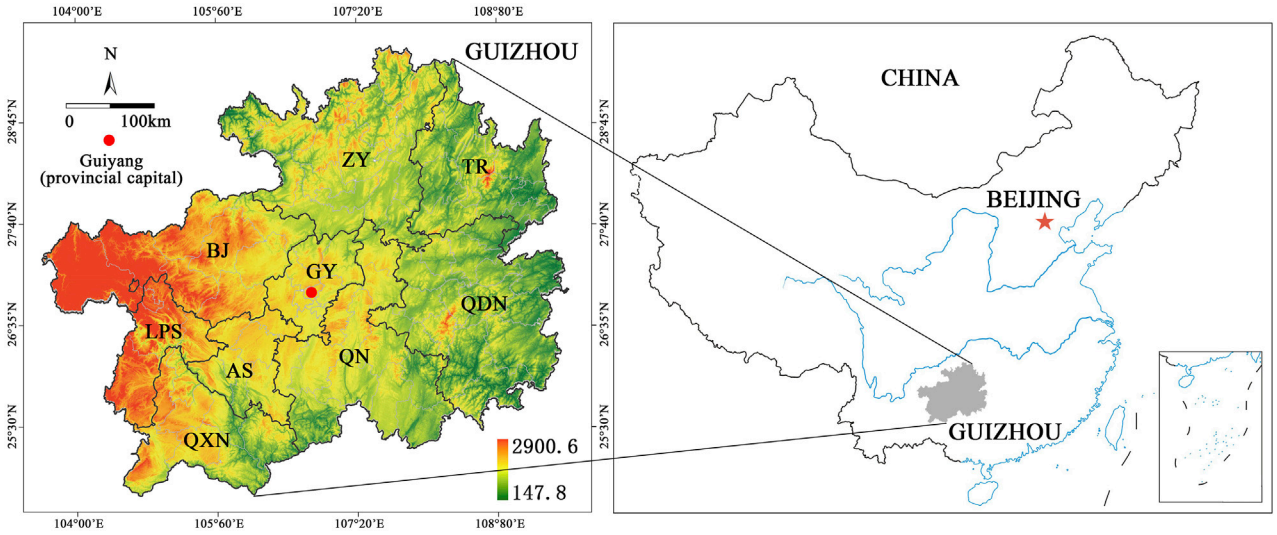


FIGURE 2
Location of the study area. (GY: Guiyang, LPS: Liupanshui, ZY: Zunyi, AS: Anshun, BJ: Bijie, TR: Tongren, QXN: Qianxinan, QDN: Qiandongnan, QN: Qiannan).

production mode, the introduction of SDGs analysis framework can provide a new perspective for explaining the impact of WLR utilization on regional sustainable development.

To sum up, the research framework and steps of this paper are as follows: Firstly, from the spatial scale of province, prefecture-level city and county, the resources bearing pressure of water resources and land resources in Guizhou Province from 2000 to 2020 were evaluated, and the changes of matching degree of WLR were further analyzed. On this basis, the WLR evaluation indicator system was established according to the SDGs analysis framework, and the sustainable development level index was used to measure the contribution of WLR in karst regions to the realization of SDGs, and analyzed the sustainable utilization potential of WLR. Finally, the driving factors of sustainable development level of WLR were analyzed by factor detector (Figure 1). By analyzing the relationship between the WLR utilization and regional sustainable development, this study revealed the potential of WLR utilization to promote regional sustainable development, and provided a scientific basis for improving the sustainable utilization level of WLR in karst regions, thus promoting regional sustainable development.

2 Study area and data

2.1 Study area

Guizhou Province is located in the southwest of China, with 9 prefecture-level cities (88 counties) covering an area of 176,000 km^2 and an average annual precipitation of 1100 mm. The area of karst landform is about 109,000 km^2, accounting for 61.9% of the province's total area, and rocky desertification is mainly distributed in the western part of the study area (Figure 2). In 2020, the *per capita* cultivated land area in the study area was about 0.089 hm^2, lower than the national average (0.097 hm^2). The *per capita* water resource was about 2,800 m^3, higher than the national average (2,240 m^3). However, due to the irregular distribution of rainfall across time and space, coupled with inadequate supporting water conservancy infrastructure, the utilization efficiency of water resources in the study area fell below half of the national average, leading to challenges like regional water scarcity, engineering water shortages, and a delicate water ecological environment (Liu Y., 2021).

TABLE 1 Evaluation indicator system of WLR utilization.

Goal layer	Criterion layer	Indicator layer
Resources utilization status	Bearing pressure of land resources	Cultivated land bearing pressure index
		Construction land bearing pressure index
		Ecological land bearing pressure index
	Bearing pressure of water resources	Water resources bearing pressure index
Resources matching status	Matching status of WLR	The matching degree of WLR
		The Gini coefficient of WLR

TABLE 2 Evaluation indicator system of sustainable development level.

Goal layer	Criterion layer	Indicator layer	Weight
End Hunger (SDG2)	2.1 safe and sufficient food	Grain output per unit area of cultivated land (kg)	0.045
	2.3 secure and equal access to land	Per capita cultivated land area (m^2)	0.077
	2.4 sustainable food production systems	Per capita permanent basic farmland area (m^2)	0.058
Clean Water and Sanitation (SDG6)	6.1 safe and affordable drinking water	Urban *per capita* water supply (m^3)	0.086
	6.3 improve water quality	Treatment rate of domestic sewage	0.043
	6.4 increase water use efficiency	Water consumption per 10,000 yuan GDP (m^3) (−)	0.054
	6.6 protect and restore water-related ecosystems	Water area growth rate	0.079
Sustainable Cities and Communities (SDG11)	11.1 safe and affordable housing	Per capita residential land area (m^2)	0.071
	11.2 sustainable transport systems	Per capita transportation land area (m^2)	0.031
	11.3 inclusive and sustainable urbanization	Ratio of construction land growth rate to population growth rate	0.089
	11.7 green and open public space	Per capita urban public green areas (m^2)	0.046
Terrestrial Ecosystems (SDG15)	15.1 terrestrial ecological protection	Forest coverage rate	0.086
	15.2 sustainable management of forests	New plantation area (m^2)	0.077
	15.3 combat desertification	Proportion of non-rocky desertification area	0.123
	15.5 conservation of natural habitat	Proportion of nature reserve area	0.035

Notes: (−) indicates a negative indicator, the smaller its value, the greater its contribution to the system.

2.2 Data sources

In this study, we have utilized various types of data: land resources, water resources, and socio-economic data. The land resources and NDVI data were obtained from the Chinese Academy of Sciences Resource and Environmental Science Data Center (https://www.resdc.cn), which was based on Landsat TM imagery and generated by manual visual interpretation, with a resolution of 30 m and included 7 land use types. The water resources data were retrieved from the Department of Water Resources (http://mwr.guizhou.gov.cn/), while the socio-economic data came from the Guizhou Macro Economic Database (http://hgk.guizhou.gov.cn/index.vhtml). The dataset encompassed various indicators such as urban *per capita* water supply, *per capita* residential land area, *per capita* investment in fixed assets and rocky desertification area. The study spanned three distinct time periods: 2000, 2010, and 2020.

3 Methodology

3.1 Indicator system design

The emphasis of this paper is to evaluate the utilization of WLR and its sustainable development level in karst regions. To accomplish this, an evaluation indicator system was established and divided into two parts. The first part is the evaluation of the utilization status and matching status of WLR, including the bearing pressure of land resources, the bearing pressure of water resources, the matching degree and Gini coefficient of WLR (Table 1). Referring to relevant researches (Tan et al., 2021), this paper categorized land resources into three distinct categories: cultivated land, construction land and ecological land (Liu et al., 2021).

The second part focused on the evaluation of the contribution degree of WLR utilization to the realization of the SDGs, that is, the

sustainable development level index of WLR (Singh, 2022). Based on the SDGs proposed by the United Nations, goals directly related to WLR were selected and an evaluation indicator system was established (Lee et al., 2016; Dickens et al., 2020). Criterion layer included SDG2, SDG6, SDG11 and SDG15 (Table 2).

Specifically, the contribution of WLR to SDG2 comes primarily from food production, so this paper used "grain output, cultivated land area, permanent basic farmland area" to measure the contributions to goals 2.1, 2.3, and 2.4 respectively. The contribution of WLR to SDG6 is related to the total amount, utilization efficiency and quality of water resources. "Water supply, sewage treatment rate, water consumption and water area growth rate" were used to measure the contributions to goals 6.1, 6.3, 6.4, and 6.6 respectively in this paper. The contribution of WLR to SDG11 comes from the supply of living space. This paper used "residential land area, transportation land area, construction land growth rate and public green areas" to measure the contribution to goals 11.1, 11.2, 11.3, and 11.7 respectively. It is important to mention that, pertaining to SDG11, the absence of statistical data pertaining to rural communities necessitates the paper's focus solely on the calculation of urban statistical data. The contribution of WLR to SDG15 is related to the quality of terrestrial ecosystem, so this paper used "forest coverage rate, plantation area, non-rocky desertification area and nature reserve area" to measure the contribution to goals 15.1, 15.2, 15.3, and 11.5 respectively.

3.2 Resources bearing pressure evaluation

3.2.1 Bearing pressure index

According to the definition of environment carrying capacity (Borja et al., 2022), the bearing pressure index of WLR is calculated, that is, the ratio of the current population to the population that resources can support. If the ratio is less than 1, it indicates that the existing resources have less pressure to support the current population, and *vice versa*. The potential index of WLR is the ratio of the difference between resource carrying capacity and current population to resource carrying capacity, and the greater the bearing pressure index, the smaller the potential index. The mathematical formula is as follows:

$$CI_{ij} = \frac{P_i}{L_{ij}/D_j}$$

$$QI_{ij} = \frac{L_{ij}/D_j - P_i}{L_{ij}/D_j}$$

In the formula: CI_{ij} is the bearing pressure index of class j resources in region i, P_i is the current population of region i, and L_{ij} is class j resources provided by region i, D_j is the *per capita* demand of class j resources, QI_{ij} is the potential index of class j resources in region i.

The demand for cultivated land area per person is equivalent to dividing the annual food requirement per individual by the yield of grain per unit area of cultivated land. According to the Food and Agriculture Organization standards, each person needs 400 kg of food per year. According to China's urban planning standards, the *per capita* demand of construction land area is 150 m^2. There is no uniform standard for the *per capita* demand of water resources and ecological land resources, this paper used the national *per capita* resource occupancy in the study year instead (Liu et al., 2023).

3.2.2 Matching degree of WLR

The matching degree of WLR is used to represent the matching status of available water resources and cultivated land resources (Zhang et al., 2020), that is, the available water resources per unit area of cultivated land (10,000 m^3/hm^2). The mathematical formula is:

$$R_i = a_i \cdot W_i/A_i$$

In the formula: R_i is the matching degree of WLR in region i, a_i is the ratio of cultivated land water consumption in region i, that is, the ratio of agricultural water consumption to available water resources, W_i is the available water resources in region i, A_i is the cultivated land area in region i. According to the available water resources and cultivated land area of each research unit, the Gini coefficient is calculated to represent the matching status of WLR.

3.3 Sustainable development level index

3.3.1 Boundary setting

The SDG Index and Dashboards Report provided a Decision Tree Approach for setting the upper and lower boundaries (Lee et al., 2016). To calculate the sustainable development level index of WLR in karst regions, two scenarios should be considered. The first scenario involves a distinct threshold, where the indicator's upper limit is set at 100%, and the lower limit is at 0%. In the second scenario, there is no clear threshold, meaning the indicator lacks a defined upper or lower limit. For indicators without a clear threshold, the upper limit was determined by averaging the top 3 rankings. To mitigate the impact of extreme values, the lower limit was established using the data in the bottom 10% position.

3.3.2 Entropy weight method

In the pertinent studies of sustainable development evaluation, there exists no standardized regulation regarding the weights assigned to the 17 goals. In this study, the choice was made to employ the entropy weight method for calculating these weights, a process that involves determining the weightage according to the information entropy associated with each indicator. A lower value of information entropy signifies that the indicator conveys a larger quantity of information, leading to an increased weight assigned to it, and *vice versa*. The entropy weight method is chosen to address the subjectivity issues of Analytic Hierarchy Process (AHP) and the challenges posed by repeated attributes due to an excessive number of indicators. To eliminate the impact of dimension, data was standardized, and the sustainable development level index was derived by calculating the information entropy, difference coefficient, and weight of the indicators.

3.4 Sustainable development potential index

Within the carrying capacity of WLR, more rational utilization of resources can improve the ability of sustainable development (Bobba et al., 1997; Mohammed et al., 2014). Assuming that rational

utilization of WLR contributes equally to sustainable development. The sustainable development level index and resources potential index can be used to estimate the sustainable development potential of WLR, that is, the potential of WLR utilization to support regional sustainable development. The mathematical formula is:

$$QS_i = \frac{1}{4}\sum_{j=1}^{4}\left(QI_{ij} \times \frac{1}{n}\sum_{i=1}^{n}\frac{S_i}{QI_{ij}}\right)$$

In the formula: QS_i is the sustainable development potential index of WLR, QI_{ij} is the potential index of resources, S_i is the sustainable development level index, n is the number of research units in the region.

3.5 Factor detector

The factor detector, a specific category within geographic detectors, serves to scrutinize the capacity of factor X in elucidating the spatial heterogeneity of attribute Y, while effectively circumventing the issue of collinearity among multiple factors. Its mathematical principle is to divide a space into several partitions according to the value of factor X, and analyze the spatial heterogeneity by comparing the relationship between the aggregate variance within these partitions and the overall spatial variance (Wang et al., 2016). The mathematical formula is:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{i=1}^{m}N_i\sigma_i^2$$

In the formula: N and N_i represent the number of samples in the whole region and the secondary region respectively, m is the layering of factor X, and σ^2 and σ_i^2 represent the variance of attribute Y in the whole region and the secondary region respectively. The value range of q is [0,1]. The range of the q statistic lies within [0,1]. A smaller q value signifies a weaker explanatory capacity of factor X in relation to the spatial heterogeneity of attribute Y, and *vice versa*.

Interaction detection can further analyze whether the synergic driving effect of the two factors is enhanced or weakened, and the criteria for determining the interaction type are as follows: If the q (X1∩X2) is greater than the sum of q (X1) and q (X2), the type is nonlinear enhancement. When q (X1∩X2) equals the sum of q (X1) and q (X2), the type is independent. If q (X1∩X2) is less than the sum of q (X1) and q (X2), but greater than Max [q (X1), q (X2)], the type is two-factor enhancement. If q (X1∩X2) is less than Max [q (X1), q (X2)], but greater than Min [q (X1), q (X2)], the type is single-factor nonlinear weakening. If Min [q (X1), q (X2)] is less than q (X1∩X2), the type is nonlinear weakening. The website http://www.geodetector.cn/ offers a downloadable software for performing factor detector analysis.

With reference to relevant studies, 6 factors were selected from the dimensions of economic society and natural environment to analyze the driving factors of the spatial differentiation of sustainable development level of WLR. Including socio-economic factors: *population density* (X1), *per capita GDP* (X2), *urbanization rate* (X3). And natural environmental factors: *annual precipitation* (X4), *river density* (X5), *NDVI* (X6). Among them, river density refers to rivers above grade 4.

4 Results

4.1 WLR evaluation

4.1.1 Variation trend of resources bearing pressure

Taking 9 prefecture-level cities as the research object, the variation trend of bearing pressure of WLR was analyzed (Table 3). The bearing pressure index in the table was based on the mean value of the whole province (GZ), where a positive value indicated it exceeded the mean, and *vice versa*.

Cultivated land resources: The bearing pressure index for provincial cultivated land resources rose from 0.49 in 2000 to 0.98 in 2020, nearing the critical value of 1. GY, where the provincial capital is located, exhibited the highest index, surging from 0.82 in 2000 to 2.21 in 2020. The pressure index of TR with less cultivated land resources was also higher than the provincial average. ZY and QN with more cultivated land resources had lower pressure index.

Construction land resources: The bearing pressure index for provincial construction land resources significantly decreased from 9.71 in 2000 to 2.02 in 2020. The pressure index of GY was significantly higher than the provincial average, and significantly decreased from 9.28 in 2010 to 2.59 in 2020. The pressure index of BJ and AS was also higher than the provincial average, and the pressure index in other regions was lower than the provincial average.

Ecological land resources: The bearing pressure index for provincial ecological land resources slightly decreased from 2000 to 2020. LPS, BJ and QXN, located in the west of the study area, served as focal points for the distribution of karst landforms, consistently exceeding the provincial average in pressure index. However, there has been a notable decline observed in their pressure index over time. Although the pressure index of TR, QDN and QN were lower than the provincial average, they showed an increasing trend. The pressure index of GY rose from 2.52 in 2000 to 3.46 in 2020, and the pressure index in 2010 and 2020 was higher than the provincial average.

Water resources: The bearing pressure index for provincial water resources slightly increased from 2000 to 2020. The pressure index of GY and AS in the central region and LPS, BJ and QXN in the western region were generally higher than the provincial average. The northern and eastern regions with relatively abundant water resources, including ZY, QDN and QN, had lower pressure index than the provincial average.

4.1.2 Spatial pattern of resource bearing pressure

The spatial distribution of the WLR bearing pressure index was further examined at the county scale (Figure 3). Here are the key findings:

Cultivated land resources: From 2000 to 2020, the bearing pressure index for cultivated land resources was low in the north and south, while the central region exhibited relatively high pressure. Other high-value units were dispersed in space, showing a pattern of "high in the middle and low at the edge."

Construction land resources: In 2000 and 2010, the northwest region had a relatively high pressure index for construction land resources, while the southern region had a low index. By 2020, the pressure index in the north, south, and southeast had decreased, and the spatial pattern of high-value units became less apparent,

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TABLE 3 Bearing pressure index of WLR from 2000 to 2020.

Bearing pressure index	Year	GY	LPS	ZY	As	BJ	TR	QXN	QDN	QN	GZ (AVG.)
		(AVG. +)									
Cultivated land	2000	0.33	−0.01	−0.16	0.02	−0.10	0.00	0.09	−0.09	−0.14	0.49
	2010	0.75	0.11	−0.24	−0.02	−0.05	0.06	−0.01	−0.13	−0.24	0.72
	2020	1.23	−0.04	−0.29	0.05	−0.13	0.08	−0.21	−0.28	−0.36	0.98
Construction land	2000	2.40	−0.77	−0.20	−0.33	2.73	−1.21	−1.59	0.04	−0.43	9.71
	2010	2.30	−0.19	−0.02	0.01	1.01	−0.79	−2.19	−1.42	−1.34	6.98
	2020	0.57	0.22	−0.52	0.22	0.39	0.10	0.15	−0.32	−0.62	2.02
Ecological land	2000	−0.14	0.76	−0.73	0.63	1.44	−1.35	1.25	−1.24	−1.41	2.66
	2010	0.77	0.23	−0.78	−0.27	1.00	−0.71	0.65	−0.51	−0.80	2.33
	2020	1.33	0.29	−0.64	−0.43	0.24	0.03	0.37	0.00	−0.30	2.13
Water resources	2000	0.83	0.16	−0.85	0.93	1.04	0.12	0.05	−0.79	−0.83	1.24
	2010	1.02	−0.01	−1.09	0.96	1.02	−0.12	0.05	−1.09	−1.07	1.59
	2020	1.11	0.13	−1.15	0.95	1.31	−0.11	−0.24	−1.29	−1.24	1.83

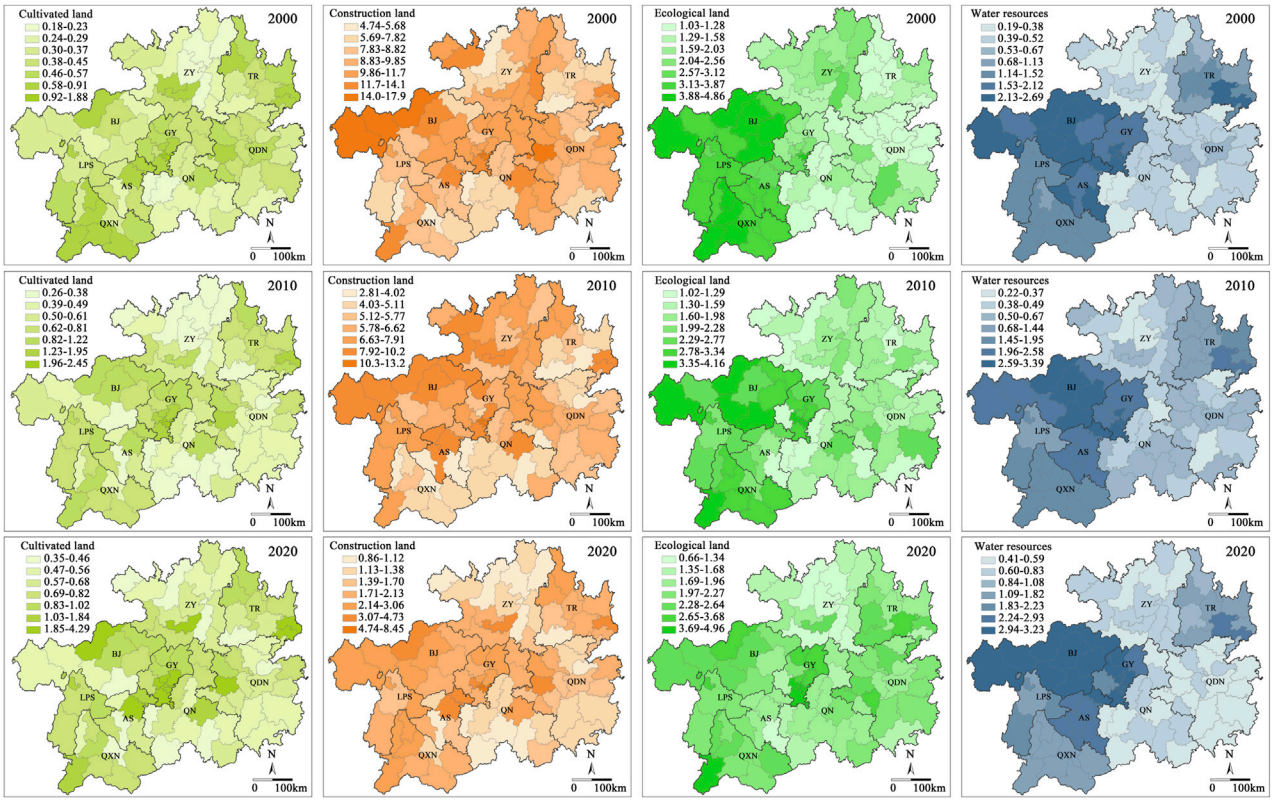


FIGURE 3
Bearing pressure of WLR from 2000–2020.

showing a pattern of "high in the middle and low in the north and south" on the whole.

Ecological land resources: It can be clearly seen that in 2000 and 2010, the bearing pressure index showed a pattern of "high in the west and low in the east". In 2020, the spatial equilibrium of the bearing pressure index was significantly improved, and the high-value units were dispersed in space.

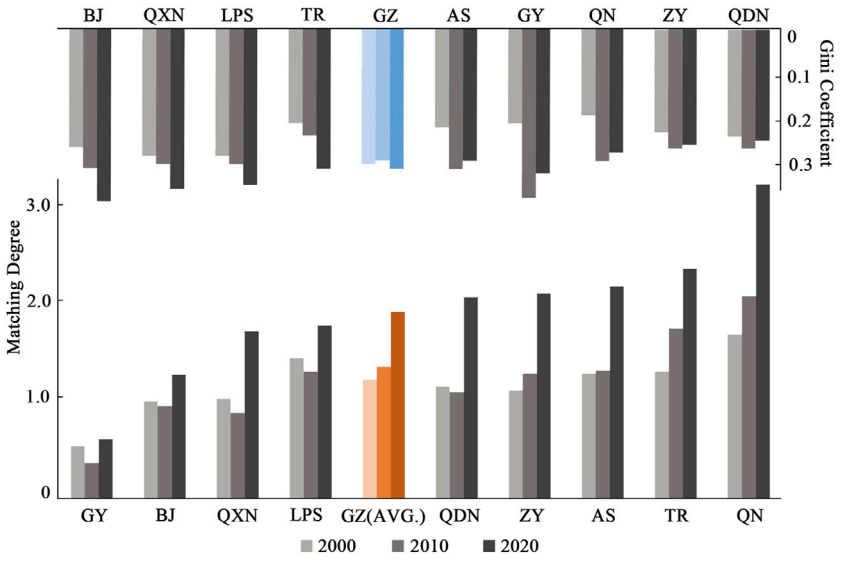


FIGURE 4
The matching degree and Gini coefficient of WLR.

Water resources: The spatial regularity of bearing pressure index was also obvious, from 2000 to 2020, it presented a pattern of "high in the west and low in the east." In addition, the pressure index was also relatively high in the central region and the northeastern fringe.

In summary, the spatial equilibrium of the bearing pressure index for the four resource types improved from 2000 to 2020. The predominant landform types in the study area are mountains and hills, lacking plains to support large population concentrations. As a result, the spatial patterns of the resource bearing pressure index were not pronounced for cultivated land and construction land closely associated with human activities. Conversely, ecological land and water resources, closely tied to natural conditions, displayed distinct spatial heterogeneity, particularly influenced by the karst landform in the western region, where the resource bearing pressure index was higher.

4.1.3 Matching degree analysis

The study employed the matching degree and Gini coefficient to analyze the spatial-temporal matching characteristics of water resources and cultivated land resources in the study area (Figure 4). Here are the main observations:

From 2000 to 2010, the average matching degree of WLR for the entire province (GZ) slightly increased. At the prefecture-level city scale, GY, BJ, QXN, LPS, and QDN experienced a slight decrease in matching degree, while ZY, AS, TR, and QN showed a slight increase. From 2010 to 2020, the matching degree increased significantly, reaching an average of 1.91 for the province. GY had the lowest matching degree, reaching only 0.61 in 2020, while QN had the highest matching degree, reaching 3.21 in 2020. It showed that the matching degree of WLR in the study area had been improved significantly from the provincial scale and the prefecture-level city scale.

However, the Gini coefficient told a different story. Taking counties as the research unit, the Gini coefficient of matching WLR of the whole province (GZ) did not change significantly from 2000 to 2010, and the Gini coefficient of 9 prefecture-level cities increased to different degrees. GY, in particular, saw its Gini coefficient rise from 0.23 in 2000 to 0.41 in 2010. From 2010 to 2020, the Gini coefficients of AS, GY, QN, ZY, and QDN began to decline, but the Gini coefficients of BJ, QXN, LPS, and TR continued to rise. This suggests that, at the county scale, the matching status of WLR in the study area did not see effective improvement during this period. In summary, while the matching degree of WLR improved significantly at both the provincial and prefecture-level city scales, the Gini coefficient revealed that the matching status at the county scale did not see substantial improvement during the study period.

From the perspective of spatial pattern (Figure 5), the matching degree of WLR in the study area displayed the following trends over time. Year 2000: The matching degree showed a "high in the east and low in the west" pattern. Particularly in the northwest, several counties belonging to BJ had a matching degree lower than 0.53, and the western fringe areas also exhibited relatively low matching degrees. Year 2010: The spatial pattern of WLR matching degree did not undergo significant changes. Although the overall matching degree increased, noticeable low-value accumulation areas persisted in the northwest region. Year 2000: The matching degree exhibited a pattern of "high in the east and south, low in the middle and west". In the central region where Guiyang, the provincial capital city with the highest urbanization rate, is located, the matching degree was less than 0.8, significantly lower than other regions.

4.2 Sustainable development evaluation

4.2.1 Sustainable development level analysis

The sustainable development level index can be used to measure the contribution of WLR utilization to the realization of SDGs (Figure 6). From the perspective of variation trend, the

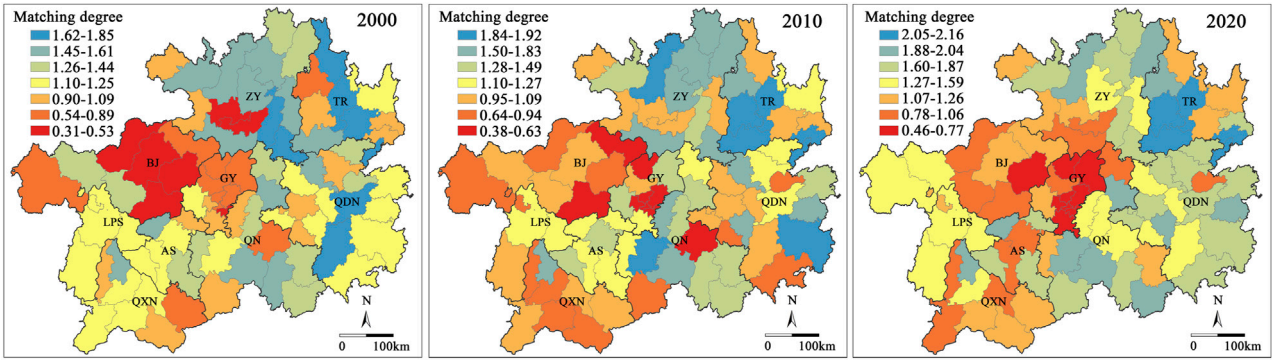


FIGURE 5
Spatial pattern of matching degree of WLR.

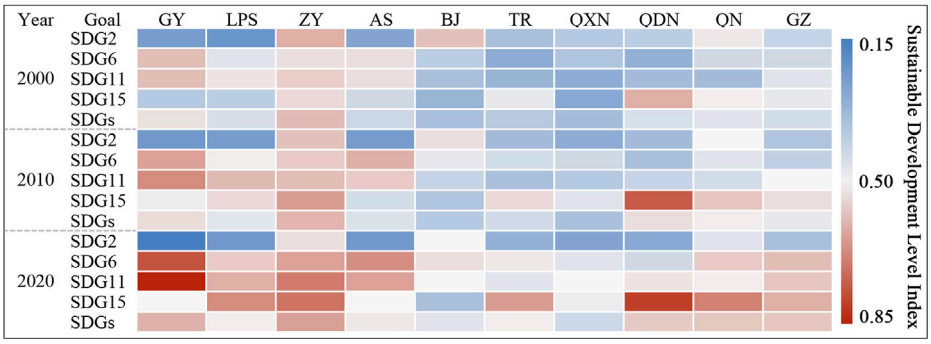


FIGURE 6
Thermal map of sustainable development level index of WLR.

sustainable development level index of WLR of the whole province (GZ) was 0.39 in 2000, and rose to 0.53 in 2020. Similarly, prefecture-level cities also demonstrated an upward trend. For instance, GY rose from 0.48 in 2000 to 0.57 in 2020, and QXN increased from 0.31 in 2000 to 0.38 in 2020. This indicated that the contribution of WLR utilization to the realization of SDGs in the study area was constantly increasing.

Further analysis of the evaluation results of individual goals. The contribution of WLR utilization to the realization of SDG2 in the study area has been low, because the cultivated land resources in karst regions were limited. In contrast, when comparing the periods of 2000–2010 and 2010–2020, a more significant increase in the contribution of water and land resource utilization to the realization of SDG6/11/15 occurred during the latter period. Furthermore, disparities among prefecture-level cities were observed, with ZY exhibiting a higher sustainable development level index, while QXN displayed a lower index. Notably, for cities like GY, LPS, ZY, and AS, characterized by higher urbanization rates, the contribution of water and land resource utilization to the realization of SDG6/11 was higher. Conversely, the contribution of WLR utilization of QDN, TR and QN to the realization of SDG15 was higher, reflecting that their sustainable terrestrial ecosystems placed them at a lower risk of rocky desertification compared to the western part of the study area.

4.2.2 Sustainable development potential analysis

Considering the trend variation, the sustainable development potential index of WLR exhibited no significant change from 2000 to 2020. The overall province's average potential index experienced a slight decrease from 0.44 in 2000 to 0.42 in 2010, followed by a marginal increase to 0.43 in 2020. Over the past 2 decades, the utilization intensity of WLR in the study area was relatively high, and the sustainable development potential has been at a low level. Consequently, there was a deficiency in the capacity to further support regional sustainable development.

From the perspective of spatial pattern (Figure 7), in 2000, the sustainable development potential index of WLR in the south was the lowest, lower than 0.35, forming a low-value accumulation area. Conversely, the northern region displayed a higher potential index, exceeding 0.45. By 2010, the potential index in the northern region had surpassed 0.5, creating an accumulation area with high values, while other regions maintained relatively low potential indices. Moving to 2020, the south and southeast evolved into a high-value accumulation area, surpassing 0.55, while the central and western regions exhibited lower potential indices. Particularly, the central region, housing the provincial capital, recorded a potential index below 0.3. It's worth noting that a lower potential index corresponds to a higher utilization degree of WLR. Since 2000, the central region has gradually become a focal point for the exploitation

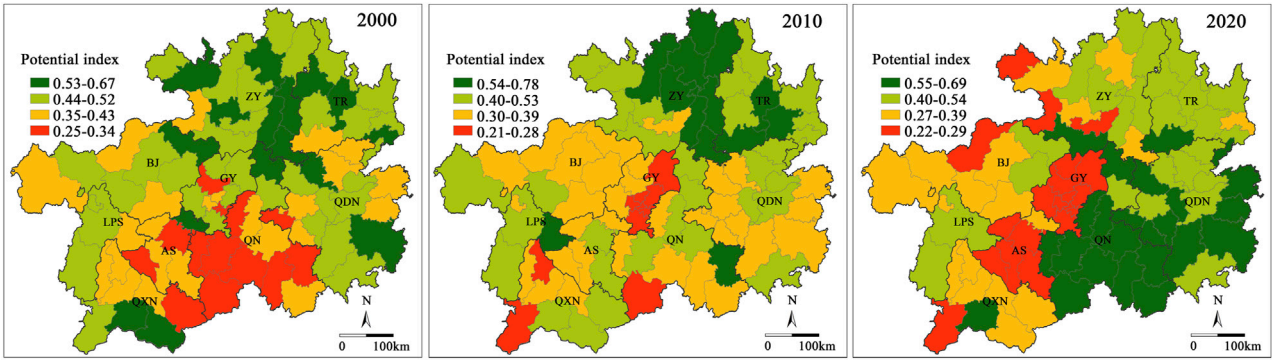


FIGURE 7
Sustainable development potential index of WLR.

TABLE 4 Single-factor detection results of sustainable development level.

year	Index	X1	X2	X3	X4	X5	X6
2000	*q*	0.14	0.21	0.25	0.15	0.22	0.27
	P	0.003	0.000	0.027	0.000	0.000	0.007
2010	*q*	0.18	0.22	0.27	0.11	0.19	0.21
	P	0.001	0.000	0.006	0.002	0.000	0.021
2020	*q*	0.17	0.24	0.31	0.12	0.16	0.18
	P	0.000	0.000	0.000	0.015	0.025	0.011

and utilization of WLR. This highlights a discernible shift in emphasis towards the central region over the years.

4.3 Driving factors

The factor detector was used to analyze the driving factors of spatial differentiation of sustainable development level of WLR (Table 4). Firstly, the Variance Inflation Factor (VIF) test was conducted using the SPSS tool. The VIF values for all six factors were found to be below 5, with an average VIF value of 3.47, indicating the absence of intolerable collinearity issues. Secondly, the single-factor detection was carried out, and the *P*-value was less than 0.05 as the standard, and the 6 factors showed significant driving effect in 2000,2010 and 2020. The single-factor detection results showed that X3 (*urbanization rate*) and X6 (*NDVI*) had the strongest driving effects, which showed that the sustainable development level of WLR can be effectively improved by increasing urbanization rate and improving vegetation status in karst regions. In addition, during 2000–2020, the driving effect of socio-economic factors had gradually increased, while that of natural environmental factors had gradually decreased, indicating that the influence of artificial intervention on the sustainable development level of WLR had been increasing.

On the basis of single-factor detection results, two-factor interaction detection was carried out (Table 5). The results showed that the interaction types within the socio-economic factors were nonlinear enhanced, as did the interaction types within natural environmental factors. For example, the interaction type of X2∩X3 was nonlinear enhancement, indicating that while improving the urbanization rate, the growth of economic strength can more effectively enhance the sustainable development level of WLR. Additionally, the interaction types between socio-economic factors and natural environmental factors were two-factor enhancement, as exemplified by factor combination X2∩X6. It showed that the simultaneous improvement of vegetation status and economic development can more effectively enhance the sustainable development level of WLR. Furthermore, the results indicated that for the spatial differentiation of sustainable development level of WLR, the explanatory power of two-factor interaction was more robust than that of the single factor, and the driving effect of the combination of the same attribute factors would be significantly enhanced.

5 Discussion

The utilization of WLR in karst regions is related to the evolution of rocky desertification. Influenced by meteorological factors such as temperature and precipitation, as well as topographic factors like elevation and slope (Yu et al., 2022), the available WLR in karst regions are insufficient, leading to an imbalanced spatial distribution (Liu L. Y., 2021). This paper selected typical karst regions to evaluate the bearing pressure and matching degree of WLR. Results revealed that, in comparison to regions in western China without extensive karst distribution, the study area experienced higher bearing pressure on cultivated land resources (Lang and Song, 2019). For example, in Chongqing, a neighboring province to the north of the study area, the bearing pressure index of cultivated land resources was about 0.6 from 2010 to 2020 (Zhou et al., 2022). Guizhou, being the only province in China devoid of a plain landform, exhibited significantly higher bearing pressure on construction land resources compared to other provinces. In 2010, for instance, the average bearing pressure index of construction land resources in 12 provinces across western China was close to 1 (Zhou et al., 2022). Karst landforms also exert a notable influence on ecological land resources and water resources. The study found that in the western part of the study area where karst landform was concentrated, the bearing pressure of ecological

TABLE 5 Results of two-factor interactive detection of sustainable development level.

Year	2000					Year	2010					Year	2020				
Factor	X1	X2	X3	X4	X5	Factor	X1	X2	X3	X4	X5	Factor	X1	X2	X3	X4	X5
X2	0.37					X2	0.44					X2	0.59				
X3	0.52	0.67				X3	0.57	0.72				X3	0.64	0.71			
X4	0.17	0.29	0.29			X4	0.22	0.29	0.3			X4	0.26	0.31	0.36		
X5	0.23	0.37	0.4	0.44		X5	0.21	0.36	0.32	0.46		X5	0.28	0.34	0.45	0.37	
X6	0.38	0.41	0.47	0.53	0.59	X6	0.38	0.42	0.39	0.48	0.53	X6	0.31	0.41	0.46	0.47	0.58

land resources and water resources was greater. In addition, the matching degree of WLR in the study area also presented a pattern of "high in the east and low in the west."

The utilization of WLR is closely intertwined with the economic and social development (Xu et al., 2018). Apart from the constraints posed by natural conditions, regional development strategy adjustments also exert a significant impact on the utilization of WLR (Gao et al., 2022). At the beginning of the 21st century, Guizhou Province consistently ranked last in China in terms of *per capita* GDP, exhibiting a relatively backward economic development level and a lack of capacity to enhance the efficiency of water and land resource utilization (Feng et al., 2022). Since 2000, China has implemented the strategy of "the grand western development", providing policy and financial support to the western region in terms of the approval of construction land and eco-environmental protection (Sun et al., 2020). From 2000 to 2010, the bearing pressure of construction land resources in the study area decreased, and the sustainable development level increased. However, the persistent issue of unbalanced distribution of ecological land resources and water resources remained unresolved (Feng et al., 2022). In 2012, the central government issued targeted policies to support the development of Guizhou. Through poverty alleviation projects, infrastructure construction and rock desertification control, the spatial imbalance of resources bearing pressure has been effectively alleviated (Lv et al., 2023). The central region has become the focus of urbanization construction, which was corroborated by the findings of this study (Ren et al., 2021). In addition, this paper also found that the matching degree of WLR increased at the provincial and prefecture-level city scales, but the matching status of at the county scale was still not effectively improved.

Reflection and prospect of this research. In the design of sustainable development evaluation system, this study has made notable advancements by eliminating certain indicators which were difficult to obtain. For example, terrestrial ecological evaluation did not take into account the value of biodiversity or the impact of climate change on WLR (Fernandes et al., 2016; Sandström et al., 2017). The evaluation results highlight an inconsistency between the bearing pressure of WLR and their contribution to the realization of SDGs. Notably, the central region exhibited high bearing pressure on construction land, yet the contribution of resource utilization to realizing SDG11 was substantial. This underscores that while basic resource conditions determine sustainable development potential, the level of sustainable development is also influenced by human activities. In addition, the analysis of driving factors can elucidate the relationship between water and land resource utilization and regional development. This study revealed that, whether through single-factor detection or two-factor interaction detection, factors X3 (*urbanization rate*) and X6 (*NDVI*) wielded strong explanatory power over the spatial heterogeneity of sustainable development level. Consequently, enhancing the sustainable development level of WLR in karst regions is of paramount significance. This can be achieved by improving resource utilization efficiency through urbanization and enhancing vegetation status through the control of rocky desertification.

6 Conclusion

Based on the SDGs framework, this paper proposed an indicator system and method for evaluating the utilization of WLR in karst regions and their contribution to the realization of SDGs. Guizhou Province in China was chosen to analyze the variation characteristics of the bearing pressure and matching degree of WLR, as well as the driving factors of sustainable development level. The main conclusions are as follows.

1) The bearing pressure index for the four resource types exhibited diverse variation trends. Between 2000 and 2020, the bearing pressure increased slightly for cultivated land and water resources, with the bearing pressure for cultivated land nearing the critical value of 1. In contrast, the bearing pressure for ecological land decreased slightly, and the bearing pressure for construction land witnessed a significant decrease from 9.71 in 2000 to 2.02 in 2020. Spatial equilibrium in the bearing pressure index for the four resource types improved from 2000 to 2020. Cultivated land displayed a "high in the middle and low at the edge" pattern, while construction land formed a spatial pattern of "high in the middle and low in the north and south" by 2020. Ecological land and water resources exhibited a clear spatial pattern of "high in the west and low in the east."
2) The results of matching degree analysis of WLR at different scales were different. From the provincial scale and the prefecture-level city scale, the matching degree increased significantly from 2000 to 2020. The spatial pattern had evolved from "high in the east and low in the west" in 2000 to "high in the east and south, low in the middle and west" in 2020. Taking counties as the basic unit, Gini coefficients of 9 prefecture-level cities increased to varying degrees from 2000 to 2010. Subsequently, in some regions, the

Gini coefficient showed a decline. In general, it showed that the matching status of WLR in the study area had not been effectively improved at the county scale.

3) The sustainable development level index of WLR showed an overall upward trend, indicating that the contribution of resources utilization to the realization of SDGs continued to rise. The contribution of resources utilization to the realization of SDG2 was always low, which was related to the limited cultivated land resources in karst regions. Regions with higher urbanization rates exhibited a higher contribution of resources utilization to the realization of SDG6/11, and regions with less distribution of karst landforms had a higher contribution of resources utilization to the realization of SDG15. Additionally, the sustainable development potential had been at a low level, indicating a deficiency in the ability to further support regional sustainable development. Since 2000, the focus of WLR exploitation and utilization has gradually shifted from the southern region to the central region.
4) Regarding the spatial heterogeneity of the sustainable development level of WLR, the single-factor detection results showed that X3 (*urbanization rate*) and X6 (*NDVI*) had the strongest driving effect, and the driving effect of socio-economic factors had gradually increased during 2000–2020, indicating that the influence of artificial intervention on the sustainable development level of WLR had been increasing. Additionally, the explanatory power of two-factor interactions surpassed that of single factors, and the driving effect of combinations of factors with the same attribute was significantly strengthened.

There is still a certain gap between the WLR utilization and the realization of SDGs in karst regions. Despite a continuous improvement in the sustainable development level of resources utilization in the study area from 2000 to 2020, the sustainable development potential had remained at a low level. According to the results of the study, it is suggested that the sustainable management of the terrestrial ecosystem should be strengthened in the process of rocky desertification control, so as to reduce the bearing pressure on resources and enhance the potential of sustainable development. In addition, efforts should be made to enhance the matching degree of WLR at county level by improving small water conservancy infrastructure. There are also different development strategies for the WLR utilization in different regions. It is suggested that the western region should improve the utilization efficiency of construction land through concentrated urbanization. For the eastern and northern regions with relatively abundant water resources, it is suggested to appropriately increase the tasks of cultivated land protection. The central region is the core of urbanization construction and economic development. It is suggested to establish a cross-regional cooperation mechanism for cultivated land protection and ecological land protection while developing efficient agriculture. These measures collectively contribute to improving the sustainable utilization level of WLR in karst regions.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HZ: Conceptualization, Formal Analysis, Methodology, Software, Writing–original draft, Writing–review and editing. QZ: Data curation, Formal Analysis, Supervision, Writing–review and editing. JY: Funding acquisition, Project administration, Resources, Visualization, Writing–review and editing. HX: Investigation, Project administration, Visualization, Writing–review and editing.

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Conflict of interest

Authors HZ, QZ, JY, and HX were employed by Power China Guiyang Engineering Corporation Limited.

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EDITED BY
Lingli Qing,
Guangzhou College of Commerce, China

REVIEWED BY
Ping Liu,
State Grid Jiangsu Electric Power Co., LTD, China
Yan Sun,
Beijing Forestry University, China

*CORRESPONDENCE
Shen Zhao,
zhaos.14s@igsnrr.ac.cn

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Spatial relationship between population shrinkage and land development in northeast China

Xueqin Wang[1], Jiacheng Hu[2], Shen Zhao[3]* and Rui Hu[4]

[1]School of Sociology and Population Studies, Nanjing University of Posts and Telecommunications, Nanjing, China, [2]Faculty of Education and Sports Studies, University Malaysia Sabah, Kota Kinabalu, Sabah, Malaysia, [3]Policy Research Center, Ministry of Housing and Urban-Rural Development, Beijing, China, [4]Business School, University of Chinese Academy of Social Sciences, Beijing, China

Introduction: Analyzing the features of population shrinkage and land development, as well as the spatial coordination relationship between population and land, has reference value for optimizing the allocation of land resources in areas with shrinking populations.

Methods: This paper analyzed space–time features of population shrinkage and land-use intensity (LUI) in northeast China, which is a typical shrinking area in China. Furthermore, the correlation coefficient measurement method and coupling coordination model were applied to explore the spatial relationship between population shrinkage and land development.

Results: The main results show that (1) Both the total population and the labor force in northeast China shrank between 2010 and 2020, while the contribution of the labor force to the whole population remained at a level above the national average throughout the period. (2) Significant differences existed in population shrinkage types among county-level units, including absolute shrinkage type, labor-growth shrinkage type, labor-loss growth type, and absolute growth type, indicating that the change trend of the labor population and that of the total population are not exactly consistent. (3) The land-use intensity of county-level units has gradually increased despite varying degrees of population loss from 2000 to 2020, presenting a paradoxical phenomenon of population loss and land spatial expansion. (4) In most county-level units, the population changes are negatively correlated with the land-use intensity change and have an uncoupled coordination relationship with it. (5) The match between population and landuse is stronger in regional central cities and shows a spatial characteristic of decreasing from the center to the periphery.

Discussion: This study helps reveal the relationship between population and land in typical areas of China with shrinking populations, laying a certain foundation for seeking ways to achieve coordinated development between humans and land.

KEYWORDS

population shrinkage, labor force, land development, spatial relationship, Northeast China

1 Introduction

Population serves as the main body of production and living activities, being an important condition for urban development. Unfortunately, more than a quarter of the world's metropolises experienced shrinkage in the 1990s, and the number continued to increase due to various factors, particularly throughout developed economies in the United States, Canada, the United Kingdom, and Europe (Wang and Long, 2023; Karp, 2024). A study of 1,600 cities in the United States showed that 367 underwent population decline while holding the geographies constant before 2010 (Ribant and Chen, 2020). This phenomenon is not unique to the United States; many shrinking cities have emerged in Europe during the drastic social and economic transition since the post-socialist era. For example, 33% of urban areas in France shrank; one-third of Germany's cities are losing population, including Schwedt, Gera, Hoyerswerda, Cottbus, and so on (Nijman and Wei, 2020).

As the largest developing country in the world, China has also experienced drastic shrinkage. Most Chinese cities are experiencing both population shrinkage and spatial expansion in the context of rapid urbanization (Meng and Long, 2022). During 2000–2010, 19,882 of 39,007 township-level census units had population loss (Long and Gao, 2019), the total area of which was almost one-third of the total territory of China. The northeast region of China is an important old industrial base, and its development has strategic significance. Unfortunately, it has become a typical shrinking area in China. After the 1990s, Northeast China began to enter the stage of revitalization of economic and structural adjustment, while the prominent population problem has become the main limiting factor for its economic and social development (Ma et al., 2023; Gao and Ryan, 2021). Nowadays, it generates consistently negative impressions such as "economic recession," "population collapse," and "profit vacuum" (Lin, 2019).

However, an increasing body of research has found that population shrinkage is not necessarily a "bad thing;" its impact on economic growth and urban vitality is not always negative (Liu et al., 2024; Feng et al., 2023). The key lies in whether population shrinkage is coordinated and aligned with other factors, including resource factors, environmental factors, and social factors. Among them, land resources are the carriers of socioeconomic activities, and the coordination between land resources and population shrinkage is particularly crucial for the sustainable development of areas with shrinking populations.

The discussion of the relationship between population change and land use has a long history. It is generally believed that there is a bidirectional relationship between population change and land use. Population growth increases demand for residential, agricultural, and industrial land, leading to urban expansion, while population decline can cause land abandonment. Conversely, land use changes, such as urbanization or deforestation, influence living conditions and economic opportunities, affecting migration and population distribution (Seto and Ramankutty, 2016). This interplay underscores the need for coordinated development and sustainable planning. Scholars have conducted extensive research on the coordinated development of population and land factors, including spatial matching and collaborative development models of population and land (Huang et al., 2024; Ren et al., 2023), measurement of coordination degree between population urbanization and land urbanization (Wu et al., 2018; Xu and Xiao, 2021), etc. The research area focuses more on economically developed regions with faster urbanization rates, while there is relatively less research on areas with shrinking populations, especially in +areas such as northeast China, which need much more attention.

Thus far, researchers have mainly focused on problems, influence mechanism analysis of population contraction in northeast China, and countermeasures studies, while the data and methods they use have become more diverse, such as mathematical statistics data, DMSP/OLS nighttime lighting data, etc. (Ma et al., 2020; Wang et al., 2022). They primarily focused on the quantitative research of case study areas with diverse research scales and perspectives, which laid a good foundation for the government's urban governance work. However, few studies stressed the spatial relationship between population shrinkage and land development. In fact, regions with prolonged and severe population shrinkage once found it difficult to reverse the trend of population loss in the short term. What is more important is to seek a model of coordinated development between population and land. The coordination between population changes and land use intensity in areas with shrinking populations has become the key to seeking healthy and sustainable development in these shrinking areas. Therefore, studying the spatial relationship between population shrinkage and land use in economic recession and areas with shrinking populations presents a certain urgency.

This paper assumes that the spatial relationship between population shrinkage and land development in shrinking areas needs more attention: (i) What are the space–time features of population shrinkage and land use? (ii) Is the relationship between population change and land development coordinated? (iii) How to counter their challenges in the future? Based on the fifth, sixth, and seventh Population Census of Mainland China and 30 m-precision land use remote sensing image data, this study mainly used the index of population change rate to analyze the shrinking features of population in northeast China at different scales of land-use intensity to explore spatial features of land development. The article used the index of correlation coefficient and coupling coordination to analyze the spatial relationship between population shrinkage and land development. Among them, the analysis of population shrinkage characteristics used two indicators of total population and labor force. This study aims to propose some policy thinking for future sustainable population development and human–land coordination in northeast China and expects to provide a reference for other areas with shrinking populations.

2 Key literature review and theoretical framework

2.1 Key literature review

Urban shrinkage has emerged as a global and multidimensional phenomenon, gaining increasing attention in spatial planning and urban studies since the early 2000s (Pallagst et al., 2017; Hu et al., 2021). As a spatial manifestation of globalization, urban shrinkage has been extensively documented in developed regions such as North America, Europe, and Japan, while its prevalence in

developing countries, particularly in China, has only recently begun to attract scholarly interest (Long and Gao, 2019; Wolff et al., 2017; Wiechmann and Pallagst, 2012). Early research focused on the drivers of shrinkage, including deindustrialization, suburbanization, outmigration, economic transformations, and demographic aging, which were particularly evident in regions like Eastern Germany and the Rust Belt in the United States (Wiechmann and Pallagst, 2012; Beyer et al., 2006; Fernandez and Hartt, 2022; Li and Mykhnenko, 2018). These factors create a "downward spiral" or "vicious circle" characterized by diminishing employment opportunities, reduced purchasing power, and further population loss, which is exacerbated by structural crises in post-industrial economies (Martinez-Fernandez et al., 2016; Baron et al., 2010). The concept of "shrinking cities" further broadened the discourse, emphasizing the global nature of the phenomenon and the need for comparative studies across different contexts (Martinez-Fernandez et al., 2012; Haase et al., 2014). In China, population shrinkage has gained attention due to its rapid urbanization and regional economic disparities, with northeast China being a prominent case due to its industrial decline and outmigration (Li and Mykhnenko, 2018). The region's historical reliance on heavy industry and state-owned enterprises has exacerbated population loss, creating a unique context for studying shrinkage (Long and Gao, 2019). The unique spatial patterns of shrinkage in China, characterized by both urban core decline and rural depopulation, underscore the need for region-specific policy frameworks. Moreover, the interplay between historical industrial reliance and contemporary economic challenges has created a complex landscape of shrinkage, necessitating innovative approaches to urban and regional planning (Long and Gao, 2019).

Population figures were often adopted as a proxy for shrinkage (Hartt and Hackworth, 2020; Deng et al., 2022), although they elided other forms of population change. However, they reveal important elements of a city's or region's economic fortunes, which were currently affected by the outmigration and population aging (Labosse, 2010). In this paper, total population is also used to judge shrinkage. It is worth noting that scholars or governments have shown less concern for labor force issues in areas with shrinking populations, as there were few relevant studies or policies. In fact, because it serves as the "blood" for regional or urban development, the labor force is the most active, dynamic, and creative part of the population group and the main force involved in all aspects of social and economic activities (Emeka et al., 2024). Thus, the shrinkage of the labor force, a critical subset of population decline, has significant implications for economic productivity and regional development. Research has consistently identified demographic aging and the outmigration of working-age individuals as key contributors to labor force shrinkage. In Europe, regions such as Eastern Germany and Southern Italy have experienced substantial labor force declines, leading to reduced tax revenues and increased dependency ratios, which in turn exacerbate socioeconomic challenges (Bontje, 2004; Wiechmann and Bontje, 2015). Similarly, the labor force in Northeast China has been shrinking at an alarming rate, driven by both demographic aging and the outmigration of young, skilled workers to more prosperous regions in the south and east (Li and Mykhnenko, 2018). This trend is further compounded by the region's industrial structure, which has historically been dominated by sectors with limited capacity for innovation and job creation.

In consideration of the importance of labor population stability, many scholars have tried to explore effective ways to meet the changing labor market environment. Unfortunately, the labor force is limited in that it can only be adjusted by the free flow of working-age people (Dobre, 2018). In areas with shrinking populations, adjusting the work-force flow to relieve labor shrinkage based on understanding their change features could be a considerable part of future development. In consequence, this article attempts to conduct relevant research, taking total population and labor force into consideration, to explore the space–time characteristics of population shrinkage and the spatial relationship between them and land use in northeast China.

Population and land are the two key fundamental elements of the regional system of human–environment relationships. The spatial relationship between them has emerged as a critical area of research, particularly on the balance or coordination relationship between them in the context of sustainable urban and regional planning (Zhang, 2021; Cheng et al., 2024; Qiao et al., 2024; Wang et al., 2024). A recurring theme in the literature is the decoupling of population decline from land development, often called "over-expansion" or "hollowing out." This phenomenon has been observed in various contexts, including post-industrial regions and shrinking cities, where infrastructure and land use patterns fail to align with declining population trends. In the United States and Europe, urban sprawl in declining cities has been well-documented, with significant environmental and economic inefficiencies arising from the maintenance of infrastructure for shrinking populations (Wiechmann and Pallagst, 2012; Schmidt, 2013). In China, the rapid urbanization and land-driven growth model have led to similar disparities, particularly in regions experiencing population decline (Jiang et al., 2012).

Northeast China, with its unique combination of population shrinkage and land development pressures, provides a compelling case study for understanding these dynamics. Advanced spatial analysis techniques have been employed to quantify the spatial mismatch between population decline and land development, revealing that land development in the region has continued despite population shrinkage, driven by local government reliance on land finance and speculative real estate investments. Compared with the weakening driving force for new construction land in shrinking cities in European and American countries, shrinking cities in China generally exhibit a contradictory development pattern of continuous expansion of construction land (Jiang, 2021).

2.2 Theoretical framework

The relationship between population and land development is a central theme in human–environment relationship studies. Human–environment relationship theory underscores the dynamic and reciprocal interactions between human systems and environmental conditions, emphasizing how population shrinkage—driven by economic restructuring, outmigration, and demographic aging—alters the demand for land resources, while simultaneously, land use changes influence the sustainability of

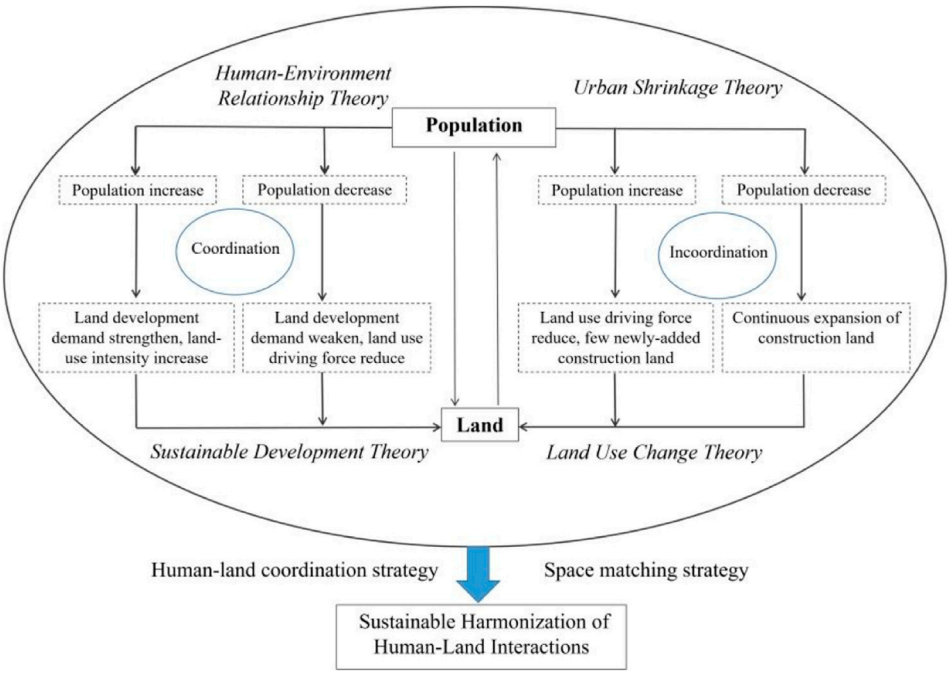


FIGURE 1
Theoretical analysis framework for the spatial relationship between population change and land development.

human settlements. This theory highlights the feedback loops that emerge when declining populations lead to underutilized infrastructure and fragmented landscapes, which in turn exacerbate environmental degradation and reduce the region's capacity to support future development. Historically, Northeast China's heavy industrialization and resource-dependent economy have shaped its population distribution and land use patterns. However, as economic restructuring and environmental degradation have intensified, the outmigration of labor and declining birth rates have disrupted this relationship, leading to a decoupling of population dynamics from land development.

In addition, urban shrinkage theory and land use change theory provide a critical lens for understanding the causes, processes, and consequences of population decline and urban expansion in urban and regional contexts. In Northeast China, urban shrinkage is driven by a combination of economic, social, and demographic factors, including deindustrialization, outmigration, and aging populations (Wiechmann and Pallagst, 2012; Martinez-Fernandez et al., 2012). Urban shrinkage theory highlights the spatial heterogeneity of shrinkage, with some areas experiencing severe depopulation while others continue to expand. Land use change theory focuses on the response to socioeconomic and environmental changes. Land use change in Northeast China has been characterized by urban expansion, agricultural intensification, and industrial land conversion, often driven by government policies and market forces (Jiang et al., 2012). However, population shrinkage has created a paradoxical situation where land development continues despite declining demand, leading to inefficiencies such as vacant housing, underutilized infrastructure, and fragmented landscapes. This mismatch is driven by local governments' reliance on land finance and speculative real estate investments, which prioritize short-term economic gains over long-term sustainability.

According to sustainable development theory, which emphasizes the need to balance economic, social, and environmental objectives, Northeast China might need to reconcile the region's industrial legacy with its shrinking population and environmental constraints. This involves promoting economic resilience through diversification and innovation, enhancing social equity by addressing the needs of vulnerable populations, and ensuring environmental sustainability through the conservation of natural resources and the reduction of ecological footprints. Relevant strategies include compact urban development to reduce sprawl, green infrastructure to enhance ecosystem services, and adaptive reuse of vacant land to revitalize declining areas (Haase et al., 2017). By integrating the above theoretical foundations and principles, this study proposed the theoretical analysis framework for the spatial relationship between population change and land development (as shown in Figure 1).

3 Materials and methods

3.1 Study area

One of China's eight economic zones, northeast China is located in the northeast of China (Figure 2). There are different ways to define the scope of this region. Some studies defined it as the three provinces in northeast China, including Heilongjiang, Liaoning, and Jilin, while some took its scope as the three provinces, five prefecture-level city units in eastern Inner Mongolia involving

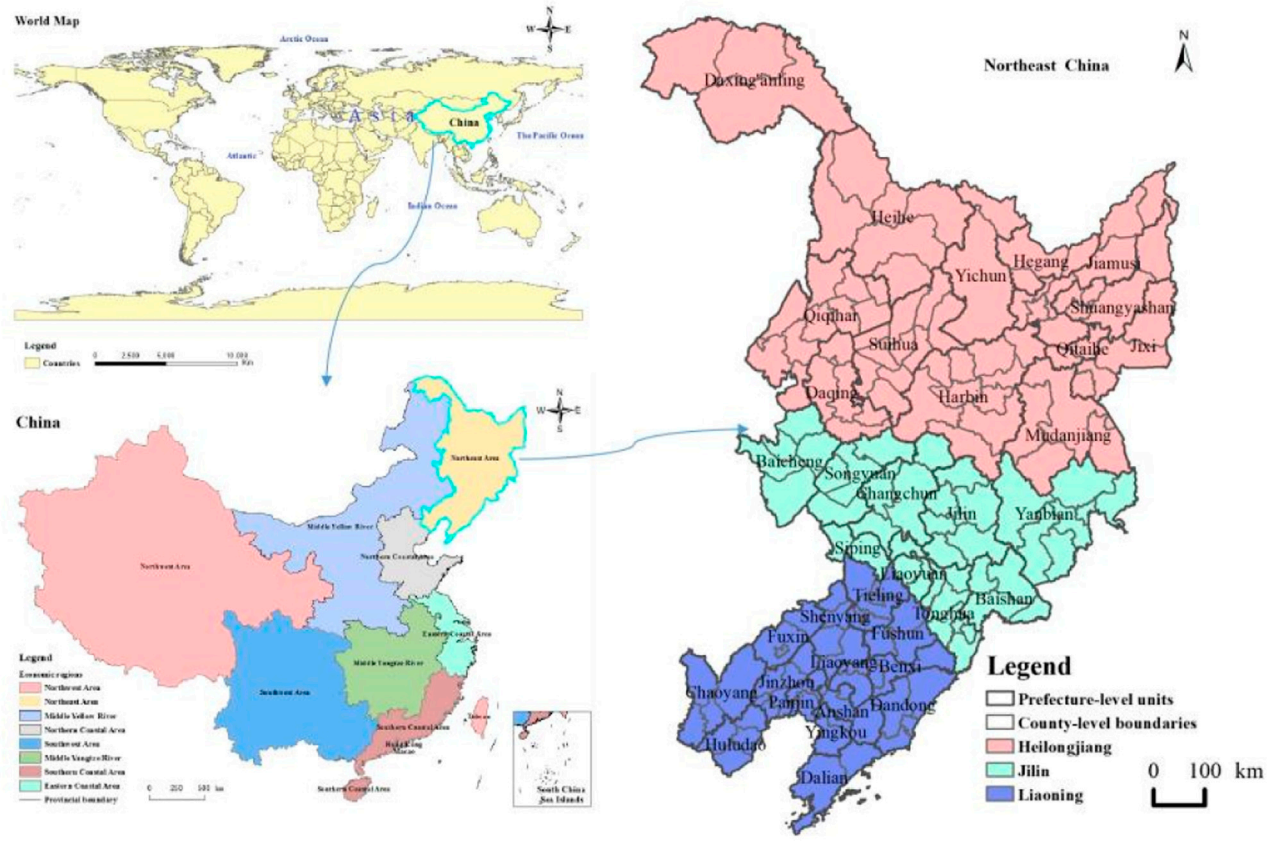


FIGURE 2
Spatial geographic location of Northeast China.

Chifeng, Tongliao, etc., and some counties in northern Hebei. The northeast three provinces are relatively independent and complete administrative units that share certain similarities in their socioeconomic development, urbanization, and industrial structure features. Considering data availability, this study adopted the three provinces as the research scope consisting of 162 county-level units.

This region has experienced economic recession and population contraction in recent years due to the depletion of natural resources and other factors. From 2000 to 2020, the population change rate in northeast China has shown a downward trend. After 2010, there has been negative population growth, indicating a population shrinkage phenomenon. Specifically, the total population in the area studied in this article has shrunk by 11 million people between 2010 and 2020. Furthermore, the labor force change rate has also shown a negative growth after 2010, shrinking 12.6 million workers during 2010–2020. It can be seen that the total population and labor force shrinkage in northeast China in recent years require the attention of the government and academic circles.

3.2 Data sources

Population data in 2000, 2010, and 2020 mainly come from the China Population Census, which is a one-time survey of the national population in a household-by-household and person-by-person manner based on a unified method, unified project, unified questionnaire, and unified standard time points set by the state. We obtained the data through the official website of the National Bureau of Statistics of China (website: https://www.stats.gov.cn/sj/pcsj/).

The 30 m-precision land use remote sensing image data are sourced from WHU IGS Data Center (http://www.igs.gnsswhu.cn). This dataset contains multiple land use and land cover (LULC) categories, including the following main categories: Construction land, including urban land, rural residential areas, industrial and mining land, and transportation land; agricultural land, including cultivated land, gardens, forests, and grasslands; Unutilized land, including deserts, bare land, swamps, etc.; and water bodies, including rivers, lakes, and reservoirs. These categories are generated based on remote sensing image interpretation and classification algorithms that have high spatial resolution and classification accuracy and can support county-level land use analysis. Subtypes of land use intensity (e.g., residential land, industrial land, etc.) can provide a more detailed perspective and help reveal the driving effects of different economic sectors on land consumption. This type of analysis provides a deeper understanding of the internal structure of land development, especially in explaining the incongruity between population contraction and land development, and it can help identify which types of land development continue to expand despite population decline.

The county-level boundary vector surface data in our study are taken from the 2020 version of China's administrative divisions, downloaded from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (website: https://www.resdc.cn/). It should be noted that the boundaries of many county-level units in northeast China were adjusted during 2000–2020, such as the establishment of cities from counties, districts from counties, and splitting or merging of county-level units' townships. This article used the 2020 administrative division data as the standard and integrated the corresponding boundary, population, and boundary data of county-level units with any type of administrative division change on the Arc GIS platform to ensure the reasonable and effective horizontal and vertical comparison of research data. Specifically, taking the county-level units' administrative boundaries of 2020 as a reference standard, it merged or split the corresponding county-level units of 2000 and 2010. After processing, 162 research units were obtained.

3.3 Study methods

This study selects two indicators for measurement and analysis to further explore the characteristics of population shrinkage in northeast China, including total population and labor population. Among them, the labor population consists of people who meet the age requirement and have the ability to work. Internationally, 15–64 is generally classified as the working age. In China, the working age of men is 16–60 years old, and that of women is 16–55. Adopting the international regulations, this study used a population aged 15–64 as the labor force. There may be two deviations in this definition. On the one hand, the labor population may continue to work after retirement, and the working-age population may be unemployed on the other hand. In view of the statistical difficulty of precisely defining the labor force population that could both reflect the distribution pattern or the shrinking characteristics of the labor force from a relatively macro perspective, this study applies this data adoption method.

3.3.1 Population change rate

This study collected total population data and calculated the labor force numbers for the whole country, northeast China, three provincial units (Liaoning, Jilin, and Heilongjiang), and 162 county-level units in 2000, 2010, and 2020. The calculated results created the total population and labor vector databases of the 162 county-level units using the attribute table association function of the vector surface data in ArcGIS software. In addition, it further calculated the total population change rate, labor change rate, labor ratio of the total population, and other indicators in the attribute table. Among them, total population change rate and labor change rate use the formula:

$$R_{(t_1,t_2)} = \frac{M_{t_2} - M_{t_1}}{M_{t_1}} * 100. \quad (1)$$

In Formula 1, $R_{(t1,t2)}$ represents the total population change rate or labor force change rate during t_1 and t_2; M_{t1} and M_{t2} represent the total population or labor in t_1 and t_2, respectively.

The natural breakpoint method of ArcGIS spatial analysis was used to spatially express the total population and labor force change rate and labor force ratio of total population distribution at the county scale to sum up the shrinkage features of the total population and labor force shrinkage in northeast China.

3.3.2 Calculation of land-use intensity

Land-use intensity (LUI) refers to the comprehensive utilization degree of land space in a region and is usually represented by the proportion of urban and rural construction land area in a region. Urban and rural construction land mainly includes urban land, rural residential areas, and other construction land such as industrial and mining land and transportation land. In the relevant research on the process of urban development and construction, different scholars have various understandings and interpretations of the concept and characterization indicators of land use intensity, taking into account the differences in the scope of the research area. When the scope of the research area is greater than or equal to the urban area, the intensity of land development is described by the proportion of construction land to the total land area of the urban area. When the research scope only involves urban built-up areas or urban areas, indicators such as plot ratio and building density are used to characterize the intensity of land development. Because this study was conducted at the county level, the proportion of construction land to the total land area of the county-level unit was used to characterize the study.

In this paper, the comprehensive land-use intensity index, LUI, is chosen as the main index to measure land development intensity, mainly based on the overall objective of the study and the availability of data. Comprehensive land use intensity can reflect the overall land development of a region, especially at the county level, providing an effective tool for analyzing the macroscopic relationship between population contraction and land development. In addition, the use of composite indicators also helps to simplify the analysis process, especially in the case of a large number of county-level units, providing a clearer global view.

Land-use intensity is obtained through the following steps: First, data preprocessing: we preprocessed the remote sensing image data, including geometric correction, radiation correction, and classification accuracy verification, to ensure the accuracy and consistency of the data. Second, construction land extraction: we extracted the categories of urban construction land and rural settlements from remote sensing data and combined them into construction land categories. Finally, the area is calculated: GIS software (such as ArcGIS) is used to calculate the construction land area in each county-level unit, and the ratio between it and the total area of the administrative area is calculated to obtain the LUI.

Based on the research of relevant scholars and data availability, this study defines the LUI expression as follows:

$$LUI = \frac{C_L}{T_L}. \quad (2)$$

In Formula 2, LUI is the intensity of land use, C_L is the total area of construction land, and T_L is the total area of administrative land. This study mainly extracted C_L based on 30 m-precision land use remote sensing image data.

To ensure that boundary changes do not affect the calculation and comparability analysis of land use intensity from 2000 to 2020, we used the 2020 county-level administrative boundaries as the baseline for spatial matching and resampling of land use data from 2000 to 2010. Specifically, we used spatial overlay analysis and resampling techniques to unify land use data from earlier years under the 2020 boundary framework to ensure that data from different years are comparable within the same spatial scope. For county-level units where boundary adjustments occurred during the study period, we identified the details of these changes by reviewing the relevant records of changes to administrative divisions. Specifically, we merged or split county units in 2000 and 2010 according to the 2020 county unit boundaries to ensure the continuity and consistency of the data.

3.3.3 Correlation coefficient measurement method

This paper chooses correlation analysis and coupling coordination models as the main analysis methods mainly because these methods can intuitively reflect the correlation between population change and land development intensity and quantify the degree of coordination between the two, especially in the study of the typical shrinking area in northeast China. These methods can effectively reveal the complex relationship between population and land. The correlation coefficient is a measure of the degree of linear correlation between variables that is widely used in disciplines such as geography, statistics, economics, and sociolog It is generally represented by the letter r and can be expressed as follows:

$$r(X,Y) = \frac{\sum(\mathrm{x}-\bar{x})(y-\bar{y})}{\sqrt{\sum(\mathrm{x}-\bar{x})^2}\sqrt{\sum(y-\bar{y})^2},} \tag{3}$$

where $\bar{x}$ and $\bar{y}$ are the sample averages AVERAGE (array1) and AVERAGE (array2). When r is greater than 0, it indicates a positive correlation between two variables, meaning that as one variable increases, the other variable also increases. When r is significantly less than 0, it indicates a negative correlation between two variables, meaning that as one variable increases, the other variable decreases. The larger the absolute value of r, the stronger the correlation between the two variables. This study mainly uses the correlation coefficient r to measure the degree of correlation between population change and LUI change.

3.3.4 Coupling coordination model

The coupling coordination model is a classic model for measuring the coupling coordination relationship between two or more systems or elements. The measurement indicators mainly involve coupling degree, coupling coordination degree, and comprehensive coordination index. The calculation formula is as follows:

$$C = \left\{ f(x)g(y) \Big/ \left[(f(x)+g(y))/2 \right]^2 \right\}^k. \tag{4}$$

In Formula 4, C represents the coupling degree between population change rate and land use intensity, with $0 < C < 1$. The larger the C value, the better the coupling; $f(x)$ and $g(y)$ represent population change rate and land use intensity, respectively; K is the adjustment coefficient, generally $2 \le k \le 5$. Considering that the research object of this study is two subsystems, the value of k is taken as 2.

$$D = \sqrt{C \times T}, T = \alpha f(x) + \beta g(y). \tag{5}$$

In Formula 5, D is the coupling coordination between population change rate and land use intensity, with a value range of [0,1]; T is the comprehensive coordination index of the two; α and β are undetermined coefficients that characterize the importance of two systems ($\alpha+\beta = 1$). According to domain experts' ratings, the importance of the population system to regional socioeconomic development is slightly higher than that of the land system. Therefore, in this study, the β value of the population system is 0.6, and the α value of the land system is 0.4. Referring to the judgment criteria set by relevant scholars on coupling coordination (Shang et al., 2017), when D is higher than 0.5, it can be determined that the two types of elements are in a basic coupling coordination state, and the closer the value is to 1, the higher the coupling coordination.

4 Space–time features of a shrinking population

4.1 Shrinking features based on two indicators of total population and labor force

Shrinkage issues have garnered wide attention from both academia and policymakers, mainly focusing on total population shrinkage, while little attention has been given to labor force shrinkage, which plays an important role in regional economic and social development and urbanization. In this study, two indicators of total population and labor force were taken to analyze shrinking features. As one of the eight regions of China, northeast China is ranked the second lowest in the whole country in terms of both economic level and population size, which is also below the national average. Comparing the changes of population and labor force in northeast China with the national average level could help to grasp its situation from a macro scale. To further explore the spatio-temporal differences between the total population and labor force in the population shrinkage area, this article analyzed the total population change, labor change, and the labor ratio of the total population of the three provinces and the 162 county-level units in northeast China. According to data and related materials analysis, this study summarized the following features:

(1) Both the total population and labor force in northeast China shrank between 2010 and 2020, while the contribution of the labor force to the whole population remained at a level above the national average throughout the period. As an important indicator to detect the shrinkage of the total population or labor population, the population change rate could reflect the development trend of the total population or labor population. When the change rate is negative, it indicates that the population has contracted. Using the data from 2000 to 2020, this paper calculated the total population and labor change rate according to Formula 1. It showed

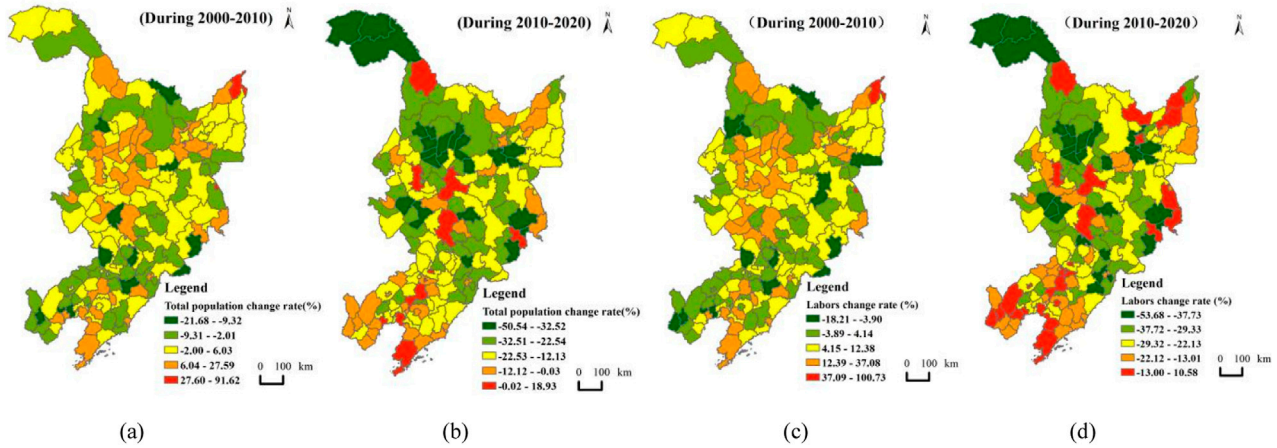


FIGURE 3
Total population and labor change rates in Northeast China on a county-level scale in 2000–2020. **(a)** Total population (2000–2010), **(b)** total population (2010–2020), **(c)** Labor (2000–2010), and **(d)** labor (2010–2020).

that the total population and labor force change rates in northeast China remained positive from 2000 to 2010 and became negative from 2010 to 2020, signifying that the total population and labor force in northeast China have shrunk severely and need attention from related governments. However, the contribution of the labor force to the whole population in northeast China presented a level above the national average, of which labor occupied 74.8% of the total population in 2000, 76.8% in 2010, and 72.6% in 2020. The national average level has a similar change trend, but it remains lower than that of northeast China. It can be seen that the labor force ratio in northeast China is not the lowest in the whole country, although its labor population has shrunk severely. In other words, the labor population structure in northeast China might be relatively reasonable.

(2) Total population and labor population of the three provinces in northeast China were all gradually shrinking on the whole during the period of 2000–2020, but there were significant differences in the degree of contraction. The total population and labor force change rate in Liaoning, Jilin, and Heilongjiang provinces all decreased and became negative after 2010. It can be seen that the labor force in inner northeast China was also shrinking in the context of total population contraction. Among them, the total population and labor force in Heilongjiang have both shrunk faster and to a greater extent. The total population change rate was −0.18 during 2010 and 2020, and the labor population change rate was −0.026 during 2010 and 2020, which are lower than that of the other two provinces. In addition, the proportion of the labor force in the total population in Heilongjiang maintained a higher level than that of Jilin and Liaoning. For example, the labor force proportions of Heilongjiang, Jilin, and Liaoning were 74.1%, 72.7%, and 71.5% in 2020, respectively. Overall, Heilongjiang remained the largest proportion of the labor force, although it faced the most severe population contraction in northeast China. It could be seen that contraction of the total population and labor force might not necessarily affect the decline in labor share, and the labor structure might not be destroyed.

(3) Almost all (94%) of the county-level units in northeast China experienced total population contraction, and 98% experienced labor force contraction from 2000 to 2020, to different degrees. The total population change rate of 152 county-level units became negative between 2000 and 2020, while only Changchun City municipal district, Shenyang City municipal district, Dalian City municipal district, Panjin City municipal district, and 10 other city municipal districts have consistently positive population change rates. Most (159) county-level units have always had a negative labor change rate, which means county-level units with a shrinking labor force account for the vast majority of county-level units in northeast China. The number of units with total population contraction and labor contraction both significantly increased between 2010 and 2020, with only three units remaining in total population and labor growth. Furthermore, a significant difference existed in the degree of total population contraction and labor contraction between units. The total population change of some county-level units was below −50%, significantly lower than that of most cities by −20% in 2000–2010 and 2010–2020. The labor contraction exhibited similar characteristics. In addition, as shown in Figure 3, total population contraction and labor contraction have similar spatial pattern characteristics: contraction units were mainly distributed in the peripheral areas of northeast China or remote areas, especially in the peripheral areas of provincial capital cities or developed cities, indicating that the core cities may have a strong "siphon effect" on the population and labor force of surrounding cities. The closer a county-level unit is to the core city, the more severe shrinkage will be, such as Linkou County, Heishan County, Mulan County, and Bayan County, etc.

(4) The proportion of labor in most county-level units in the total population maintained a relatively high level, while the

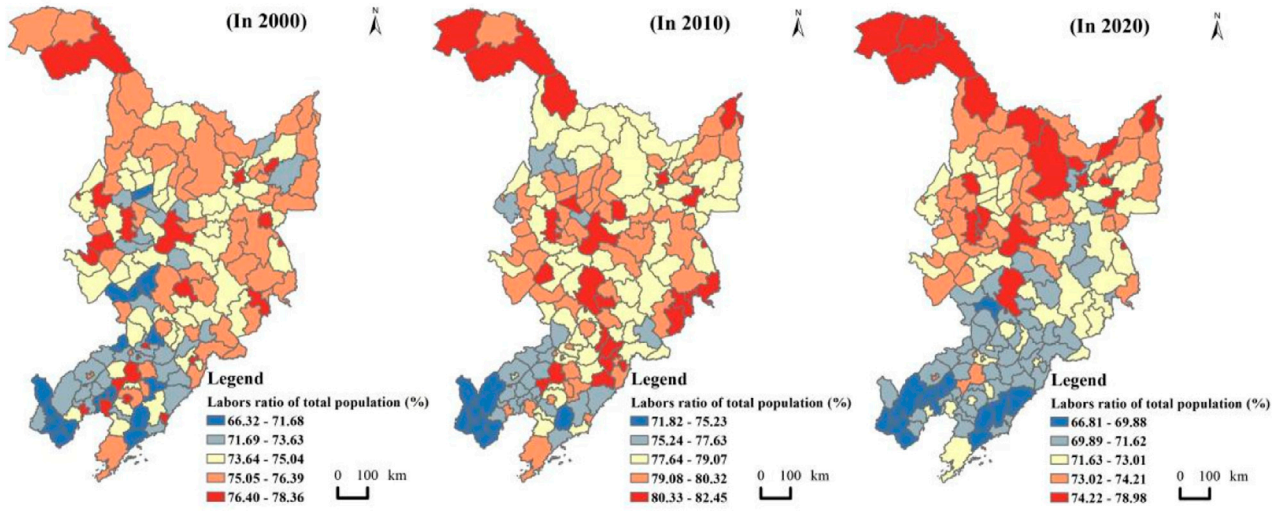


FIGURE 4
Labor ratio of the total population in Northeast China on the county-level scale during 2000–2020.

total population and labor force of most units experienced varying degrees of contraction. During 2000–2010, the labor ratio of the total population of the 162 county-level units in northeast China increased, but they decreased during 2010–2020. However, the labor ratios in most units are higher than the national average for the same period. Some of the 162 county-level units' labor ratio of the total population accounted for more than 80% in 2010, such as Huichun City, Mohe City, Qianan County, and Tonghua County, and 96% of the units' labor ratio accounted for more than 75% (as can be seen from Figure 4). This showed that the proportion of labor in the total population of the county-level units in northeast China still remained relatively high, although most of them have experienced the total population and labor shrinking problem, implying that labor still had a benign supporting role for production activities.

4.2 Shrinkage type difference

The labor force, functioning as both producers and consumers, is the core group of the population system, and its growth is crucial to urban development. From the statistical results, this study found that the labor of some shrinking county-level units is showing growth, although most are shrinking. In other words, there is a certain inconsistency between the trend of the labor population and that of the total population. To explore this inconsistency in depth, this study summarized four shrinkage types of 162 county-level units in northeast China based on the changes in the total population and the labor population. This could help to explain the current development vitality status of county-level units and the health status of population structure, laying an important foundation for formulating the future economic policy, social resource allocation, and population policy or labor policy as a shrinking city or county may still have advanced vitality and sustainability if its labor forces increase. In this paper, the four types include:

(1) Total population shrinks while the labor force decreases, which is called absolute shrinkage type. This type indicates that while the total population is declining, the labor supply is also decreasing, limiting the city's development vitality. This could be caused by resource depletion, ecological degradation, economic decline, and other factors leading to a large-scale population loss.
(2) Total population shrinks while the labor force increases, called labor-growth shrinkage type. This type suggests that despite the overall population decline, the city still retains development vitality due to the growth of the working-age population. This may result from long-term low birth rates and aging, which reduce the total population. At the same time, the city actively adjusts its industrial structure and increases employment opportunities, attracting the return of the labor population or an influx of migrant workers.
(3) The total population increases while the labor force decreases, named labor-loss growth type, indicating that although the total population is increasing, the population energy is continuously declining and possibly facing population structure imbalances. This may be mainly due to the downturn in regional economic development and the low vitality of enterprises, resulting in a poor employment environment and outflow of the labor force.
(4) Total population increases while the labor force rises, named absolute growth type, reflecting the city's increasing population agglomeration and development vitality, with a balanced and continuously optimized population structure. It suggests that the city's socioeconomic development may continue to improve, and policies related to employment, education, and social welfare are being optimized, indicating that the city's scale will continue to expand in the future. Four examples are shown in Figure 5.

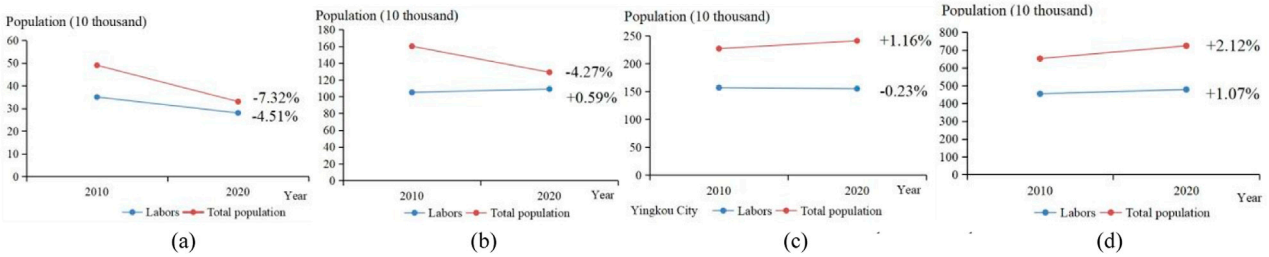


FIGURE 5
Examples of four shrinkage types. **(a)** Absolute shrinkage type, **(b)** labor-growth shrinkage type, **(c)** labor-loss growth type, and **(d)** absolute growth type.

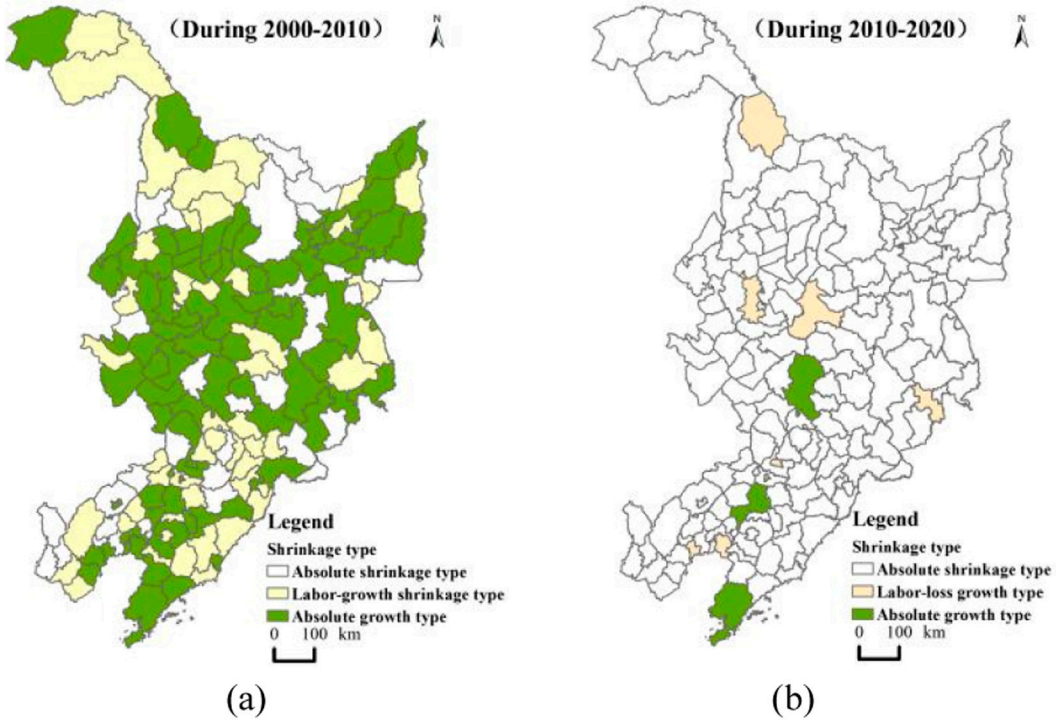


FIGURE 6
Shrinkage type of county-level units in northeast China. **(a)** Shrinkage type in 2010 and **(b)** shrinkage type in 2020.

This study calculated the total population change rate and labor change rate during 2000–2010 and 2010–2020 and determined the type division results shown in Figure 6. It showed that the absolute shrinkage type and the absolute growth type accounted for more than half of all county-level units during the two periods. They are the two main types, indicating that the changing trends in the labor force and total population are relatively consistent on the whole. Specifically, 84 county-level units were identified as absolute growth type during 2000–2010, while the units of this type sharply decreased to three during 2010–2020, which is mainly because some of the 84 units experienced resource exhaustion, leading to economic recession. Most absolute growth type county-level units are economically developed with stable agglomeration capacity or achieve further growth due to successful economic transformation, including Changchun City municipal district, Shenyang City municipal district, Dalian City municipal district, Yushu County, Mulan County, and Bin County This phenomenon is a realistic response to the shrinkage problem throughout northeast China.

Thirty-one county-level units were classified as absolute shrinkage type during 2000–2010, and they increased to 74 units in the period of 2010–2020, with an overall feature of expansion from the periphery of northeast China to the interior, demonstrating that labor shrinkage is the more common trend in the region. Figure 6 shows that an increasing number of county-level units in northeast China during 2010–2020 are undergoing both population shrinkage and development vitality decay. From the perspective of location distribution, they were mainly situated in the peripheral areas of the northeast economic zone in the first period,

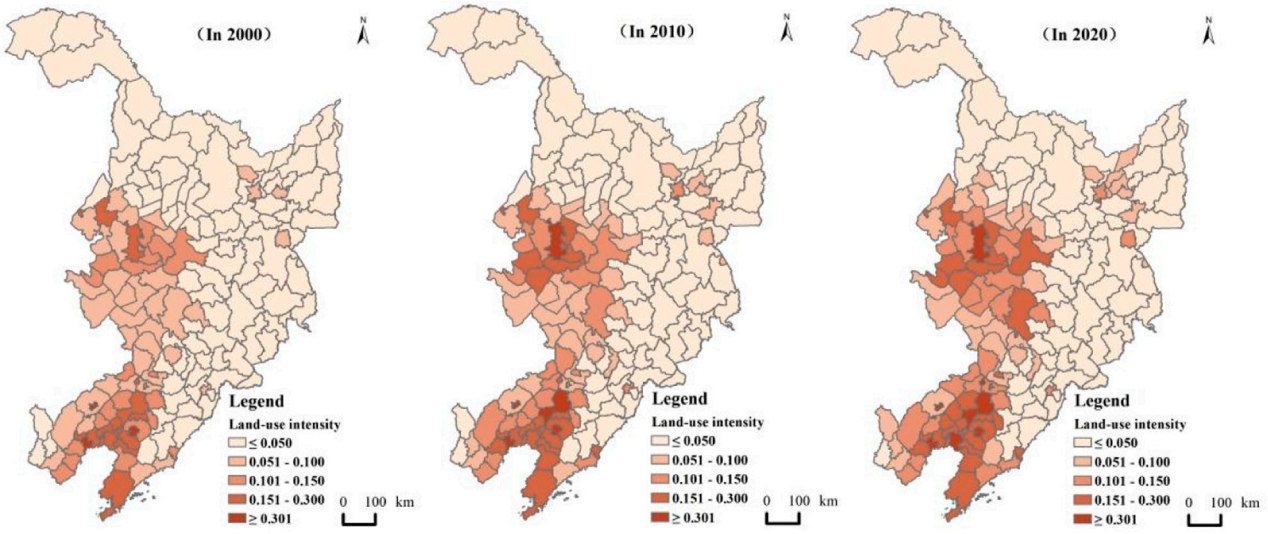


FIGURE 7
Land-use intensity in northeast China in 2000 and 2020.

expanded and extended to the internal area, and spread to nearly the whole region in the second period. Many of the absolute shrinkage units during 2000–2010 are in the mountains and away from main traffic routes; as a result, their economic systems are relatively closed, such as Luobei county in Hegang, Mishan City in Jixi, *etc.*

The labor-growth shrinkage type appeared in the 2000–2010 period, and labor-loss growth type appeared in the 2010–2020 period, which typically represents inconsistency between the labor population and the total population. This is a special phenomenon that scholars have paid little attention to at present. The labor-growth shrinkage type units are more common than the labor-loss growth type units, which are located between absolute shrinkage type and absolute growth type, involving Tonghua County, Liuhe County, Tahe County, Bayan County, *etc.* They are influenced by the strong forces of the absolute shrinkage type and absolute growth type around them, so that part of their population or labor moves to the surrounding strong population-aggregated units, and some of them absorb certain flows from the neighboring strongly contracted areas. It can be said that they stand in the middle of strong population outflow areas and strong population inflow areas, which have a buffering effect. This is an important reason for explaining the inconsistency in the change trend between the labor force and the total population.

It should be noted that the recovery of the labor force is not achieved overnight, and policies need to be appropriately adjusted according to shrinkage type. Cities with absolute shrinkage should focus on replacing leading industries to promote economic output. Cities with labor-growth shrinkage whose total population shrinks while labor rises should concentrate on improving infrastructure to attract school-age children and their parents to increase the total population. Labor-loss growth type cities where the total population increases while the labor force decreases should aim at promoting enterprise projects to expand employment and attract labor.

5 Spatial relationship between population shrinkage and land development

5.1 Land use features

Based on Formula 2 and 30 m-precision land use remote sensing image data, this study calculated the land-use intensity (LUI) of 162 county-level units in northeast China, as shown in Figure 7. The features it found were as follows.

(1) The land-use intensity of county-level units in northeast China gradually increased from 2000 to 2020, and more than half of them improved their land-use rate. The average LUI increased from 0.067 in 2000 to 0.081 in 2010 and 0.095 in 2020. Among them, Fuxin City municipal district's LUI grew the most, increasing by 0.164 in 2020 compared with 2000, while Changbai Korean Autonomous County's LUI grew the least, only increasing by 0.002 over 20 years. The municipal districts of Changchun, Harbin, and Shenyang, which are the three provincial capital cities in northeast China, have respectively increased by 0.073, 0.062, and 0.123 during 2000–2020. Furthermore, it is worth noting that the rate of land development in more than 50% of 162 county-level units in northeast China has improved, and the vast majority of them are county-level units with severe population shrinkage. For instance, the total population of Mingshui county shrank by 122,000 people from 2010 to 2020, with a population change of −38.17%, while its LUI increased by 59.5%. It implied that a typical paradox of population loss and land-use expansion existed in northeast China, which is not beneficial for the coordinated development of human–land relationships.

(2) Significant spatial differences exist in the land-use intensity among county-level units in northeast China, that the LUI

values in the western and southern regions are generally higher than that in the eastern and northern regions, and the overall pattern remains relatively stable. As seen in Figure 7, county-level units in the western and southern regions of northeast China have obviously higher LUI values than those in other regions, especially in areas centered around Daqing, Shenyang, and Dalian, such as Zhaoyuan County, Zhaozhou County, Fushun County, Dengta City, Zhuanghe City, and Gaizhou City. Meanwhile, several county-level units in the northeast region have relatively high LUI, significantly higher than other surrounding county-level units in the eastern and northern regions, including Jiamusi City municipal district, Shuangyashan City municipal district, Hegang City municipal district, Qitaihe City municipal district, Jixi City municipal district, Huachuan County, Jixian County, etc. Moreover, these units have further increased their LUI between 2000 and 2020. Overall, this spatial feature is relatively stable, almost without much change in the past 20 years. In addition, Anshan City municipal district (0.008), Daqing City municipal district (0.007), and Daan City municipal district (0.007), which had a fast LUI growth rate during 2000–2010, experienced a great decline in LUI growth during 2010–2020, recording increases of only 0.005, 0.004 and 0.002, respectively. This indicates that in the past decade, due to the depletion of mineral resources or the protection of natural resources and other reasons, the urban development of some resource-based county-level units has been significantly limited.

5.2 Spatial relationship

To explore the correlation between population shrinkage and land development from multiple dimensions, this study measured the correlation coefficient based on Equation 3 between total population change and LUI change, as well as the correlation coefficient between labor force change and LUI change. At the same time, this study used the coupling coordination model to measure the coupling coordination degree of the population change indicator and land use intensity change indicator. The research findings are as follows:

(1) The population changes in most county-level units are negatively correlated with the LUI change. Specifically, 88.9% of county-level units' total population changes are negatively correlated with LUI changes, and 90.1% of county-level units' labor force changes are negatively correlated with LUI changes. It can be seen that in the context of population shrinkage, the amount of land development has actually increased in most counties and cities in northeast China, which may result in the waste of land resources or the imbalance of human–land relationships. Among them, the absolute value of the correlation coefficient between total population change and LUI change in 44 county-level units, including Jiayin County, Keshan County, Dongning City, Changhai County, Tieling County, *etc.*, is close to 1, reflecting a relatively strong negative correlation. These counties and cities may need more attention from the government, with a focus on conducting further on-site research and problem analysis on population changes and land development and taking measures to make timely adjustments.

(2) The small number of county-level units with a positive correlation between population change and LUI change are mainly distributed around core cities such as Harbin, Changchun, Shenyang, Dalian, *etc.*, and show a spatial characteristic of decreasing from the center to the periphery. The correlation coefficients between the total population change and LUI change in 18 county-level units, including Harbin, Changchun, Shenyang, Dalian, Daqing, Tieling, Heihe, Panjin City municipal districts and other counties, are all greater than 0, and the absolute values of their correlation coefficients are almost all above 0.5. These units are the central cities of their respective regions and are generally able to gather population from surrounding areas, resulting in population growth or lower shrinkage levels. At the same time, land development continues to advance, so population and land development tend to be generally coordinated. The results shown in Figure 8 imply that the correlation coefficient of county-level units gradually decreases as the distance from these central cities increases. Overall, the match between population change and LUI change is stronger in regional central cities, and there is a certain degree of blind expansion in small and medium-sized cities.

(3) The coupling coordination degree between population change and land use intensity change in most county-level units in northeast China is below 0.5, indicating an uncoupled coordination state. Only 28 county-level units showed a coupling coordination state of total population and land during 2010–2020, whose coupling coordination degree D is higher than 0.5 and the same as that of the labor force and land. This is relatively consistent with the analysis results of the correlation coefficient, further indicating that the pace of population change and land development in northeast China might not be coordinated. From the spatial distribution pattern, counties and cities with high coupling coordination degrees are mainly concentrated near central cities such as Harbin, Changchun, Shenyang, Dalian, and Daqing, which is relatively matched with the spatial distribution pattern of correlation coefficients. It shows that the more developed the economy and the stronger the comprehensive strength, the more harmonious the relationship between humans and land is in northeast China. The government in northeast China needs to focus on human–land relationships in small and medium-sized cities as well as relatively underdeveloped county-level units.

6 Discussion

The findings of this study reveal a significant paradox in northeast China: widespread population shrinkage coexists with continuous land expansion, a phenomenon that contrasts sharply

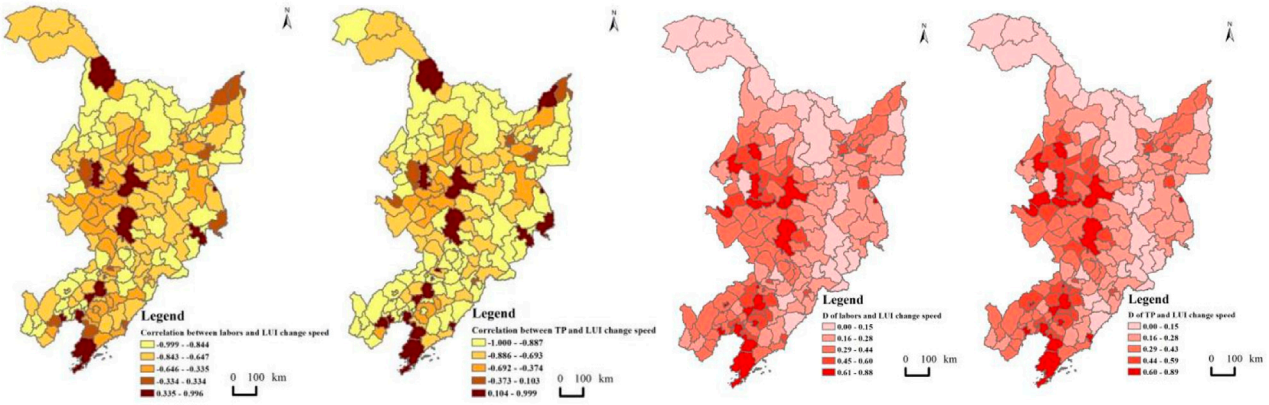


FIGURE 8
Correlation and coupling coordination degree between population and LUI in northeast China.

with patterns observed in shrinking cities in Europe and North America (Wiechmann and Pallagst, 2012; Martinez-Fernandez et al., 2016). While international studies have documented population loss leading to reduced land development demand and the repurposing of vacant land (Haase et al., 2014; Bontje, 2004), the situation in northeast China is characterized by persistent land expansion despite severe population decline. This discrepancy highlights the unique socioeconomic and institutional context of China's shrinking cities, particularly the reliance on land finance and the growth-oriented urban planning paradigm (Jiang, 2021).

6.1 Population shrinkage and spatial heterogeneity

The severe population shrinkage observed in Northeast China, particularly in Heilongjiang Province, aligns with existing studies that highlight the region's demographic challenges, including aging populations, outmigration, and declining birth rates (Xie et al., 2022). However, this study extends the understanding of population shrinkage by differentiating between total population and labor force dynamics. The higher proportion of the labor force relative to the national average, despite overall population decline, suggests that labor productivity and economic activities may still be sustained in the short term. This finding challenges the conventional assumption that population shrinkage invariably leads to economic stagnation, as noted by Martinez-Fernandez et al. (2016) in the context of shrinking cities globally.

The spatial heterogeneity of population shrinkage types, particularly the emergence of labor-loss growth types (e.g., Harbin, Daqing, and Panjin), underscores the need for nuanced policy interventions. These areas, characterized by total population growth but labor force decline, may face unique challenges in maintaining economic vitality. The phenomenon of labor-loss growth type has received limited attention in the literature, and its identification in this study calls for further investigation into the underlying causes, such as aging populations or mismatches between labor demand and supply.

6.2 Paradox of population loss and land expansion

The paradoxical phenomenon of population loss coexisting with land-use intensity (LUI) increase is a striking finding of this study. This aligns with the global trend of "peripheralization" in shrinking regions, where urban cores continue to expand despite population decline (Haase et al., 2014). In northeast China, this pattern is particularly pronounced in the western and southern regions, such as Daqing and Shenyang, where rapid land development contrasts sharply with severe population loss. This imbalance reflects a potential misalignment between land-use policies and demographic realities, leading to inefficient land resource utilization and potential environmental degradation.

The increase in LUI in shrinking regions may be driven by local government reliance on land-based financing and infrastructure development as a strategy to stimulate economic growth (Ye and Wu, 2014). However, this approach risks exacerbating the mismatch between population and land resources, as highlighted by the negative correlation between population change and LUI change in 88.9% of county-level units.

6.3 Human–land coordination and regional disparities

The uncoupled coordination relationship between population change and land development in most county-level units underscores the challenges of achieving sustainable human–land relationships in shrinking regions. The stronger coupling coordination observed in regional central cities (e.g., Harbin, Changchun, and Shenyang) suggests that economic vitality and comprehensive strength play a critical role in harmonizing population and land dynamics. This finding supports the "core-periphery" theory, which posits that central cities exert a "siphon effect" on surrounding areas, attracting population and resources while leaving peripheral regions more vulnerable to shrinkage (Friedmann, 1966). However, the spatial gradient of coupling coordination, decreasing from central cities to peripheral areas,

highlights the need for targeted policies to address disparities in human–land relationships. Small and medium-sized cities and underdeveloped county-level units, where blind land expansion is prevalent, require tailored strategies to balance population retention and land-use efficiency.

6.4 Policy implications

The concept of "smart shrinkage," which advocates for targeted land use planning and infrastructure downsizing, has been proposed as a potential strategy for aligning land development with population trends (Pallagst et al., 2011). However, the implementation of such strategies in the Chinese context remains challenging due to institutional barriers and the lack of a comprehensive policy framework for managing population–land mismatches (Hartt and Hackworth, 2020). In view of this, land-use policies need to be recalibrated to reflect demographic realities, with a focus on curbing inefficient land expansion and promoting compact urban development. Policymakers should prioritize strategies to address labor-force decline, particularly in areas exhibiting labor-loss growth type. This may include promoting enterprise projects, enhancing vocational training, and creating incentives for labor retention and attraction. Further, regional development strategies should aim to strengthen the economic resilience of peripheral areas, reducing their dependence on central cities and fostering more balanced human–land relationships.

6.5 Limitations

This study also had certain limitations. For instance, the population and land use data were at the county level, which cannot depict the population and land use changes at finer scales such as township or village levels. Furthermore, it did not distinguish between shrinkage resulting from outmigration and shrinkage caused by population aging and death surplus due to little official authoritative data on the outflow or inflow of population at the county level. Therefore, in future studies aiming to deepen the research on population shrinkage in northeast China, it may be beneficial to use interpolation and partition adjustment to estimate relevant data and to further interpret and analyze the shrinkage process and features. In addition, the importance of quantitatively measuring and analyzing the influence mechanism of population change and land development spatial relationship is constantly highlighted, and future research needs to continue to deepen and improve the analysis of influence factor and excavate the mechanism behind the spatial relationship in the new period, to lay some foundation for orderly coordinating human–land relationships. Finally, the study is limited to northeast China, and its findings may not directly apply to other shrinking regions with different socioeconomic and institutional contexts. Comparative studies across regions and countries could provide a more comprehensive understanding of the dynamics of population shrinkage and land development.

7 Conclusion

Population and land are important fundamental elements in the regional system of human–land relationships that complement each other (Dong and Xue, 2022). In the process of urbanization, coordinated human–land development is an inherent requirement for optimizing the regional system of human–land relationships. This study, based on the total population indicator and labor force indicator, employed population change to analyze the population shrinkage features on different administrative unit scales in northeast China. Furthermore, it calculated the LUI of 162 county-level units in northeast China and analyzed their spatial features. Finally, it explored the spatial relationship between population shrinkage and land development based on the correlation coefficient measurement method and coupling coordination model. Overall, we have identified several key findings that contribute to the understanding of human–land relationships in shrinking regions.

(1) Northeast China has experienced severe population shrinkage in terms of both the total population and the labor force, with a notable decline after 2010. Despite this, the labor force's contribution to the total population remained above the national average, indicating a relatively stable labor structure. However, the spatial heterogeneity of population shrinkage types, including absolute shrinkage, labor-growth shrinkage, labor-loss growth, and absolute growth, highlights the complexity of demographic changes in the region. This diversity in shrinkage types underscores the need for differentiated policy interventions to address the varying development trajectories of different county-level units.

(2) The study reveals a paradoxical phenomenon of population loss coexisting with land-use expansion. Despite a significant population decline, LUI in most county-level units has increased, driven by local government reliance on land finance and speculative real estate investments. This mismatch between population dynamics and land development has led to inefficiencies in land resource utilization, with potential long-term environmental and economic consequences. The negative correlation between population change and land-use intensity change in most county-level units further emphasizes the need for more sustainable land-use planning.

(3) The coupling coordination analysis indicates that population change and land development are largely uncoupled in most areas, particularly in small and medium-sized cities. Regional central cities, such as Harbin, Changchun, and Shenyang, exhibit stronger coordination between population and land development, and were generally able to gather population from surrounding areas while land development continues to advance, reflecting their economic vitality and ability to attract population and resources. However, peripheral regions face greater challenges in achieving balanced human–land relationships, necessitating targeted policies to address disparities and promote sustainable development, especially in response to their blind land expansion.

In conclusion, this study highlights the complex interplay between population shrinkage and land development in northeast China, providing some valuable insights for policymakers and urban planners. By addressing the spatial mismatches and promoting sustainable land-use practices, it is possible to achieve a more harmonious relationship between population dynamics and land development, ultimately contributing to the long-term sustainability of shrinking regions. Future research should continue to explore the underlying mechanisms of population–land relationships and develop more nuanced policy frameworks tailored to the unique challenges of shrinking cities and regions.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval were not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the [patients/ participants OR patients/participants legal guardian/ next of kin] was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

XW: formal analysis, funding acquisition, resources, supervision, visualization, writing–original draft, and writing–review and editing. JH: data curation, formal analysis, methodology, software, writing–original draft, and writing–review and editing. SZ: methodology, project administration, supervision, visualization, writing–original draft, and writing–review and editing. RH: conceptualization, investigation, validation, writing–original draft, and writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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EDITED BY
Cunyi Yang,
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Svitlana Delehan,
Uzhhorod National University, Ukraine
I Gusti Ngurah Parikesit Widiatedja,
Udayana University, Indonesia

*CORRESPONDENCE
Aruhan,
aruhan@imau.edu.cn

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Research on the suitability of production, living and ecological space development in Duolun County, Inner Mongolia

Dongchang Liu[1], Aruhan[1,2]* and Sai Na[3]

[1]College of Desert Control Science and Engineering, Inner Mongolia Agricultural University, Hohhot, China, [2]Key Laboratory of State Forest Administration for Desert Ecosystem Protection and Restoration, Inner Mongolia Agricultural University, Hohhot, China, [3]College of Basic Medical Science, Inner Mongolia Medical University, Hohhot, China

The Production-Living-Ecological Space (PLES) serve as a crucial link for regional sustainable development, making the study of their development suitability of significant importance. This research focuses on Duolun County in Inner Mongolia, utilizing meteorological and soil data from 2000 to 2020. Advanced statistical models, including geographically weighted regression and spatial autocorrelation analysis, were employed to systematically analyze the spatiotemporal evolution characteristics of PLES development suitability and spatial conflicts. The findings reveal that: (1) The suitability of production space, ecological space, and the comprehensive suitability of PLES in the study area exhibit a spatial differentiation pattern with higher values in the southwest and lower values in the northeast. Specifically, the suitability of production space and the average suitability index of living space show a slight upward trend, while the suitability of ecological space and the comprehensive suitability index of PLES display a downward trend. (2) From the perspective of spatial center migration, the suitability centers of production space and living space have shifted towards the southwest, whereas the functional centers of ecological space and the comprehensive suitability centers of PLES have moved towards the northeast. (3) The spatial distribution characteristics indicate that the suitable areas for PLES are mainly concentrated in the central and southern parts of the county, with the ecological space suitable area being the largest. The non-suitable areas are predominantly distributed in the northern part of the county. The study suggests that the incoordination of PLES suitability is the primary contradiction restricting the development of land space in the county, and land use patterns are the key factors affecting the coupling coordination degree of PLES suitability. Based on these findings, it is recommended that county spatial planning should fully consider the suitability evaluation results and formulate differentiated development strategies according to local conditions to achieve regional sustainable development goals.

KEYWORDS

production-living-ecological space (PLES), suitability evaluation, Duolun county, Inner Mongolia, the analytic hierarchy process (AHP)

1 Introduction

Production - life - ecological space (hereinafter referred to as PLES) is a comprehensive way of land spatial zoning (Zhang et al., 2023). With the continuous deepening of Rural Revitalization and ecological civilization construction, the suitability evaluation of regional PLES land is an important basis for the sustainable and efficient use of regional land and resources (Wang J. et al., 2023) As early as the end of the 19th century and the beginning of the 20th century, the United States began to use hand-painted and superimposed images to evaluate land suitability (Hopkins, 1977). With the advancement of 3S technologies—specifically Remote Sensing (RS), Global Positioning System (GPS), and Geographic Information System (GIS)—the use of GIS technology for land suitability analysis has become the mainstream approach. The high-intensity development of land and space has led to the imbalance of regional spatial development, the aggravation of the conflict of "three living spaces", the tightening of resource and environmental constraints, and other land relationship problems (Zhu et al., 2022), the imbalance of land and space structure (Li et al., 2023), and the phenomenon of mutual occupation of three living spaces (Liu et al., 2022), which has limited the stable and healthy development of regional social economy (Wang et al., 2022), and led to the greater pressure of space conflict on ecological protection and food security (Shangshang et al., 2024). In response to the increasingly prominent conflicts between human activities and land resources, countries have adopted land suitability evaluation methods to explore rational land use strategies. For example, V.K. Kalichkin conducted a land suitability assessment for the forest-steppe region of Western Siberia, Russia. Using the GIS-MCDA (Geographic Information System–Multi-Criteria Decision Analysis) approach, he applied a weighted linear combination to calculate the land suitability index for selected ecosystems. Based on the index values, suitability levels for different ecosystems were determined. Ultimately, a land suitability map was generated, specifically evaluating the optimal areas for spring wheat cultivation (Kalichkin et al., 2021). Amanjot Bhullar et al. conducted a multi-crop land suitability assessment using semi-supervised learning for remote sensing-based simultaneous prediction. Their findings revealed that barley, oats, and mixed grains exhibit greater resilience to variations in soil, climate, and landscape conditions, making them suitable for cultivation across many regions of Canada. In contrast, non-grain crops were found to be more sensitive to environmental factors (Bhullar et al., 2023). Ullah et al., conducted a land suitability assessment focusing on Dhaka, Bangladesh, a rapidly developing urban area. Through literature review and expert consultations, they identified 14 key factors based on local environmental conditions and data availability. By defining influencing factors and criteria, they developed a multi-criteria land suitability evaluation model using the Analytic Hierarchy Process (AHP) within a GIS framework. This approach enables regional planning to better align with local development needs (Ullah and Mansourianet al., 2016). Ramya et al. focused on Tehri Garhwal district in India, developing a multi-criteria Geographic Information System (GIS) framework to automate the selection of suitable land uses. Through this framework, they conducted a land suitability assessment, enabling more efficient and data-driven land-use planning (Ramya and Devadas et al., 2019). Through the comprehensive integration of regional resource endowment, ecological environment, social economy and other factors (Wang et al., 2022), evaluating the suitability of human development and protection of land and space activities is the basic content of realizing the sustainable development of land and resources (Wang et al., 2022), and also an important basis for the optimization of spatial pattern (Wang S. et al., 2023). In order to meet the needs of production development, livable life and ecological protection, exploring the suitability of land and space development has become a hot issue in land science (Zhao Y. et al., 2022). At present, scholars at home and abroad mainly use the multi factor overlay comprehensive model (Yang et al., 2022), niche model (Zhao Z. et al., 2022), machine learning model (Ismaili et al., 2023), cellular automata model (Chen et al., 2022), matter-element analysis model (Luo et al., 2022), and cumulative resistance model (Wang C. et al., 2023) to evaluate the suitability of the spatial development of land PLES. In terms of the research scale, most studies have focused on the macroscopic national scale (Toba et al., 2023), provincial (Ma et al., 2023) and municipal scales (Xiao and Gu, 2022), as well as the scales of resource-based urban agglomerations, etc. Moreover, the selection of specific regional types is highly distinctive, covering ecologically sensitive areas (Cheng, 2013), mountainous and hilly areas (Zhanjun and Chengtai, 2009), and nature reserves (Xu, 2018), etc. However, the research achievements regarding the county-level and village-town-level scales are relatively scarce. The Beijing Tianjin sandstorm source area is an ecological engineering treatment area divided by the Chinese government to improve and optimize the ecological environment of Beijing Tianjin and its surrounding areas and reduce sandstorm disasters. It is an important ecological barrier in northern China (Zhao et al., 2020). Duolun county is located in the central part of Inner Mongolia and the southern edge of Hunshandake sandy land. It is a typical ecological fragile area in the Beijing Tianjin sandstorm source area. It is the nearest flag County in Inner Mongolia to Beijing, with a straight-line distance of 180 km (Zhu H. et al., 2023). It belongs to the farming pastoral ecotone in Northern China. It is clear that the spatio-temporal evolution of the suitability of the three living spaces in Duolun County of Inner Mongolia is an effective basis for identifying and mediating potential conflicts in land space. Therefore, based on the remote sensing images, meteorological and soil data of Duolun County in Inner Mongolia from 2000 to 2020, this paper analyzes the suitability and spatial conflict of the development of the rural PLES in Duolun County by using the statistical model, so as to provide a scientific basis for optimizing the land spatial structure and improving the land spatial function in the sandstorm source area of Beijing and Tianjin.

2 Study area and data sources

2.1 Study area

Duolun county (Figure 1) is located in the southern edge of Hunshandake Sandy Land in the farming pastoral ecotone of northern China (Yang et al., 2024). The terrain is high around and low in the middle, with an altitude of 1,039–1795 m. The geomorphic types are mainly low mountains, hills, valleys and depressions, piedmont sloping plains and accumulation type

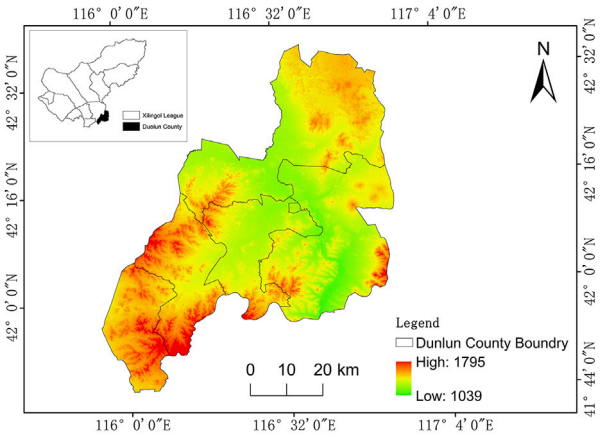


FIGURE 1
Location map of the study area.

dunes. The climate belongs to the typical continental climate of the transition from semi-arid to semi humid in the temperate zone. It is rainy and hot in the same season. The annual average temperature is 2.8°C, the annual average precipitation is 378 mm, the annual average wind speed is 3.3 m/s, and the number of strong wind days is 49.1 days. The soil types are mainly chestnut soil, meadow soil and aeolian sand soil, and the vegetation types are typical grassland vegetation, meadow grassland vegetation, sand; y vegetation, swamp vegetation, etc. Duolun county is rich in water resources, with the only surviving natural elm forest in Asia, 65 administrative villages and relatively developed transportation. In 2020, the Gross Regional Product of Duolun County will reach 4.79 billion yuan, with a total population of 104000.

2.2 Data sources

In this paper, remote sensing images and DEM data are derived from geospatial data cloud (http://www.gscloud.cn/) The meteorological data is from the official website of the National Meteorological Data Center (https://data.cma.cn/) The soil data is from the Geographical remote sensing ecological network (http://www.gisrs.cn/). Using remote sensing images, DEM data and arcgis10.8 software from 2000 to 2020, the slope, topographic relief, annual average temperature and the distance from the main water areas are obtained. Use ENVI 5.3 software to obtain vegetation coverage.

3 Research methodology

3.1 Identification and delimitation of PLES

PLES is a complex multi-functional complex. Its delimitation and classification should follow scientific principles and legal basis (Song et al., 2024). The land administration law of the people's Republic of China clearly stipulates that the rational use and protection of land resources should be achieved through the scientific delimitation of permanent basic farmland protection red line and ecological protection red line (Li et al., 2024). Based on this, this paper constructs the classification system of PLES with the principle of keeping the permanent basic farmland red line and ecological red line, and guided by the land use function. In the process of classification, not only the main functions of land use are fully considered, but also the secondary functions are taken into account, so as to ensure full connection with the standards such as the general plan for land use, the classification of land use status (GB/t 21010–2007), the classification of urban planning land (GB 50137–2011), and the national ecological protection red line - Technical Guide for the delimitation of ecological function red line (Trial) (Liu, 2017). At the same time, referring to the identification and classification methods of liujilai and other scholars, combined with the current situation of land use in Duolun County, and taking the dominant function of land as the criterion, the land space is divided into three categories: production space, living space and ecological space (Table 1).

3.2 Construction of evaluation index system

The Analytic Hierarchy Process (AHP) is an important method for multi-objective decision-making proposed by Saaty (2001). According to the Analytic Hierarchy Process, the problem to be solved is divided into three levels: the goal layer (A), the criterion layer (B), and the alternative layer (C) (Saaty, 2008). This

TABLE 1 PLES delimitation.

Primary classification	Secondary classification	Land use type
Production space	Agricultural production space	Paddy field, irrigated land, dry land, orchard, tea garden, and other gardens
	Industrial production space	Industrial land, mining land, transportation land
Living Space	Urban living space	Urban land
	Rural living space	Rural residential area
Ecological space	Forest ecological space	Woodland, shrub, open woodland and other woodlands
	Grassland ecological space	High coverage grassland, medium coverage grassland and low coverage grassland
	Aquatic ecological space	Canals, lakes, reservoirs, ponds, tidal flats and beaches
	Other ecological spaces	Saline alkali land, swamp, bare land, bare rock and stone land, and other land

TABLE 2 Suitability evaluation index system and its weight of PLES space development.

Target layer	Criterion layer and weight	Indicator layer	Index weight	Index classification and score			
				5	4	3	2
Carrying capacity of the PLES	Production space (0.1818)	Slope (X_1)	0.0304	<3°	3°–15°	15°–25°	25°<
		Topographic relief (X_2)	0.1007	0–20 m	20–35 m	35–65 m	65 m<
		Vegetation coverage (X_3)	0.154	1–0.6	0.6–0.4	0.4–0.2	0.2–0
		Average annual rainfall (X_4)	0.1316	400 mm<	400—350 mm	350—250 mm	<250 mm
		Distance from main water area (X_5)	0.0905	0–500 m	500–1500 m	1500–3000 m	3000 m<
		Effective soil layer thickness (X_6)	0.1097	100-90 cm	90-70 cm	70-40 cm	<40 cm
		Soil organic matter (X_7)	0.0721	4<	4–2	2–0.6	<0.6
		Soil texture (X_8)	0.1141	Clay	Loam	Silt	Sand
		Soil erosion (X_9)	0.0858	Micro erosion	Slight erosion	Moderate erosion	Intensity erosion
	Living Space (0.0909)	Slope (X_{10})	0.0322	<3°	3°–15°	15°–25°	25°<
		Topographic relief (X_{11})	0.0917	0–20 m	20–35 m	35–65 m	65 m<
		Vegetation coverage (X_{12})	0.1194	1–0.6	0.6–0.4	0.4–0.2	0.2–0
		Average annual rainfall (X_{13})	0.1061	400 mm<	400—350 mm	350—250 mm	<250 mm
		Effective soil layer thickness (X_{14})	0.0822	100-90 cm	90-70 cm	70-40 cm	<40 cm
		soil organic matter (X_{15})	0.1069	4<	4–2	2–0.6	<0.6
		Soil texture (X_{16})	0.1017	Clay	Loam	Silt	Sand
		Soil erosion (X_{17})	0.14	Micro erosion	Slight erosion	Moderate erosion	Intensity erosion
		Distance from main road (X_{18})	0.1087	0–500 m	500–1500 m	1500–3000 m	3000 m<
	Ecological space (0.7273)	Slope (X_{19})	0.052	25°<	<15°–25°	<3°–15°	<3°
		Topographic relief (X_{20})	0.0288	65 m<	65—35 m	35—20 m	20—0 m
		Vegetation coverage (X_{21})	0.0457	0–0.2	0.2–0.4	0.4–0.6	0.6–1
		Average annual rainfall (X_{22})	0.0345	<250 mm	350—250 mm	400—350 mm	400 mm<
		Distance from main water area (X_{23})	0.053	3000 m<	3000—1500 m	1500—500 m	<500 m
		Effective soil layer thickness (X_{24})	0.0785	<40 cm	70-40 cm	90-70 cm	100-90 cm
		Soil organic matter (X_{25})	0.0542	<0.6	0.6–2	2–4	4<
		Soil texture (X_{26})	0.1277	Sand	Silt	Loam	Clay
		Soil erosion (X_{27})	0.4146	Intensity erosion	Moderate erosion	Slight erosion	Micro erosion

study, based on the specific characteristics of the research area, considers factors such as evaluation objectives, evaluation content, and evaluation scale. Administrative villages are selected as the basic units for the suitability evaluation, which is structured into three hierarchical levels: the target layer, the criterion layer, and the indicator layer. The study employs a research methodology integrating the Analytic Hierarchy Process (AHP) and the Delphi Method to construct the judgment matrix. A panel of 20 experts specializing in land resource management, urban and rural planning, and

landscape ecology was invited to systematically assess the relative importance of various evaluation factors. The expert ratings were subjected to a consistency check using the Yaahp software platform (version 10.3) to ensure reliability. Based on the verified results, the weight values of each indicator were calculated, establishing the suitability evaluation system for the three-function spatial zones in Duolun County, as presented in Table 2.

3.3 Graded assignment

Using the Delphi method (Toumbourou, 2020) and the hierarchical assignment method (Cengiz and Akbulak, 2009), and in accordance with the geographical location and natural environmental conditions of the research area, starting from several key factors such as slope, topographic relief, vegetation coverage, average annual rainfall, distance from the main water bodies, effective soil layer thickness, soil organic matter, soil texture, soil erosion, and distance from the main roads, score, screen, and determine the cultivated land suitability evaluation factors. Based on the alternative factors, conduct Delphi expert scoring and calculate the weights to obtain a suitable factor system. Then, divide the assignment of various evaluation indicators into four levels, with the values assigned as 5, 4, 3, and 2 respectively (Table 2).

3.4 Determine indicator weight

First, the Analytic Hierarchy Process (AHP) (Toumbourou, 2020) is employed. Specifically, the problem is disassembled into multiple levels and factors. Subsequently, experts conduct pairwise comparisons of the importance of each factor, gradually establishing a judgment matrix. Based on this, the maximum eigenvalue and eigenvector are calculated, and the consistency index of the judgment matrix is computed and a consistency test is carried out. After completing all the tests, the final decision result is obtained through the overall hierarchical ranking (Rabiul Islam et al., 2024).

$$\lambda_{max} = \sum_{i=1}^{n}\left(A_i/nW_i\right)$$

tIn the formula: λ_{max} is the maximum eigenvalue of the matrix; A_i is the i-th factor of vector A; W_i represents the weight of the i-th factor; and n is the order of the judgment matrix. To determine whether the weights of the judgment factors are reasonable, it is also necessary to utilize the consistency index (CI) and the consistency ratio (CR) to test the deviation consistency and comprehensive randomness of the judgment matrix.

$$CR = CI/RI$$

In the formula: CI is the consistency index of the judgment matrix. The closer CI is to 0, the better the consistency is, and the larger CI is, the worse the consistency is. RI is the average random consistency index. If CR < 0.1, it is considered that the judgment matrix passes the consistency test. Otherwise, the judgment matrix needs to be adjusted according to the actual situation until it meets the standard so that the results can continue to be verified (Panchal and Shrivastava et al., 2022).

In this research, the weights of three subsystems, namely, production space, living space, and ecological space at the criterion layer, as well as the index weights of the index layer of production space, living space, and ecological space, have been calculated, and all the results have passed the consistency test (CR < 0.1). By using ArcGIS 10.8 software, the expert assignment data of various evaluation indicators of the production space is opened. Then, the weighted sum tool of ArcGIS 10.8 software and the index weights of the production space are utilized to acquire the suitability data of the production space from 2000 to 2020. Using the same method, the suitability data of the living space and ecological space from 2000 to 2020 are obtained.

3.5 Suitability classification

Using Excel software and the suitability evaluation results of PLES, and Using ArcGIS10.8 natural breakpoint classification method, the suitability evaluation results of PLES from 2000 to 2020 are divided into four levels: high suitability area, higher suitability area, lower suitability area and low suitability area (Figures 2–5). The formula for calculating the suitability value is:

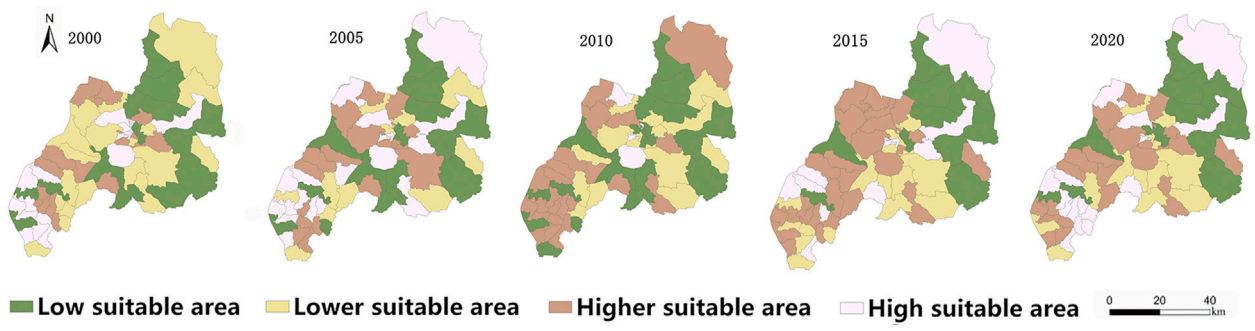


FIGURE 2
Spatio temporal distribution map of production space suitability.

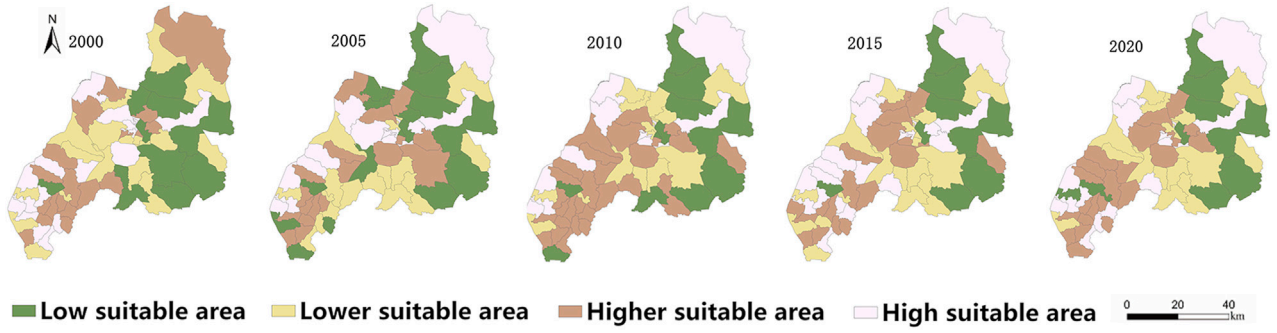


FIGURE 3
Spatio temporal distribution map of living space suitability.

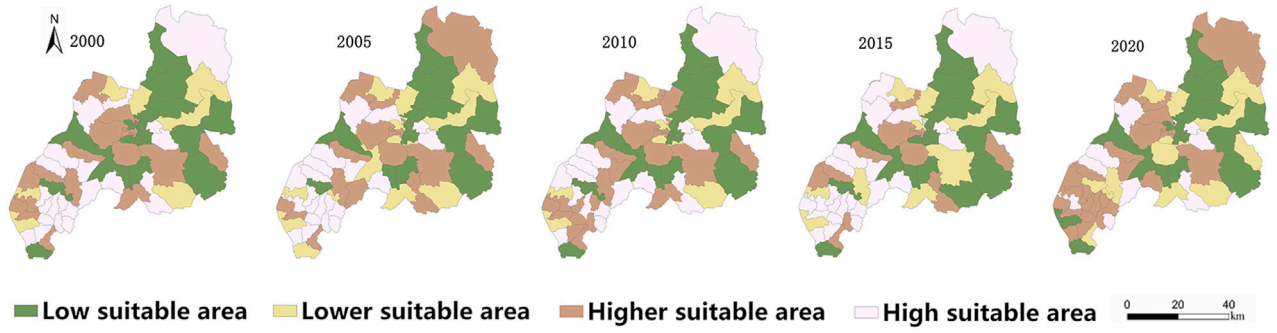


FIGURE 4
Spatio temporal distribution map of ecological space suitability.

$$\mathbf{f(x) = \frac{1}{n}\sum_{i=1}^{n} x_i}$$

In the formula: f(x) represents the suitability value of each criterion layer; x_i represents the score of the evaluation factor; and n represents the number of evaluation indicators in each criterion layer.

4 Results

4.1 Spatiotemporal evolution characteristics of PLES suitability

4.1.1 Suitability change of production space

As depicted in Figure 1, the changes in production space suitability in Duolun County from 2000 to 2020 profoundly reflect the optimization process of land use structure in China's northern agro-pastoral ecotone under national spatial planning policy guidance. Data indicates that the county's production space underwent a transition from low-suitability area dominance to an increased proportion of high-suitability areas, with the average suitability index exhibiting a "V-shaped" pattern, first decreasing then increasing. This transformation can be divided into two phases: First, the 2000–2005 suitability structure adjustment period, when under the influence of the "Returning Farmland to Forest Regulation" (2002) and the "National Ecological Environmental Protection Outline" (2000), the lower-suitability areas decreased significantly from 1,578.98 km^2 (40.9%), while the proportion of high-suitability areas increased to 30.7%. The average suitability index declined from 4.398 to 3.967, with the production space centroid shifting 0.169 km northeast, reflecting the initial constraints of ecological policies on production land. Second, the 2005–2020 suitability optimization and enhancement period, when with the implementation of the "Land Use Master Plan" and the "Xilingol League Grassland Ecological Protection and Construction Plan," the higher-suitability areas reached 35.0% (1,351.79 km^2) in 2010, with significant improvements in the central and western regions of the county. The average suitability index recovered to 4.495, with the centroid shifting 0.320 km southwest (Table 3). This evolutionary process exhibits three core characteristics: spatial structure optimization—substantial reduction in lower-suitability areas, conforming to the "inefficient land reduction" requirement in the "National Land Spatial Planning"; functional layout adjustment—notable improvement in the suitability of central and western county areas, consistent with the "Township and Village Layout Planning" direction; and policy guidance effectiveness—the suitability index pattern reflects the policy shift from ecological protection priority to coordinated ecological and production development. From a regulatory framework perspective,

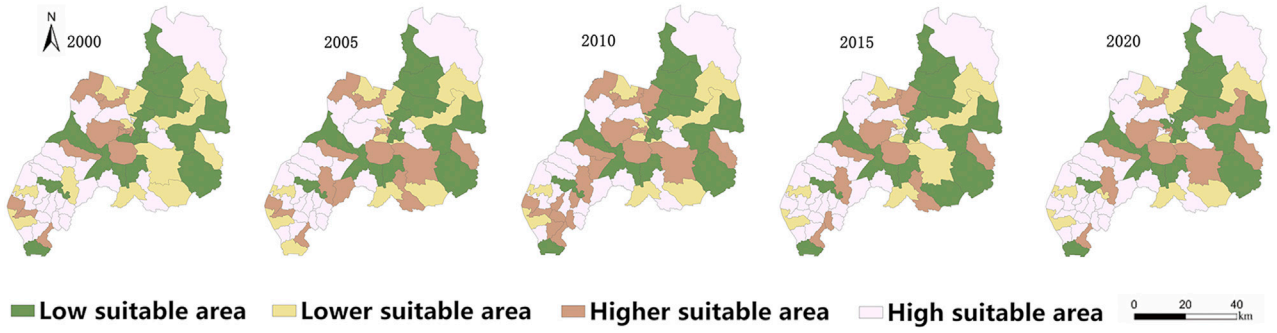


FIGURE 5
Distribution map of PLES carrying capacity in Duolun County.

TABLE 3 Changes in the suitability index of PLES.

Grade	2000	2005	2010	2015	2020
Production suitability	4.398	3.967	4.261	4.042	4.495
Living suitability	4.372	3.98	4.296	4.207	4.411
Ecological suitability	3.361	3.381	3.399	3.401	3.323
Production-Living-Ecological suitability	3.642	3.542	3.637	3.591	3.635

the optimization of Duolun County's production space results from the combined effects of multiple policies including the "Land Management Law," "Basic Farmland Protection Regulations," and "Inner Mongolia Autonomous Region Grassland Protection Regulations," demonstrating the evolution of national spatial governance concepts for agro-pastoral ecotones.

According to the "National Land Spatial Development and Protection 14th Five-Year Plan" and the "Inner Mongolia Autonomous Region Land Spatial Planning" (2021–2035), future optimization of production space suitability in Duolun County should continue to promote ecologically friendly production methods to achieve high-quality coordinated development of production, living, and ecological spaces. This regional case provides valuable reference for spatial planning practices in similar ecologically fragile areas in northern China, reflecting the significant enhancement of national spatial governance capabilities.

4.1.2 Suitability change of living space

As illustrated in Figure 3, from 2000 to 2020, the suitability of living spaces in Duolun County exhibited pronounced spatiotemporal heterogeneity, characterized by a general decline in low- and moderately low-suitability areas and an expansion of high-suitability zones, indicating a gradual improvement in regional habitability. In 2000, low- and moderately low-suitability areas were predominantly concentrated in the central region, accounting for 55.8% of the total land area, with the largest low-suitability zone (1,144.29 km^2) located in the east. By 2005, the proportion of low- and moderately low-suitability areas decreased to 53%, yet the low-suitability area expanded further to 1,218.12 km^2, suggesting a temporary decline in living space quality, likely due to extensive urban sprawl during early-stage urbanization or insufficient implementation of ecological conservation policies. A notable shift occurred in 2010, when high- and moderately high-suitability areas surged to 54% of the total area, with the latter becoming dominant (1,180.02 km^2) and spatially reoriented toward the northern and southwestern regions—a change potentially linked to infrastructure upgrades or ecological migration initiatives. By 2015, high-suitability zones reached 51.11%, expanding from the southern core to central-northern and western areas, with the largest high-suitability area (1,202.96 km^2) reflecting enhanced human settlement conditions. In 2020, low- and moderately low-suitability areas slightly rebounded to 51.4%, though the moderately low-suitability area (1,011.06 km^2) remained below 2000 levels, indicating localized fluctuations possibly influenced by ecological constraints or regulatory adjustments.

Dynamically, the overall reduction in low- and moderately low-suitability areas and the steady growth of high-suitability zones from 2000 to 2020 were accompanied by a decline in the mean suitability index during 2000–2005, likely attributable to resource overexploitation or imbalanced coordination among production-living-ecological spaces (PLES). In contrast, the index showed a consistent annual increase (cumulatively 0.039%) from 2010 to 2020 (Table 3), underscoring the positive impact of later-stage spatial planning policies, such as the National Major Function-Oriented Zoning Plan and ecological redline mechanisms, on living space optimization. Furthermore, centroid shift analysis revealed that the living space centroid migrated 0.298 km northeastward during 2000–2005, possibly signaling intensified development pressure in eastern regions, while a 0.338 km southwestward shift from 2005 to 2020 aligned with western ecological restoration and compact urban

planning strategies, consistent with national initiatives like the Western Development Strategy and New-Type Urbanization.

In conclusion, the evolution of living space suitability in Duolun County reflects the interplay of natural conditions, policy interventions, and development models: early-phase expansion of low-suitability areas exposed the drawbacks of extensive growth, whereas later-phase gains in high-suitability zones demonstrated the efficacy of ecological-priority spatial planning. Future efforts should further harmonize PLE space allocation, strengthen the synergy between living space development and ecological conservation, and ensure regional sustainable development.

4.1.3 Suitability change of ecological space

As manifested in Figure 4, from 2000 to 2020, the ecological space suitability of Duolun County underwent significant dynamic changes. Specifically, the areas of both highly suitable and low-suitability zones showed a general declining trend, while the areas of moderately high and moderately low suitability zones increased. These changes reflect adjustments in land use and ecological conservation patterns and were jointly influenced by natural environmental changes, policy regulations, and socio-economic development.

In 2000, highly and moderately highly suitable ecological zones were primarily distributed in the southwestern region, covering 55.2% of the total land area. The low-suitability zone was the largest, occupying 1,212.48 km^2, or 31.4% of the total land area, mainly located in the northeastern region. By 2005, the highly and moderately highly suitable zones in the southwestern region further expanded, covering 61.4% of the total land, with the highly suitable area reaching 1,307.39 km^2. During this period, the ecological suitability index declined, indicating a decrease in the ecological carrying capacity of the region.

In 2010, highly and moderately highly suitable zones remained concentrated in the southwestern region, occupying 56.7% of the total land area, while the low-suitability zone slightly decreased to 1,178.02 km^2. However, by 2015, the spatial distribution changed: the area of highly and moderately highly suitable zones shrank to 48.3%, still mainly in the southwestern region, while the moderately low and low-suitability zones expanded toward the northeastern part of the county, reaching 51.7% of the total land area. This trend became more pronounced by 2020, when the proportion of highly and moderately highly suitable zones further declined to 31.4%, shifting from the southwestern region to the eastern and southern parts of the county. Meanwhile, the moderately low suitability zone became the largest, occupying 51.9% of the total land area, mainly in the northeastern region.

In terms of the ecological suitability index, it exhibited a declining trend between 2000 and 2005, indicating a deterioration in ecological conditions. However, from 2005 to 2020, the index showed a gradual increase, reflecting improvements in ecological suitability. Despite this upward trend, the overall index still declined by 0.038 compared to 2000, suggesting that although ecological conservation efforts have been strengthened, the quality of ecological space has not fully recovered to its original state (Table 3).

The spatial distribution of production and living spaces also changed, as analyzed through the center of gravity model. From 2000 to 2005, the center of gravity of the living space shifted southwest by 0.219 km. In contrast, between 2005 and 2020, the center of gravity of the production space moved northeast by 0.315 km. These shifts may have been influenced by changes in industrial structure, urbanization processes, and ecological conservation policies.

Several key factors contributed to the changes in ecological space suitability in Duolun County:

1. Implementation of national and regional ecological conservation policies–Projects such as the "Three-North Shelterbelt" program and the "Grain for Green" policy have improved ecological suitability in certain areas while simultaneously affecting the spatial distribution of production land.
2. Land use changes–Urban expansion and agricultural restructuring have led to the reduction of highly suitable ecological zones while increasing moderately low suitability areas.
3. Natural environmental factors–Climate change and variations in water resources have affected ecosystem stability and vegetation restoration capacity, influencing ecological suitability.

Overall, from 2000 to 2020, Duolun County experienced significant changes in ecological space suitability, with a reduction in highly suitable and low-suitability zones, while moderately high and moderately low suitability zones expanded. Although the ecological suitability index showed an increasing trend after 2005, it remained lower than in 2000. The spatial shifts in production and living spaces reflect the adjustments in ecological, urban, and economic structures. In the future, it is necessary to balance ecological conservation with production and living space optimization to promote coordinated and sustainable development of the ecological, economic, and social systems.

4.1.4 Suitability change of PLES

In this research endeavor, the functions of production space, living space, and ecological space are accorded equal significance. Based on the results of the suitability evaluation of individual spaces, the comprehensive suitability index value of PLES was computed using the arithmetic mean method. Subsequently, the comprehensive suitability evaluation outcomes of PLES from 2000 to 2020 were categorized into four levels, namely, high suitability area, higher suitability area, low suitability area, and lower suitability area, by employing the ArcGIS 10.8 natural breakpoint classification technique.

As illustrated in Figure 5, the analysis of comprehensive suitability evolution of PLES in Duolun County from 2000 to 2020 reveals significant spatiotemporal differentiation characteristics, which align closely with China's ecological protection policies and regional development strategies. Research demonstrates that the total area of low suitability zones (decreasing from 54.6% to 43.8%) and relatively low suitability zones (decreasing from 17.1% to 14.6%) has continuously contracted, while high suitability zones (increasing from 11.3% to 56.2%) and relatively high suitability zones have exhibited exponential growth, portraying an overall optimization pattern of "two decreases and two increases" in spatial suitability. This transformation validates the effective implementation of the "dual emphasis on farmland quality improvement and ecological restoration" strategy proposed in the National Land Consolidation Planning (2016-2020). By 2010, high

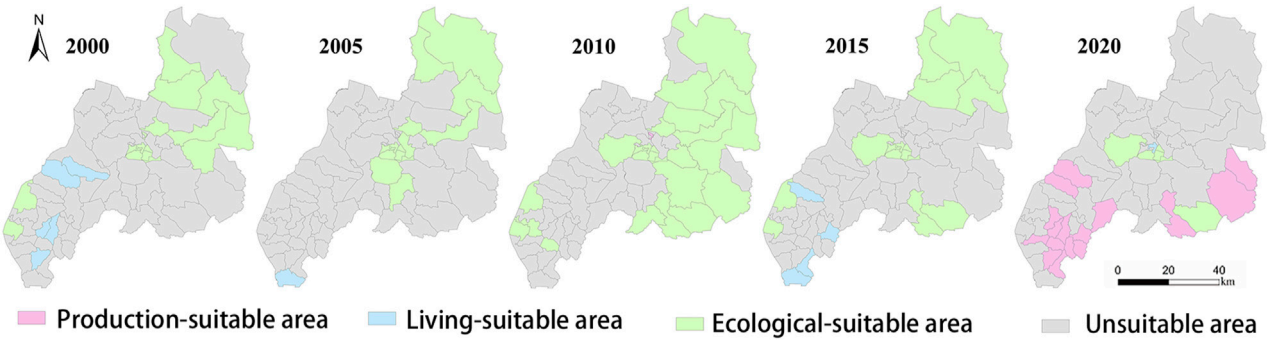


FIGURE 6
Spatial Distribution map of suitable land types in PLES.

and relatively high suitability zones further expanded to 2,123.11 km^2, accounting for 55% of the total area, maintaining their aggregation characteristics in the southwestern region. The proportion of relatively low suitability zones decreased to 14.6%, with their spatial distribution center shifting eastward. In 2015, high and relatively high suitability zones experienced some contraction, declining to 1,946.98 km^2 (50.4% of the total area), still concentrated in the southwestern region, while low and relatively low suitability zones increased to 49.6%, predominantly distributed in the northeastern region. By 2020, high and relatively high suitability zones significantly rebounded to 2,170.23 km^2 (56.2%), maintaining their southwestern aggregation pattern, while low and relatively low suitability zones decreased to 43.8%, with their distribution pattern remaining primarily in the northeastern region.

Throughout the 2000-2020 research period, the comprehensive suitability of PLES in Duolun County exhibited spatial pattern evolution characterized by a gradual reduction in low and relatively low suitability zones, coupled with an overall increasing trend in high and relatively high suitability zones. It can be seen from Table 3, the comprehensive suitability index of PLES showed a declining trend during 2000-2005, followed by continuous growth during 2005-2020, though the overall suitability index slightly decreased (by 0.007) compared to the base period. Analysis using the gravity center migration model indicates that the suitability spatial center shifted 0.094 km southwestward during 2000-2005, while it migrated 0.12 km northeastward during 2005-2020, reflecting the dynamic fluctuation characteristics of regional production-living-ecological space suitability.

This spatiotemporal evolution pattern reveals that the suitability of PLES in Duolun County results from the combined effects of natural-social composite systems, exhibiting distinct regional differentiation and phased variation characteristics, thereby providing a scientific basis for future optimization and allocation of PLES in Duolun County.

4.2 Evolution characteristics of PLES conflict

This research thoroughly analyzes the evolutionary characteristics of PLES conflicts and systematically identifies three representative types of spatial conflicts: (1) Areas that are legally compliant but ecologically suboptimal, which meet current regulatory requirements but have not achieved ecological optimization from the perspective of ecosystem health and sustainable development; (2) Areas with resource competition between legal land uses, manifested as tensions in resource allocation among production, living, and ecological functions, which do not constitute regulatory violations but require coordination and balance at the policy level; (3) Potential ecological optimization areas, which have high ecological conservation value where strengthened protection would bring significant ecological benefits, but remain outside appropriate protection categories under the current regulatory framework.

Based on the suitability evaluation of production, living, and ecological land use, combined with ArcGIS10.8 spatial overlay analysis (Al-Najjar et al., 2024). we observed clear patterns in the spatiotemporal evolution of suitable land types in Duolun County: Between 2000–2015, suitable areas for the three types of land use were mainly distributed in the northeastern region of the county, while in 2020, they became concentrated in the piedmont plains and Luan River basin in the southern part of the county. The proportion of suitable areas experienced a “rise-fall” fluctuation process, increasing from 27.27% in 2000 to 54.2% in 2010, then decreasing to 24.9% in 2020. Among these, the ecological suitable area showed the most significant change, rising from 22.8% in 2000 to 54.2% in 2010, and then sharply declining to 6.1% in 2020. The proportion of living suitable areas remained consistently low and was mainly distributed in the southwestern part of the county. Production suitable areas were almost non-existent in 2000 and 2010, but developed to occupy 18.7% of the total area by 2020, primarily distributed in the sloping plains and Luan River basin in the southern part of the county. Overall, Duolun County has relatively small areas suitable for production and living land use, resulting in obvious conflicts in land resource competition.

This research does not focus on regulatory non-compliance issues, but rather explores the potential for spatial optimization within the existing legal framework. By scientifically identifying these three types of spatial conflicts, it provides decision-makers with scientific basis for optimizing spatial planning, aiming to promote coordinated development of intensive and efficient production space, moderately livable living space, and ecologically pristine space within the framework of production-living-ecological spaces. The research finds that the suitability pattern of the three spaces in Duolun County has undergone

significant changes, with the substantial fluctuation of ecologically suitable areas being particularly noteworthy, reflecting the dynamic interplay between ecological protection and economic development in regional development processes. Future spatial planning should focus on balancing the proportional relationships among the three spaces, especially enhancing the intensive efficiency of production spaces, ensuring the livable quality of living spaces, and emphasizing the restoration and protection of the authenticity of ecological spaces. Through scientific planning and policy guidance, the strategic goal of regional sustainable development can be achieved.

5 Discussion

Duolun County in Inner Mongolia is situated at the southern periphery of the Hunshandake Sandy Land (Yi et al., 2023), constituting a paradigmatic farming-pastoral ecotone and an area highly susceptible to land desertification (Dai et al., 2024). Owing to the protracted influence of natural and anthropogenic factors, the incessant expansion of the land desertification area has exacerbated the deterioration of its ecological milieu. Concomitantly, the area of natural land suitable for utilization has been continuously contracting, while the area suitable for non-land use has been expanding. Since 2000, Duolun County has initiated a plethora of ecological projects, such as the treatment project of the Beijing-Tianjin sandstorm source area, ecological immigration, conversion of farmland to forest, prohibition of grazing and adoption of stall-feeding, afforestation of one million mu of Pinus sylvestris var. Mongolica, and the establishment of the Hunshandake large-scale forest farm (Dai et al., 2024). These initiatives have led to the remediation of a substantial expanse of desertified land, thereby resulting in a reduction of cultivated land, an augmentation of artificial grassland and other forest land with production functions, an increase in the area of suitable production land, and a significant diminution of the area of suitable ecological land, predominantly desertified land. This phenomenon is intricately correlated with the enhancement of vegetation coverage in Duolun County.

Under the aegis of the ecological immigration policy, the reduction of rural residential land area has concomitantly led to a decrease in the area of suitable living land (Liu X. et al., 2022). The comprehensive suitability of the three growth spaces has not exhibited an overt alteration, which is attributable to the paucity of production land and living land in Duolun County. Agriculture and animal husbandry constitute the preponderant industries in Duolun County. The progression of local agriculture and animal husbandry has augmented the demand for the utilization of land space, thereby intensifying the conflict among the three types of land uses and precipitating an annual increment in the area of the conflict zone.

Based on the developmental requisites of ecological, living, and production spaces, this study, from the vantage point of the PLES, constructed a suitability evaluation index system for PLES in Duolun County, Inner Mongolia. Subsequently, an in-depth analysis was conducted regarding the suitability of PLES development within the district. The resultant findings can serve as a valuable reference for the optimal configuration of land space.

Due to the limitations of time and data acquisition, the changes of the suitability of the Sansheng space from 2020 to 2024 are not considered, but Duolun county is located in the temperate continental climate zone, and its natural environment and socio-economic factors have changed little in recent years. Therefore, the results of this paper can provide a scientific basis for the optimization and management of land space in Duolun region. In the follow-up study, we can focus on the further improvement of the evaluation index system to make up for the deficiencies of the current research.

6 Conclusion

(1) During the period from 2000 to 2020, the production space in the southwest exhibited a higher degree of suitability in comparison to that in the northeast. Concurrently, its average suitability index manifested a mildly ascending propensity. The center of gravity of production space suitability underwent a translocation of 0.151 km towards the southwest, which could potentially be attributed to a confluence of factors such as differential land endowments, patterns of resource allocation, and the impact of anthropogenic activities on the spatial configuration of production-related land uses.

(2) Over the same temporal span from 2000 to 2020, the living space in the southwest also demonstrated a superior level of suitability relative to the northeast. Its average suitability index likewise evinced a feeble upward trend. The center of gravity of living space suitability migrated 0.04 km in the southwesterly direction. This shift might be ascribed to alterations in demographic distributions, urban-rural development dynamics, and the evolving preferences and requirements of the populace regarding living environments and associated land uses.

(3) The ecological spatial suitability was more pronounced in the southwest than in the northeast. However, its average suitability index exhibited a marginally descending trajectory. The center of gravity of ecological spatial function displaced 0.096 km towards the northeast. Such a displacement could be the result of complex ecological processes, including but not limited to changes in vegetation cover, soil quality degradation or improvement in different regions, and the influence of climate change on ecological habitats and their spatial distributions.

(4) The comprehensive suitability of PLES was preponderantly higher in the southwest and relatively lower in the northeast. Its average suitability index displayed a slight downward inclination. The comprehensive suitability center of PLES shifted 0.026 km towards the northeast. This overall trend implies a complex interplay of the three major spatial components - production, living, and ecological - and reflects the challenges and opportunities in achieving a balanced and sustainable spatial development paradigm.

(5) The areas suitable for ecological land use were principally concentrated in the central and southern precincts of the county, and they occupied the largest proportion of the total suitable areas. Notably, the area of the intense conflict zone, which might arise from competing demands between different land use functions, has been progressively expanding year by year. These conflict areas were mainly distributed in the central and western regions of the county, signifying the need for more refined land use planning and management strategies to reconcile the diverse and often

conflicting interests and requirements of various stakeholders and ecological imperatives.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

DL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Methodology, Writing – original draft, Writing – review and editing. A: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing, Methodology, Investigation, Project administration, Resources. SN: Conceptualization, Data curation, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

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EDITED BY
Lingli Qing,
Guangzhou College of Commerce, China

REVIEWED BY
Ziheng Shangguan,
The University of Melbourne, Australia
Zhiyong Zheng,
Nanjing Audit University, China
Lizhao Du,
Lanzhou Jiaotong University, China

*CORRESPONDENCE
Ke Xu,
1920220015@stu.nufe.edu.cn

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Road to green urbanization: how does urbanization process affect the green land use efficiency

Ruoxi Yang[1], Jiayao Wang[1], Minghao Xu[1] and Ke Xu[2]*

[1]School of Economics and Management, Henan Polytechnic, Zhengzhou, Henan, China, [2]Institute of Food and Strategic Reserves, Nanjing University of Finance and Economics, Nanjing, Jiangsu, China

Introduction: As the process of urbanization accelerates, high energy consumption, pollution, and low land use efficiency have led to many significant negative impacts on production and daily life.

Methods: In order to investigate the impact of urbanization construction on green land use efficiency and its potential mechanisms, the indicators of China's urbanization evaluation system are constructed, and the SBM-GML model is used to measure green land use efficiency. Based on this, data from 30 provinces in China from 2013 to 2023 are used to test them using fixed effects, mediating effects and threshold effects.

Results: (1) The construction of the urbanization process can directly contribute to the improvement of green efficiency in land use. This conclusion remains valid after conducting endogeneity and robustness tests. (2) The mediating effect test shows that the urbanization process can increase synergistic industrial agglomeration and promote the optimization of the industrial structure, thus indirectly promoting the improvement of green land use efficiency. (3) The threshold effect test shows that a threshold effect exists in the relationship between the level of economic development and green land use efficiency, based on the urbanization process. As urbanization deepens, the role of economic development in improving green land use efficiency gradually strengthens. (4) Heterogeneity analysis reveals that the construction of the urbanization process has a more significant impact on driving green land use efficiency in cities in eastern China.

Discussion: This paper suggests optimizing the allocation of land resources in the process of accelerating urbanization and improving the efficiency of land use in terms of green. Attention should be given to the regional differences in carbon emissions during urbanization, and it is essential to continuously optimize the realized low-carbon urbanization model. Special attention should be paid to enhancing carbon emission control in underdeveloped regions, in order to promote the nationwide improvement of green land use efficiency.

KEYWORDS

urbanization process, green land use efficiency, super-efficient EBM, synergistic industrial agglomeration, threshold effect

1 Introduction

As the material foundation for human survival and a key support and fundamental source for constructing ecological civilization, transforming the inefficient and rough land use pattern is crucial for promoting the high-quality, sustainable development of the region (Hou and Wu, 2024). Since the reform and opening up, guided by 'land finance' and high-speed transportation, the spatial structure, scale, and growth mechanism of Chinese cities have changed significantly (Wei et al., 2023). China's urbanization rate has increased from 17.92% in 1978 to 67% in 2024, far exceeding the global average. During China's rapid urbanization, the level of industrialization has surged, the urban population has grown significantly, and the scale of urban land use has expanded, leading to a sharp rise in energy consumption and a corresponding increase in carbon emissions. This poses a serious challenge to both the land use system and the climate system (Wu et al., 2024a, b). As the fundamental element and spatial carrier of urban production and life, the green and use of urban land emphasizes integrating the concept of green and low-carbon development throughout the entire process of urban land utilization (Li et al., 2023a, b). Therefore, improving the green land use efficiency (GLUE) and resolving various structural contradictions in production are key to achieving the 'dual carbon' goal and promoting sustainable urban development.

Urbanization is an inevitable trend of economic and social development and a necessary path to modernization (Duan et al., 2022). Existing studies on the impact of urbanization on GLUE mainly focus on three aspects. First, urbanization has a positive impact on GLUE (Xiang et al., 2023). With the advancement of urbanization, land resources are effectively allocated and the structure of urban construction land is optimized, thus improving urban GLUE. Second, urbanization has a negative impact on GLUE (Li and Luo, 2015). In the process of urbanization, the agricultural population is transferred to cities and towns, the demand for urban infrastructure increases, urban land becomes a scarce resource, a large amount of arable land is occupied, the construction land is rapidly expanding, and the urban spatial planning lags behind the development of cities and towns. In addition, the land development strategy centered on economic growth has led to irrational spatial structure and lower land use efficiency. However, the impact of urbanization on GLUE is nonlinear, and the overall relationship is similar to a "U" shape (Yue and Xue, 2020). When the level of urbanization is low, the GLUE will decrease with the advancement of urbanization; however, after the development of urbanization to a certain extent, with the ISO and the improvement of technology, the land use structure tends to be rationalized, and the use of land resources is increasingly intensive, and the urban GLUE will be significantly improved.

In summary, the significant impact of the urbanization process (UP) on the green efficiency of land use has become a key issue in current research. The network externalities associated with its spatial correlation make it one of the key factors in promoting the efficient and intensive use of land resources. Exploring the impact of urbanization on green efficiency is not only an essential step toward achieving efficient and intensive land use, but also a crucial path for synergistically advancing high-quality economic development and ecological protection. This study not only contributes to the formulation of more scientifically grounded urbanization policies, but also provides theoretical support for the realization of green and low-carbon development.

The existing literature has developed a framework for studying the UP and GLUE, but several deficiencies remain. First, the evaluation system of the UP is still underdeveloped and remains in the exploratory stage. Second, there is a lack of research, particularly on urban GLUE, and the causal relationship between the UP and GLUE is not yet well understood. Finally, the transmission mechanism of the UP on GLUE is unclear, with insufficient consideration of the influence of synergistic industrial agglomeration (SIA) and industrial structure optimization (ISO).

Compared to existing studies, the potential marginal contributions of this paper are as follows: First, the paper constructs UP indicators. Building upon existing research, a comprehensive UP indicator system is developed, focusing on four dimensions: population, economy, society, and ecology, to provide more scientific and standardized support for China's urbanization evaluation system. Second, while the existing literature lacks studies on the land use carbon efficiency within the context of urbanization, leading to an incomplete understanding of the influencing factors, this paper uses data from 30 provinces in China from 2013 to 2023 and conducts a series of endogeneity and robustness tests to explore the impacts of the UP on GLUE, providing important references for improving China's UP and land use carbon efficiency. Third, existing studies have not sufficiently addressed the roles of SIA and ISO, which may result in an overestimation of the positive impact of the UP on GLUE. This paper clarifies the transmission mechanism of the UP on GLUE from the perspectives of SIA and ISO.

The rest of the paper is organized as follows: the second part is the literature review; the third part presents the theoretical analysis and research hypotheses; the fourth part discusses the research design, including data sources, variables, and models; the fifth part covers baseline regressions, endogeneity tests, robustness tests, mediation mechanism tests, and heterogeneity analyses; the sixth part examines further research on the threshold effect of the level of economic development; and finally, the paper concludes with the study's conclusions and policy recommendations.

2 Literature review and hypotheses development

2.1 Literature review

2.1.1 Study on the measurement and influencing factors of GLUE

GLUE is an input-output efficiency indicator that characterizes the inputs and outputs associated with regional land use activities. Its essence is the result of the combined effect of the inputs of capital, labor, energy, technology and other factors, as well as the outputs of economic efficiency and environmental pollution in the process of land-use activities under the constraint of carbon emissions. This concept extends the definition of GLUE by emphasizing the effective use of the smallest unit of input factors and resources to obtain the maximum "desired" outputs (e.g., economic benefits) and the minimum "non-desired" outputs (e.g., environmental pollution (carbon emissions)).

Existing studies have mainly used carbon emissions as the "undesired" output to measure GLUE, and the methods used are also mainly based on traditional models, such as the SBM model (Pang and Wang, 2020), data envelopment analysis (Yang et al., 2024) and stochastic Frontier analysis (Dong et al., 2020). With the passage of time, scholars have paid more and more attention to the green efficiency from land use. In addition, studies have explored the influencing factors of GLUE and found that the regional heterogeneity of GLUE is a result of the combined effects of land use structure, economic development, technological innovation and industrial structure. However, traditional DEA models fail to adequately consider the impact of undesired outputs when measuring efficiency, which may lead to overestimation of efficiency. In addition, the SFA method, although capable of portraying random errors through parameterization, relies on specific functional form settings, which may lead to subjective bias.

In order to overcome these limitations, this paper adopts the SBM-GML model to measure GLUE, which can effectively deal with non-desired outputs and avoid the problem of overestimation of efficiency due to the failure to consider non-desired outputs compared with the traditional DEA model. In addition, the SBM-GML model incorporates the global Markov index, which can dynamically portray the trend of GLUE and provide a reliable measurement basis for the long time axis assessment. In the eastern region, due to the higher degree of industrialization, the GLUE is more influenced by technological innovation and industrial upgrading, while the efficiency improvement in the central and western regions relies more on infrastructure improvement and policy support.The SBM-GML model is more applicable to different regions, and is able to portray the efficiency levels and their evolution paths in different regions with greater precision.

2.1.2 Relevant studies on UP

The UP is people-oriented, green, low-carbon, and sustainable, emphasizing intensive efficiency and ecological livability. Over the years, scholars have studied the connotation of the UP, the construction of evaluation index systems, and the influencing factors. Wang et al. (2021) elaborated on the core connotation of "human-centeredness" in the UP from the perspective of "modernization." Fang et al. (2021) constructed an UP evaluation index system that covers both internal and external human factors, based on an explanation of the connotation of "human-centeredness" in the UP. Chen et al. (2024a), Chen et al. (2024b) constructed an UP evaluation index system based on the actual development of the Yangtze river delta region, incorporating five dimensions of urbanization—population, economy, space, society, and ecology—in line with the development goals of the UP. Li et al. (2024a), Li et al. (2024b) found that the digital economy significantly promotes the development of the UP, based on panel data from 285 prefecture-level cities in China. Zhou and Lin. (2022) constructed a spatial econometric model using panel data from 104 prefecture-level cities in the Yangtze river economic belt (2010–2019) and found that the level of informatization significantly and positively promotes the development of the UP.

2.1.3 Research related to SIA

Due to external economies of scale, the agricultural population is flowing to towns and cities at an accelerated rate, leading to an increase in both the number and size of towns and cities. Marshall's theory on the externalities of SIA highlights the close link between external economies of scale and industrial agglomeration. According to classical economic theory, SIA can enhance economic efficiency by reducing transportation costs, promoting technology diffusion, and increasing market competitiveness. In the context of the UP, SIA has become a crucial factor in driving regional economic growth and improving GLUE.

In recent years, academic research on SIA has become increasingly in-depth, primarily focusing on its causes, influence mechanisms, and improvement strategies. One of the key drivers of SIA is the economy of scale effect. Studies have shown that SIA maximizes economic benefits by improving production efficiency, reducing unit costs, and optimizing resource utilization (Chen et al., 2019). Especially during the process of urbanization, urban agglomeration facilitates the concentration of resources such as labor, capital, and technology, which helps to enhance the green efficiency of land use. Peng et al. (2022) found that, with the accelerated development of SIA, the technological cooperation and innovation capacity among enterprises has significantly improved, which positively impacts the reduction of carbon emissions.

However, SIA also brings the problem of resource mismatch. On the one hand, the agglomeration effect may lead to the overconsumption of environmental resources, thereby exacerbating environmental issues. Lu et al. (2024) pointed out that in some regions, excessive SIA overloads the carrying capacity of land resources and the environment, leading to the deterioration of the ecological environment. On the other hand, the agglomeration effect may cause the resource allocation in certain industries and regions to become overly concentrated, neglecting the synergistic development of other regions and industries, thus creating an imbalance in resource allocation (Xing et al., 2023). This imbalance leads to an increase in emission intensity, thereby affecting the green efficiency of land use.

In terms of improving the impact of SIA on carbon efficiency, scholars have proposed various strategies. Guo et al. (2020) argued that green SIA can not only improve resource utilization efficiency but also play a significant role in emission reduction. Peng et al. (2021) pointed out that the government, through rational planning and policy support, can guide SIA toward environmentally friendly and low-carbon development, thereby improving GLUE.

2.1.4 Research related to ISO

ISO refers to the process of transferring production factors from inefficient traditional industries to more efficient modern industries during economic development, accompanied by technological progress, the refinement of the industrial division of labor, and changes in market demand. With the advancement of the UP, ISO has become one of the key means to improve GLUE. Academic research on ISO mainly focuses on its causes, influence mechanisms, and how to achieve industrial structure optimization.

Firstly, the reasons for the formation of ISO are discussed. One of the main driving forces behind ISO is technological innovation. With the progress of science and technology, especially the continuous development of digital and green technologies, the production methods in traditional industries have undergone fundamental changes. Tan et al. (2024) found that the extensive

application of emerging technologies, particularly in smart manufacturing and clean energy, has facilitated the efficient transformation of industrial structures and the optimization of resource allocation. As industries evolve toward higher technology, greater value-added production, and low-carbon environmental protection, the green efficiency of land use is also significantly improved. Additionally, changes in market demand are key factors in ISO. With increasing consumer demand for high-quality, low-carbon, and environmentally friendly products, traditional industries face the pressure to transform and upgrade. For example, Zhang et al. (2024a), Zhang et al. (2024b) suggest that in the process of China's economic transformation, shifts in consumption patterns—driven by rising incomes and improved living standards—have spurred the development of green consumption and service industries. Traditional high-carbon-emission industries have been gradually replaced by low-carbon, environmentally friendly, and high-value-added industries, thereby enhancing the GLUE.

Secondly, the impact of ISO on the green efficiency of land use is discussed. One of the key objectives of ISO is to achieve the efficient use of resources and the reduction of carbon emissions. Numerous studies have shown that optimizing the industrial structure can significantly improve the green efficiency of land use. Dong et al. (2020) pointed out that as the proportion of high-technology and service industries increases, energy consumption and carbon emissions are gradually reduced, thereby achieving the low-carbonization of land use. In the context of the UP, ISO can promote the development of green industries, reduce the excessive consumption of land resources, and simultaneously improve green efficiency.

Finally, to realize the positive impact of ISO on carbon efficiency, government policy guidance is crucial. Li and Liu (2023) suggest that the government should promote the rapid development of green technologies and low-carbon industries through tax incentives, subsidies, and green finance. Additionally, promoting the greening and upgrading of industrial clusters can further enhance resource utilization efficiency and inhance green output by strengthening industrial synergies and technology sharing.

2.1.5 Research on the impact of UP on the GLUE

Both the UP and GLUE are key issues explored by scholars. From the perspective of urbanization policy implementation, most existing research has analyzed the connotation and spatial-temporal evolution of urbanization from multidisciplinary perspectives such as economics, sociology, geography, and others (Yang et al., 2023a; Yang et al., 2023b). It has also revealed the economic, social, and ecological effects of urbanization through the lens of coupling relationships and spatial spillover effects (Zhang et al., 2024a; Zhang et al., 2024b; Zhu et al., 2023a; Zhu et al., 2023b).

From the perspective of GLUE, this concept originated from the study of eco-environmental efficiency. The term "eco-environmental efficiency" emerged in the 1990s (Tang et al., 2021) and has since been widely applied to agricultural production, tourism development, and land use (Jin et al., 2024; Wu and Liang, 2023; Su et al., 2024).

Regarding research on measuring land use carbon efficiency, You and Wu (2010) first developed the traditional DEA model, which was later replaced by the SBM model as the mainstream measurement tool. In addition to measuring the carbon efficiency of individual land use types, such as construction land (Wang et al., 2024) and agricultural land (Janus and Ertunç, 2023), green efficiency in different regions, such as the Yellow River Basin (Rong et al., 2022), Jiangsu Province (Li et al., 2024a), Nanjing (Chuai and Feng, 2019), Zhejiang (Zhu et al., 2023a, b), and Ningxia (Huang and Li, 2022), has also been incorporated into these measurements.

Internationally, scholars have mainly focused on measuring greenhouse gas (GHG) and energy emissions in regions such as the EU (Kortelainen, 2007), OECD (Zhou and Ang, 2008), the UK (Cecchini et al., 2018), and Italy (Molinos-Senante et al., 2022). Concerning the influencing factors of land use carbon efficiency, scholars have found that factors such as industrial structure and greening levels (Luo et al., 2022), low-carbon pilot policies (Penazzi et al., 2019), carbon emission trading pilots (Merfort et al., 2023), and collaborative technological innovation (Chen et al., 2022) all significantly affect GLUE.

Regarding the relationship between the UP and green efficiency, Shi et al. (2024) found that a coupled and coordinated relationship exists between the UP and agricultural green efficiency in China's provincial areas. Additionally, Jiang and Wang (2022) discovered a spatial effect of the level of urbanization on the green efficiency of the tourism industry.

In addition, the current study draws on limited international experience, while European and American countries have accumulated rich practical experience in improving green land-use efficiency. For example, the United Kingdom controls urban sprawl and improves land use efficiency through the "green belt" policy (Pourtaherian and Jaeger, 2022); Germany promotes a compact city development model to optimize land resource allocation (Wellmann et al., 2020); and the United States uses tax incentives to promote the construction of green buildings and low-carbon communities (Jabeen et al., 2025). These experiences can provide lessons for China to optimize land use efficiency under the "dual-carbon" goal (Wu et al., 2024a, b). Therefore, future research needs to further compare the policy tools, land management systems, and urban planning strategies of different countries to enhance the international perspective of the study.

Generally speaking, the existing studies have laid a foundation for exploring the impact of UP on GLUE, but the following shortcomings still exist: (1) the research methods are mostly based on traditional methods such as DEA and SBM, and there is a lack of multi-methods comparative analysis or dynamic evolution perspective; (2) there is insufficient exploration of the impact mechanism, and the impact on GLUE has not yet been adequately revealed from the perspectives of industrial agglomeration and industrial structural adjustment; (4) there is less reference to international experiences; and (5) there is a need to further compare different policy tools and land management systems and urban planning strategies in order to enhance the international perspective of the study. (3) Less reference to international experience, especially in the context of "dual-carbon", the discussion on how to improve GLUE through intelligent and green means is still insufficient.

2.2 Research hypotheses

2.2.1 The direct mechanism of UP on GLUE

China's top-down administrative policy dictates that urbanization development is government-led and driven from the top. As a result, local governments wield significant power in the allocation of land resources and the selection of advantageous industries, which directly impacts the speed and quality of urbanization. For a period after the reform and opening-up, taxes related to land concessions became a crucial source of local financial income, and 'land finance' promoted large-scale urban land expansion, which had negative effects on the ecological environment. Under fiscal incentives and the traditional, crude, and aggressive urbanization development model, local governments focused on industrial investment projects with quick returns and low risks, often neglecting the provision of public goods such as environmental governance. This neglect has contributed to increased energy consumption and carbon emissions (Sloot and Scheibehenne, 2022).

At the level of population urbanization, it can improve the overall education level, provide intellectual support for the low-carbon and efficient use of resources and energy, as well as for environmental protection (Chen et al., 2024a; Chen et al., 2024b), and help reduce energy consumption. The general improvement in population quality, along with increased publicity and education on green environmental protection, will raise public awareness of green, low-carbon practices and environmental protection (Li et al., 2023a; Chen et al., 2024b). This will, in turn, increase demand for green, low-carbon products across society and drive the green, low-carbon transformation of land use, including arable land, grasslands, forest land, and watersheds.

At the level of economic urbanization, it promotes the optimization of regional industrial structure and the creation of agglomeration effects, providing strong support for the development of low-carbon technologies and green industries (Bakirtas and Akpolat, 2018). With the rapid development of the regional economy and industrial upgrading, the popularization and application of green technologies help improve the efficiency of land resource use. In the process of economic urbanization, the combination of a modernized industrial system and a low-carbon economic model promotes the green and efficient use of land resources. Additionally, economic urbanization fosters the growth of green investment by increasing the agglomeration of capital, technology, and talent, which further accelerates the low-carbon transformation of land use structure.

At the level of social urbanization, it has promoted the mobility of urban and rural populations, diversified social structures, and enhanced public awareness and acceptance of environmental protection and green, low-carbon lifestyles (Zhang et al., 2023). With the acceleration of urbanization, residents' green consumption awareness has been strengthened, driving the growth in demand for green products and low-carbon technologies. Social urbanization has also led to improvements in public service facilities and facilitated the construction of low-carbon transport, green buildings, and other infrastructure, thereby increasing GLUE. Public support for and participation in environmental protection policies have promoted the formation of a green, low-carbon lifestyle across society, further advancing the sustainable development of land use.

At the level of eco-urbanization, it focuses on eco-environmental protection and the sustainable use of resources, promoting the construction of green infrastructure and the implementation of ecological restoration projects (Wang et al., 2023). Eco-urbanization emphasizes protecting the ecological environment and reducing carbon emissions, while also promoting the development of urban greening, eco-agriculture, and environmentally friendly industries, thus optimizing GLUE. In the process of eco-urbanization, the planning and construction of green spaces and eco-protected areas help improve the carbon absorption capacity of land, thereby achieving the goal of a low-carbon economy. At the same time, eco-urbanization fosters harmonious symbiosis between human activities and natural ecosystems, promoting the transformation of land use toward low carbon and green, which reduces carbon emissions and enhances the eco-efficiency of land use.

In summary, under the constraints of the green low-carbon, efficient, and intensive objectives, and within the context of the ecological civilization development concept, the UP will increase the output benefits of land use per unit area and improve the green efficiency of land use. Accordingly, the following hypotheses are proposed.

Hypothesis 1: The national comprehensive pilot policy of UP will improve the GLUE.

2.2.2 The mediating mechanism of UP on the GLUE

In the process of urbanization, the land use structure is gradually optimized through the advancement of urbanization and the clustering of industries in the region. This industrial concentration not only effectively improves the allocation efficiency of land resources but also promotes the innovation and application of technology, particularly breakthroughs in green production and low-carbon technologies (Wei et al., 2022; Han and Cao, 2024). With the concentration of industries, cooperation and competition among enterprises intensify, which helps improve overall resource use efficiency and reduces the over-exploitation and waste of land resources. Industrial concentration increases the intensity of land use through scale and synergy effects, promotes the green use of land resources, and enhances GLUE (Wang et al., 2018).

In addition, in the context of urbanization, the government promotes the agglomeration of green industries and the rapid development of low-carbon technologies through reasonable land policies and industrial guidance, thereby achieving the efficient use of land resources and improving green efficiency (Wang et al., 2018). Especially in the construction of science and technology innovation parks and green industrial parks, SIA plays an important role and provides theoretical and practical support for the improvement of GLUE in the region. Accordingly, hypothesis 2 is proposed.

Hypothesis 2: UP improves GLUE by promoting SIA.

In the process of promoting urbanization, with the continuous ISO, the green transformation and efficient development of the regional economy have gradually become the dominant trend. ISO promotes the improvement of GLUE by facilitating the introduction

and application of low-carbon and green technologies (Dong et al., 2021).

With the gradual elimination of traditional high-pollution and high-energy-consuming industries and the rapid development of green industries, the efficiency of land use has been significantly improved, and the efficiency of green output has been effectively improved. In particular, in emerging industry clusters and green industrial parks, the intensive use of land resources has been promoted through the clustering of advanced technologies and high value-added industries, thus enhancing GLUE (Ge et al., 2024). ISO not only promotes the widespread application of green technologies but also improves land use intensification by promoting the agglomeration of green industries and technologies (He et al., 2021). Efficient and low-carbon SIA can create higher economic benefits on limited land resources while reducing carbon emissions through technological innovation, optimizing resource allocation, and reducing unnecessary land waste.

In addition, ISO also brings about the transformation of production methods and promotes the greening and intelligentization of the industrial chain, thus further enhancing the efficiency of land resources (Dong et al., 2020). In the context of urbanization, the government encourages the agglomeration of green industries and technological innovation through the implementation of reasonable industrial guidance policies, which not only promotes the optimization and upgrading of the regional industrial structure but also fosters the green and efficient use of land resources. The government's policy support promotes the green transformation of traditional industries and further improves GLUE by guiding funds, technologies, and talent toward green and low-carbon industries.

Hypothesis 3: UP increases the GLUE through ISO. After a series of theoretical analyses, this paper produces the technical roadmap shown below (Figure 1).

3 Research design

3.1 Model construction

In order to test hypothesis 1, i.e., the impact of the UP on GLUE, this paper constructs a two-way fixed effect model (Equation 1).

$$GLUE_{it} = \mathbf{a_0} + \mathbf{a_1} UP_{it} + \mathbf{aControls_{it}} + u_i + \delta_t + \varepsilon_{it} \quad (1)$$

Among other things, $GLUE_{it}$ is the green land use efficiency; UP_{it} is urbanization process; $\mathbf{Contrals_{it}}$ is control variable; $\mathbf{a_0}$ is the constant term; $\mathbf{a_1}$ is the coefficient of the core explanatory variable; a is the parameter to be estimated; u_i, δ_t, ε_{it} denote individual effects, time effects, and random perturbation terms, in that order.

3.2 Variable selection

3.2.1 Explained variable

GLUE: The non-desired output SBM model is used to assess the GLUE in 30 provinces in mainland China. Combined with Lu et al. (2023) and Bian and Zhong (2023), we selected land, capital, labor and technology as input indicators for measuring GLUE, and used the area of urban construction land, the *per capita* investment in fixed assets, the *per capita* number of people employed, the *per capita* R&D expenditure, and the *per capita* GDP as desired output indicators and the *per capita* net carbon emissions as non-desired output indicators, respectively. expenditure; land-per-capita GDP is used as the desired output indicator, and land-per-capita net carbon emission is used as the non-desired output indicator. It should be noted that an increase in the intensity of capital, labor, and technological inputs per unit area will raise the level of intensive land use and increase the economic expenditure on land use, and to a certain extent, affect the carbon balance of the region. The number of people employed refers to the total number of labor force in primary, secondary, and tertiary industries at the city level. Land parity refers to the ratio of the total amount of each indicator to the land area, which includes the sum of arable land, land area for construction, forest land, grassland, and wetland/watershed per year in each city.

Based on the above indicators, it is assumed that there are n decision-making units (provinces) with input vectors: $X=(x_{ij}) \in R^{M*}n$, The desired output vector is: $Y=(y_{ij}) \in R^{E*}n$, The non-expected output vector is: $Z=(z_{ij}) \in R^{U*}n$, let $X > 0$, $Y > 0$ and $Z > 0$ Equation 2.

$$\rho = \min \frac{1 - \frac{1}{M}\sum_{i=1}^{M} \frac{S_i^x}{X_{i0}}}{1 + \frac{1}{E+U}\left(\sum_{k=1}^{E_1} \frac{S_k^y}{y_{k0}} + \sum_{q=1}^{U_1} \frac{S_q^z}{z_{q0}}\right)} \quad (2)$$

The constraints are shown as Equation 3:

$$\begin{cases} x_{i0} = \sum_{j=1}^{n} \beta_j x_j + S_i^x, \forall i \\ y_{k0} = \sum_{j=1}^{n} \beta_j y_j - S_k^y, \forall k \\ Z_{q0} = \sum_{j=1}^{n} \beta_j z_j + S_q^z, \forall q \\ S_i^x \geq 0, S_k^y \geq 0, S_q^z \geq 0, \beta_j \geq 0, \forall j, i, k, q \end{cases} \quad (3)$$

where ρ is the combined efficiency value assuming constant returns to scale; M is the number of input indicator categories, E is the number of desired output indicator categories, and U is the number of non-desired output indicator categories; β is a vector of weights; $\sum_{j=1}^{n} x_j$ is the input matrix; $\sum_{j=1}^{n} y_j$ is the desired output matrix; $\sum_{j=1}^{n} z_j$ is the non-desired output matrix; S^x is the amount of input redundancy; S^y is the amount of desired output shortfalls; S^z is the excess of non-expected output. When $\rho = 1$, S^x, S^y and S^z are absent (i.e., the province is green performant.) Please see Table 1 for the input and output variables of the SBM model.

3.2.2 Explanatory variable

UP: Based on the Five-Year Action Plan for the In-depth Implementation of the People-Centered Urbanization Strategy issued by the State Council, and with reference to existing studies, this study defines the UP as a process centered on the comprehensive development of human beings. It achieves orderly population movement and agglomeration, spatial layout optimization and intensive utilization, environmentally friendly

and ecologically livable environments, economic restructuring and upgrading, sustainable development, as well as social harmony and public affluence equalization in the process of modern city construction. Based on the connotation of the UP, this study constructs a comprehensive evaluation index system of urbanization in four dimensions: population, economy, society, and ecology, and uses the entropy value method to measure the level of urbanization Table 2.

3.2.3 Mediating variables

(1) SIA: Since this study mainly analyzes the impact of SIA in the UP on the efficiency of green land useemissions, and since land data primarily come from the secondary industry, the data from the secondary industry are used to measure the level of SIA (AG).

Equation 4 is shown below:

$$AG_{ij} = \frac{E_{ij} \Big/ \sum_{j} E_{ij}}{\sum_{i} E_{ij} \Big/ \sum_{i} \sum_{j} E_{ij}} \quad (4)$$

where AG_{ij} is the level of j-industry agglomeration in province i, E_{ij} is employment in j-industry in province i, $\sum_j E_{ij}$ is employment in all industries in province i, $\sum_i E_{ij}$ is employment in j-industry in the 30 provinces, and $\sum_i \sum_j E_{ij}$ is total employment in the country.)

(2) ISO. Upgrading the industrial structure means improving the overall quality and efficiency of the industry. This includes not only changes in the proportion of the three industries within the national economy but also the optimization of the degree of coordination among industries. Based on the Cadet-Clarke theorem on the evolution of industrial structure (Sjödin et al., 2020), the overall ISO occurs in stages. This process is characterized by the transformation and upgrading of the primary industry to the secondary industry and ultimately to the tertiary industry. The proportion of the tertiary industry continues to increase, the proportion of the secondary industry rises and then declines, and the proportion of the primary industry gradually decreases. This study portrays the process of ISO through the relative change in the proportion of the output value of the three industries. According to this, the primary, secondary, and tertiary industries are assigned weights in descending order and multiplied by the proportion of the output value of each industry in the total output value. These are then combined in the measurement system, weighted, and used to obtain the index of the overall ISO, R (Equation 5).

$$R = \sum \text{Percentage of output value of the i} - \text{th industry} \times i \quad (5)$$

R value close to one indicates that the overall development level of industrial structure is lower; R value closer to three indicates that the overall development level of industrial structure is higher.

3.2.4 Control variables

With reference to existing research, this paper selects the following control variables: financial support (FS), measured as public financial expenditure as a proportion of GDP; human capital level (HCL), measured by the number of students enrolled in colleges and universities per total population; labor force level (LFL), represented by the natural logarithm of the number of employed people; industrialization level (IL), measured as industrial added value over gross regional product; and environmental regulation (ER), measured by completed investment in industrial pollution control over industrial added value. The results of the descriptive statistics of the variables are shown in Table 3.

3.3 Data sources

This study explores the relationship between the UP and GLUE based on panel data from 30 provinces (including municipalities and autonomous regions) in China from 2013 to 2023. The data come from the China Energy Statistical Yearbook, the China Rural Statistical Yearbook, the China Environmental Statistical Yearbook, the China Urban Statistical Yearbook, the National Statistical Bulletin of Scientific and Technological Funding Input, and the China Carbon Emission Accounting Database. In order to ensure the coherence of the data, the indicator interpolation method is used to address any missing values.

4 Empirical results

4.1 Benchmark regression results

The regression analysis of Equation 1 was conducted using a two-way fixed effects model, and the results of the benchmark regression on the influence of the UP on the efficiency of green land useemissions are reported in Table 4. In columns (1) and (2), the regression coefficients of the core explanatory variables are positive and pass the significance test, indicating that the UP can enhance GLUE, thus verifying hypothesis 1. As for the control variables, the regression coefficients for the labor force level and industrialization level are positive, suggesting that as the labor force and industrialization levels increase, the GLUE also increases. This may be due to technological progress and lifestyle transformation, which have made production activities more intensive. This intensification can effectively utilize land resources and increase the green output per unit of land. The effects of FS, HCL, ER, and the degree of government intervention on GLUE are not significant, likely due to the lag effect of these factors in practical application, insufficient implementation, or the limitations of the research period. The regression coefficient for FS is negative, indicating that FS fails to effectively promote GLUE and may even decrease it. This could be because financial investment is not precisely directed toward low-carbon initiatives.

4.2 *Endogeneity* analysis test

The omission of variables may lead to endogeneity problems in the model. Although this study has controlled for some variables affecting GLUE in the previous section, there may still be reverse

TABLE 1 Relevant indicators for the SBM model of non-expected outputs.

Variable	Indicator type	Form	Description of indicators	Indicator unit
GLUE	Input indicators	Land	Urban construction land area	hm^2
		Principal	Indicator description	$10^4/hm^2$
		Labor	Per capita fixed asset investment	Per/hm^2
		Technical	Per capita employment	10^4/hm2
	Output indicators	Economic benefits	Per capita R&D expenditure	10^4/hm2
		Environmental pollution	GDP *per capita*	t/hm2

TABLE 2 Indicator system for UP level.

Level 1 indicators	Level 2 indicators	Level 3 indicators	Specific definitions of indicators	Attributes
UP	Population urbanization	Percentage of employed persons in secondary and tertiary industries	Employed persons in secondary and tertiary industries/total employment	+
		Urbanization rate of resident population	Urban population/year-end resident population	+
		Urban registered unemployment rate	Data-direct	-
		Urban population density	Data-direct	+
	Economic urbanization	Economic level	GDP *per capita*	+
		Per capita disposable income of urban residents	Data-direct	+
		Percentage of tertiary sector value added	Tertiary value added/GDP	+
		General local budget revenue *per capita*	General budget expenditure of local finances/year-end resident population	+
		Total retail sales of consumer goods *per capita*	Total retail sales of consumer goods/resident population at the end of the year	+
	Social urbanization	Investment in education	Expenditure on education/general budget expenditure of local finances	+
		Scale of education	Average number of students enrolled in higher education per 100,000 population	+
		Level of healthcare	Number of beds in healthcare institutions	+
		Total number of public library books *per capita*	Data-direct	+
		Level of public transport development	Public transport vehicles per 10,000 population	+
	Eco-urbanization	Level of green space in parks	Parkland area *per capita*	+
		Daily urban wastewater treatment capacity	Data-direct	+
		Waste disposal level	Non-hazardous domestic waste disposal rate	+
		Forest cover	Data-direct	+

causality between the control variables and the UP. Therefore, with reference to established studies, all control variables are treated with a one-period lag to reduce the endogeneity problem of the model. Column (1) of Table 5 shows that the enhancement effect of the UP on GLUE still holds, and the significance and sign of the regression coefficients remain consistent with the benchmark regression results.

Secondly, cities with higher GLUE will be prioritized in the development of informatization, thus giving UP a "first-mover advantage", which makes the causality judgment in this paper face the problem of endogeneity. This paper tries to alleviate the endogeneity problem through the instrumental variable method, referring to the practice of Xu,et al. (2024), and taking the number of fixed-line telephone use in each city in 1984 as the instrumental variable of UP(Iv). The reason for choosing the number of landline telephone use per million people as an instrumental variable is that the impact of traditional telecommunication tools such as landline telephones on various socio-economic activities and the environment, which are carried by land, will diminish with the decline in the frequency of use, which satisfies the exclusionary characteristics of instrumental variables.

TABLE 3 Results of descriptive statistics of variables.

Variable	Variable name	Mean	Standard	Min	Max
Explained variable	GLUE	0.381	0.740	0.000	4.130
Core explanatory variables	UP	0.338	0.102	0.150	0.625
Intermediary variable	SIA	0.946	0.213	0.294	1.615
	ISO	0.186	0.186	−0.326	1.043
Control variables	FS	0.255	0.122	0.107	1.457
	HCL	0.022	0.006	0.009	0.045
	LFL	7.586	0.779	5.247	8.864
	IL	0.313	0.079	0.097	0.545
	ER	1.124	0.724	−1.163	5.481

From the regression results in columns (2) and (3) of Table 5, it can be seen that the effect of UP raising GLUE still holds and passes the significance test at the 1% level after accounting for endogeneity. In the weak instrumental identification test, the Gragg-Donald's Wald F statistic is greater than the critical value at the 10% level, and the test results reject the original hypothesis that the instrumental variables are weakly correlated, suggesting that the instrumental variables are reasonably selected. In conclusion, the previous results remain robust after considering the endogeneity issue.

TABLE 4 Baseline regression results.

Variable	(1)	(2)
UP	0.828** (0.299)	1.235*** (0.364)
FS		0.374** (0.156)
HCL		−4.171 (2.544)
LFL		0.197*** (0.069)
IL		0.371*** (0.131)
ER		0.008 (0.008)
Individual fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Constant	0.032 (0.099)	−1.744*** (0.624)
Observations	330	330
R-squared	0.9765	0.977

Cluster robust standard errors are in parentheses; *, **, *** indicate significant at the 10 percent, 5 percent and 1 percent levels, respectively. Same table below.

4.3 Robustness test

4.3.1 Changing the sample time

Considering that the National Development and Reform Commission issued the Outline of the 13th Five-Year Plan for National Economic and Social Development in 2016, which proposes to 'accelerate the pace of UP, improve the level of construction of new socialist countryside, strive to narrow the development gap between urban and rural areas, and push forward the integration of urban and rural development', the sample time is changed to 2016–2023. The regression results in column (1) of Table 6 show that the regression coefficient of UP is 1.394, which is significant at the 5% level. Therefore, it can be seen that the enhancement effect of UP on GLUE still exists after changing the sample timeframe, and the significance and sign of the regression coefficient remain consistent with the benchmark regression.

4.3.2 Excluding the effect of outliers

In order to avoid the influence of outliers on the regression results, a 5% truncation is applied to both ends of the explanatory variables. The regression results in column (2) of Table 6 show that the regression coefficient of the UP is 1.233, which is significant at the 1% level. Therefore, it can be concluded that the benchmark regression results remain robust after excluding sample selection bias.

4.3.3 Replacement of core explanatory variable

The urban social security participation rate can measure the soundness of the social security system and is a key indicator for assessing the effectiveness of livelihood protection work in the UP. It can also intuitively reflect the social security coverage in towns and cities (Bertinelli and Black, 2004). The level of urbanization was re-measured using the social security participation rate in each province's towns as a proxy for the core explanatory variable. The regression results in column (3) of Table 6 show that the regression coefficient of the urban social security participation rate is 0.701, which is significant at the 5% level. This indicates that after replacing the urbanization measurement indicator, the results are consistent with the baseline regression, further confirming that the UP significantly improves the efficiency of green land useemissions.

4.3.4 Excluding some samples

Municipalities directly under the central government typically attract a large inflow of factor resources due to their location

TABLE 5 Endogeneity problem test.

Variable	(1)	(2)Phase I	(3)Phase II
UP	0.712*** (0.273)		5.864*** (1.758)
Iv		0.119*** (0.035)	
F		10.941	
Individual fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	300	330	330
R-squared	0.967	0.579	-

AR(2) and Sargan's test report p-values. The following table is identical.

advantages, favorable policies, market environment, and other conditions, which in turn generates a clustering effect. Therefore, to exclude the special political and economic status of Beijing, Tianjin, Shanghai, and Chongqing, as well as the potential influence of policy favoritism, this study excludes the data from these four municipalities to test the stability of the benchmark regression results. Column (4) of Table 6 shows that the regression coefficient of UP is 0.804, which is significant at the 1% level, and is largely consistent with the conclusion of the benchmark regression. This indicates that excluding the special municipalities does not affect the conclusion, and the empirical results are robust.

4.3.5 Increasing control variables

The more attention the government pays to environmental issues, the more it will increase the implementation of environmental regulations, thus causing a 'reverse emission reduction' effect. Based on the original model, this study adds the degree of government intervention as a control variable, measured by the ratio of local fiscal protection expenditure to local fiscal general budget expenditure. The regression in column (5) of Table 6 shows that the regression coefficient of the UP is 1.259, which is significant at the 1% level and is largely consistent with the benchmark regression results, indicating that the conclusions of this study are robust.

4.4 Mechanism test

In order to verify the indirect effect of the UP on GLUE, the model constructed above is used for analysis. The results in column (1) of Table 7 show that the regression coefficient of new towns is positive and significant at the 5% level, indicating that the UP has a positive impact on SIA. This also suggests that there may be a mediating effect of SIA in the impact of the UP on GLUE, although the specific effect needs to be further tested. Column (2) shows the regression results obtained after introducing both core explanatory variables and mediating variables. The positive effect of the UP on GLUE still holds, indicating that SIA plays a mediating role. Similarly, the mediating role of ISO also holds.

4.5 Heterogeneity

China is a vast country with unbalanced regional economic development, and there is significant heterogeneity in the development levels of urbanization and the efficiency of green land useemissions across different regions. Therefore, it is necessary to explore the regional heterogeneity of the UP on GLUE. In this study, the sample is divided into three regions: East, Central, and West, and Table 8 presents the regression results.

For the eastern region, the regression coefficient of the UP is 1.633, which is significant at the 1% level, indicating that the UP in the eastern region promotes improvements in GLUE. For the central region, the regression coefficient of the UP is - 0.398, which is significant at the 5% level but with the opposite sign, indicating that the urbanization pilot policy in the central region inhibits the efficiency of GLUE. For the western region, the regression

TABLE 6 Robustness tests.

Variable	(1)	(2)	(3)	(4)	(5)
	Change sample time	Troubleshooting outliers	Replacement of core explanatory variables	Excluding some samples	Adding control variables
UP	1.388** (0.596)	1.231*** (0.362)	0.821*** (0.138)	0.801*** (0.193)	1.264*** (0.363)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Constant	−1.817** (0.774)	−1.744*** (0.624)	−1.771** (0.624)	−1.391** (0.491)	−1.902*** (0.645)
control variables	Yes	Yes	Yes	Yes	Yes
Observations	240	330	330	286	330
R-squared	0.976	0.978	0.979	0.204	0.978

TABLE 7 Mechanism tests.

Variable	(1)	(2)	(3)	(4)
UP	0.663** (0.297)	1.161*** (0.351)	2.344*** (0.457)	1.028*** (0.316)
SIA		0.107*** (0.035)		
UIS				0.089** (0.039)
Individual fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Constant	−1.581** (0.741)	−1.578* (0.613)	−8.326*** (1.422)	−1.008** (0.474)
Control variables	Yes	Yes	Yes	Yes
Observations	330	330	330	330
R-squared	0.881	0.976	0.798	0.978

coefficient of the UP is 0.096 and insignificant, indicating that the urbanization pilot policy in the western region does not significantly affect GLUE.

Comparing the regression coefficients of the UP across regions, it is found that the western region has the smallest and insignificant coefficient. On the one hand, the lagging infrastructure, low level of economic development, and insufficient application of green technology in the western region have led to a slow UP and difficulties in improving the green efficiency from land use. On the other hand, the low land use efficiency in the western region, coupled with a lack of support for green development and insufficient ecological protection measures, makes it difficult to effectively control carbon emissions during the UP, thereby hindering the improvement of the green efficiency level. The value of the regression coefficient for the UP in the central region is smaller than that in the eastern region, indicating that the effect of the pilot urbanization policy on GLUE in the central region is weaker than in the east. This may be because the eastern region has a stronger economic base, a greener industrial structure, widespread application of green technologies and innovations, and greater support from local governments for low-carbon development, which makes the UP in the eastern region more effective in promoting the improvement of GLUE. On the other hand, the central region has a relatively low level of economic development, still relies on traditional high-carbon industries, has insufficient application of green technologies, and experiences weak implementation of local government policies, leading to a limited effect on improving green land usecarbon efficiency. Therefore, the impact of the UP on GLUE in the central region is smaller than in the eastern region.

5 Further analyses

The results of the regional heterogeneity analysis indicate that the impact of the UP on GLUE differs significantly across regions (Niu et al., 2021). Accordingly, this study hypothesizes that this impact may exhibit a threshold effect related to economic development, meaning that at different stages of economic development, the effect of the UP on GLUE varies. To test whether these threshold effects exist, a panel threshold model is constructed based on Hansen's (1999) study (Equation 6).

$$GLUE_{it} = \mathbf{a_0} + \mathbf{a_1} UP_{it} I(q_{it} \le \gamma) + \mathbf{a_2} UP_{it} I(q_{it} > \gamma) + \mathbf{aControls_{it}} + u_i + \delta_t + \varepsilon_{it} \quad (6)$$

Model (6) is a single-threshold model, and both double-threshold and multi-threshold models can be extended based on this model. The specific number of thresholds will be examined subsequently through the threshold effect. In Model (6), I is the threshold variable. This study uses the level of economic development level (EDL) as the threshold variable, measured by real GDP *per capita*, with a logarithmic transformation applied in the regression.

5.1 Threshold effect test

The threshold effect test is a necessary condition for determining whether the panel data can be used in the threshold model. The test results in Table 9 show that the p-values of the double-threshold and triple-threshold tests are greater than 0.1, while the p-value of the

TABLE 8 Heterogeneity analysis.

Variable	Eastern region	Central region	Western region
UP	1.634*** (0.631)	−0.396** (0.197)	0.013 (0.451)
Individual fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Constant	−2.261 (1.717)	0.198 (0.369)	0.138 (2.372)
Control variables	Yes	Yes	Yes
Observations	121	110	99
R-squared	0.978	0.970	0.781

TABLE 9 Threshold effect bootstrap sample test results.

Modelling	F statistic	P Worth	Bootstrap	Threshold value			Estimated threshold
				10%	5%	1%	
Single threshold	43.47	0.043	500	32.961	40.683	57.968	10.614
Double threshold	14.64	0.289	500	36.046	64.896	124.854	

single-threshold test is less than 0.1, indicating that there is a single threshold effect in the model.

As shown in Table 9 above, the threshold estimate for the UP affecting GLUE is 10.614. To test whether this threshold estimate is valid, the study constructs a likelihood ratio function and a 95% confidence interval, with the results shown in Figure 2. The LR statistic corresponding to the threshold estimate of EDL is significantly smaller than the critical value, indicating that the threshold estimate passes the validity test.

5.2 Threshold effect regression

Table 10 shows the results of the threshold effect regression of the UP affecting GLUE. When the level of EDL is lower than the threshold value of 10.614, the regression coefficient of the UP is 0.843, which passes the significance test at the 1% level. When the level of EDL is higher than the threshold value of 10.614, the regression coefficient of the UP is 1.009, which also passes the significance test at the 1% level. Additionally, comparing the regression results of the two intervals around the threshold, the value of the coefficient has increased substantially. Overall, as the level of EDL increases, the promotion effect of the UP on land use carbon efficiency becomes greater. Therefore, there is a threshold effect based on EDL, i.e., the impact of the UP on GLUE in China exhibits a non-linear characteristic, gradually increasing as EDL progresses.

However, the threshold value of 10.614 requires further deepening of its economic interpretation. First, this threshold is based on sample data through a threshold regression model and is not artificially set. It may correspond to the critical point at which an economy moves from the middle-income stage to the high-income stage. At a lower level of economic development, factors such as infrastructure, industrial structure and technological innovation are not yet perfected, resulting in a lesser contribution of UP to GLUE, while factors such as industrial upgrading, application of green technology and optimization of urban planning start to play a greater role after the level of economic development crosses a certain threshold (10.614), thus enhancing the contribution of UP to GLUE.

It is also worth noting that there may be differences in the thresholds of different regions. For example, the eastern region is industrialized earlier and has a higher level of economic development, so it may require a higher threshold value to reflect the nonlinear impact; while the central and western regions may be able to observe the presentation of the threshold effect at a lower level of development. The appearance of this difference may be differently influenced by industrial structure, policy and environmental protection standards, and the stage of regional development.

6 Conclusions and implications

The UP, while promoting rapid urban economic development, has also brought about structural changes in land use and resource consumption. As the level of urbanization continues to rise, profound changes have occurred in land use patterns, industrial layout, and residents' lifestyles. However, despite the fact that urbanization has promoted economic growth and enhanced urban functions, the green efficiency of land use has not been significantly improved. On the contrary, in some areas, it has resulted in higher carbon emission intensity, reflecting inefficiencies in resource utilization and an increased environmental burden during the UP. Therefore, improving the green efficiency of land use by optimizing land use during urbanization has become a key issue in promoting green and low-carbon development. This not only helps to achieve environmentally sustainable development but also promotes the coordinated advancement of high-quality economic development and ecological civilization.

Different from previous studies, this paper provides a feasible explanation for optimizing the GLUE from the perspective of the UP. To explain the core logic, this paper: (1) empirically examines the impact of the UP on GLUE; (2) uses a mediating effect model to examine the role of SIA and ISO; (3) applies the threshold effect model to explore the threshold characteristics of EDL; and (4) analyzes the heterogeneous impact of the UP on GLUE from a regional perspective.

This paper selects data from 30 provinces in China from 2013 to 2023. After conducting empirical analyses using the fixed effects model, the mediating effects model, and the threshold effects model, the following findings are made: First, the UP improves the GLUE, and the results remain valid after endogeneity and robustness tests. Second, the mechanism analysis shows that the UP promotes GLUE by enhancing SIA and ISO. Third, the heterogeneity analysis reveals that the UP has a stronger effect on improving GLUE in the eastern region of China, while its impact is relatively weaker in the western region. Finally, the threshold effect analysis finds that once the EDL surpasses the threshold value of 10.614, the promotion effect of the UP on GLUE becomes stronger.

In the context of the "dual-carbon" goal and efficient land use, the UP and GLUE are included together in the research model. The findings of the study have the following implications for the promotion of pilot policies for the UP and the improvement of GLUE.

Firstly, the empirical results show that the UP helps promote the improvement of GLUE. Therefore, localities need to continuously

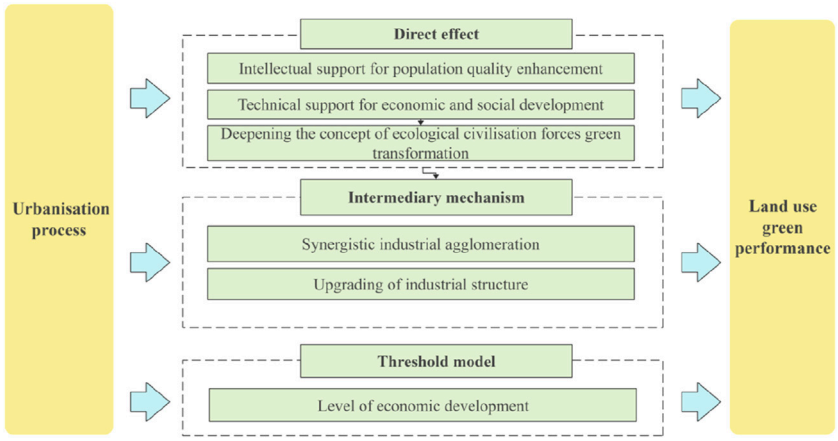


FIGURE 1
Technology roadmap.

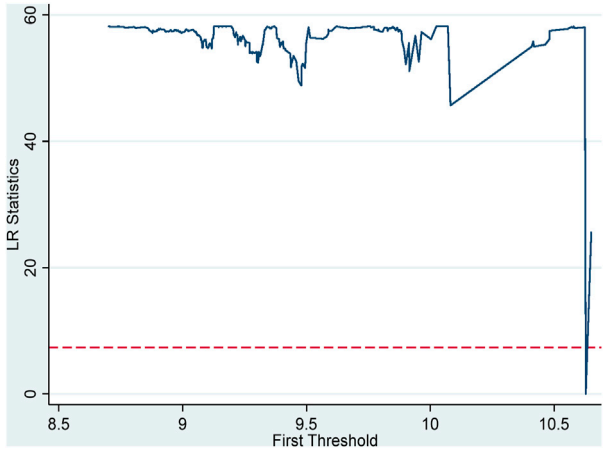


FIGURE 2
Threshold estimate test.

TABLE 10 Threshold estimation results.

Variable	Ratio	Robust standard error
UP(Ln EDL≤10.614)	0.876***	0.149
UP(Ln EDL>10.614)	0.834***	0.163
Individual fixed effect	Yes	Yes
Time fixed effect	Yes	Yes
Constant	−1.569*	0.564
Control variables	Yes	Yes
Observations	330	330
Within R-sq	0.176	

advance the construction of urbanization and comprehensively deepen the coordinated development of the four dimensions: population, economy, society, and ecology. In future development, emphasis should be placed on strengthening infrastructure across all dimensions of urbanization, optimizing urban spatial layout, and improving GLUE.

In the demographic dimension, it is necessary to promote the movement of the population to reasonable areas, optimize the functional zoning of cities, avoid over-expansion, and ensure that population concentration matches the carrying capacity of resources and the environment. In the economic dimension, it is necessary to increase investment in green industries and the low-carbon economy, promote efficient energy utilization and green building development, and further enhance the energy efficiency and resource allocation efficiency of the city. In the social dimension, it is necessary to strengthen the construction of social service facilities, promote the development of urban public services in the direction of being green, intelligent, and shared, improve the quality of urban life, and enhance residents' awareness of sustainable development. In the ecological dimension, it is necessary to strengthen the construction of green infrastructure, promote the implementation of ecological restoration and environmental protection policies, build a low-carbon city, and enhance the carrying capacity of the urban ecological environment. Through the comprehensive promotion of the UP, land use efficiency can be effectively improved, green transformation can be promoted, and the coordinated development of economy, society, and ecology can be realized, thereby laying a solid foundation for the improvement of green efficiency from land use and promoting green, low-carbon sustainable development.

Secondly, the empirical results show that the UP can further improve the GLUE by enhancing SIA and upgrading the industrial structure. Therefore, in future development, we should explore how the UP can effectively improve GLUE by optimizing industrial layout and promoting industrial transformation and upgrading.

Regarding SIA, urban spatial planning should be optimized to

promote the concentration of industries in agglomeration areas, enhance resource allocation efficiency, and reduce the idle and wasteful use of land resources. By strengthening infrastructure construction and promoting the clustering of green industrial parks and low-carbon technology industries, not only can the synergistic effect of industries be improved, but carbon emissions in the process of industrial development can also be reduced while intensively utilizing land resources. In terms of ISO, the green transformation of traditional industries should be accelerated, the development of high-tech and high value-added industries should be encouraged, and the wide application of low-carbon technologies and sustainable development concepts should be promoted. The green efficiency of land use should be enhanced through industrial structure optimization. By reasonably guiding SIA and upgrading, the UP can promote the efficient use of land resources, provide solid support for the realization of low-carbon development goals, and create a win-win situation for economic development and environmental protection during urbanization.

Again, the empirical results show that the UP has a heterogeneous impact on GLUE, which can address the unbalanced characteristics of urbanization development levels triggered by regional location. Specifically, the eastern region has a higher EDL, stronger resource allocation capacity, and technological advantages. In the future, it can reasonably plan the layout of land use according to environmental carrying capacity, expand the space for the green development of land use in the process of urbanization, and focus on the efficient use of land resources and environmental protection to promote the low-carbon transformation of land use. At the same time, the eastern region should strengthen the development of green industries and promote an intelligent and green urban construction model to maximize the efficiency of GLUE.

In contrast, the empirical results show that UP has a heterogeneous impact on GLUE, so future policies should take differentiated measures for different regions. The eastern region should rely on its strong resource allocation capacity and technological advantages, promote the development of green high-end manufacturing and modern service industries, optimize the land use layout, promote the construction of the carbon trading market, and make use of digital technology to enhance the refinement of land resource management. The central region should focus on improving the efficiency of land use, strengthening urban planning and management, preventing disorderly expansion, optimizing the land use structure through town clusters and industrial clusters, and at the same time perfecting the green financial support system and promoting the implementation of policies such as green credit and optimal allocation of land resources. The western region, on the other hand, needs to strengthen ecological protection, enhance land use efficiency through green infrastructure investment, while establishing a cross-regional technology transfer platform, introducing advanced technology and management experience, improving the ecological compensation mechanism, and promoting green upgrading of the industrial chain. In addition, digital technologies such as intelligent monitoring systems and remote sensing technology are being used to improve the ability to dynamically supervise land resources and further enhance the decarbonization of land use. Through these measures, regional coordinated development will be promoted, the efficiency of carbon emissions from land use nationwide will be enhanced, and a win-win situation will be achieved in terms of both environmental and economic benefits in the process of new urbanization.

Finally, the empirical results show that the marginal effect of the UP on GLUE becomes more significant after crossing the threshold of EDL. This finding suggests that when the regional EDL reaches a certain threshold, the promotion of the UP has an accelerating effect on the improvement of GLUE. In this process, economic development provides more sufficient resources and technical support for the UP, promoting the application of green technology and the expansion of low-carbon industries, thus significantly improving the efficiency of land resource use and the effect of carbon emission reduction.

However, in regions with a lower EDL, due to the lack of sufficient financial, technological, and policy support, the effect of the UP on the improvement of green efficiency in land use is relatively lagging. Therefore, it is necessary to formulate phased policy measures in response to the differences in EDL across regions, especially in regions that have crossed the threshold. Policy guidance and technical support should be increased to maximize the positive impact of the UP on the GLUE and to promote the high-quality development of green and low-carbon economies.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

RY: Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review and editing. JW: Investigation, Methodology, Software, Validation, Writing – original draft. MX: Writing – review and editing, Software, Supervision, Validation. KX: Writing – review and editing, Conceptualization, Data curation, Formal Analysis, Writing – original draft.

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EDITED BY
Lingli Qing,
Guangzhou College of Commerce, China

REVIEWED BY
Wenfang Pu,
Huazhong Agricultural University, China
Haixin Huang,
Northwest University, China
Yedong Chen,
China University of Mining and Technology, China
Guihai Liu,
Jiangxi Normal University, China

*CORRESPONDENCE
Lili Zhao,
zhaolili@mdjnu.edu.cn

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Land use policy and green utilization efficiency in border cities: evidence from northeastern China's carbon reduction practice

Xuncheng Fan and Lili Zhao*

School of History and Culture, Mudanjiang Normal University, Mudanjiang, China

Introduction: Efficient land resource utilization is increasingly important for regional development as global attention focuses on sustainable development in border regions. This study develops an innovative 'border location-functional differentiation-efficiency coupling' theoretical framework.

Methods: Using this foundation, we employ regression-based path analysis and spatial analytical methods to evaluate the relationship between land use policies and green utilization efficiency across fourteen northeastern China border cities from 2010 to 2020.

Results: Our research reveals significant spatial heterogeneity in land use patterns. Industrial cities show lower land green utilization efficiency (8.14-12.48 tons CO2/10,000 yuan). In contrast, port cities maintain higher utilization efficiency (average 1.54 tons CO_2/10,000 yuan). Land use policies oriented toward industrial transformation and ecological protection significantly enhance land green utilization efficiency. Energy intensity (–6452.09, $p < 0.05$) and industrial structure (–4664.92, $p < 0.01$) are key inhibiting factors. Different types of cities present differentiated policy responses.

Discussion: Industrial cities promote technological upgrades through digital transformation. Ecological cities emphasize protection-oriented smart development. These findings enrich theoretical research on land use efficiency in border regions. They also provide a scientific basis for formulating differentiated land use policies. This has important practical significance for promoting ecological civilization construction and high-quality development in China's northern border regions.

KEYWORDS

land-use policy, green utilization efficiency, border cities, carbon reduction, spatial heterogeneity, sustainable development, policy effects, northeastern China

1 Introduction

As the global economy expands and world population grows, sustainable land utilization has emerged as a global challenge. Border regions serve as critical connections between countries. In these areas, land use efficiency affects both regional economic transformation and ecological security. Reviewing the developmental trajectory of relevant research, studies on land use efficiency in border regions have formed several

distinct research trends, involving different geographical focuses and methodological approaches.

The first research trend focuses on the spatial heterogeneity of land use efficiency across different border regions. Comparative studies have revealed significant regional differentiation patterns: developed border regions tend to emphasize ecological protection, while developing regions face intensified development pressure. For instance, Angelstam et al. (2020) documented relatively low forest loss rates in the Finnish-Russian border (0.42% and 0.09% annually, respectively), reflecting the strong ecological protection orientation in developed regions. In contrast, Wang and Xiao (2023) discovered evident forest reduction and farmland expansion in the Laotian border region, indicating the transformation pressure faced by developing regions. This spatial differentiation is particularly pronounced in resource-based border cities, where Qian and Luo (2024) found land use efficiency to be 20.4% lower than in non-resource-based cities. These studies collectively indicate that the research paradigm is shifting from viewing border regions as homogeneous entities to recognizing their inherent heterogeneity in development paths and efficiency patterns.

The second research trend centers on cross-border comparative analysis, with the China-Russia border receiving considerable academic attention due to its unique geopolitical characteristics and complex development dynamics. This body of research emphasizes significant differences in land management patterns across national boundaries. Chen et al. (2022) found that the Chinese side exhibits intensive agricultural development characteristics, while the Russian side maintains relatively pristine vegetation conditions. These differences reflect not only different choices in development paths but also policy framework differences affecting regional land use efficiency. The cross-border comparative approach has extended to policy effectiveness assessment, such as Qu et al. (2023) 's evaluation of black soil protection policies in Heilongjiang Province (projected to reduce carbon stock loss by 107.44×10^6 tons by 2030) and Li H. et al. (2024)'s demonstration of how urban agglomeration spatial planning optimization can achieve substantial carbon emissions reduction (643.42×10^4 tons). Song et al. (2022) further advanced this approach by establishing connections between resource endowment differences, development cycles, and land use efficiency, particularly during transitions.

The third research direction examines policy implementation and effectiveness in border regions. China's policy framework for border regions has evolved from general spatial control to a more differentiated approach based on functional positioning. The "National Main Functional Zone Planning" laid the foundation by dividing border regions into different functional zones based on resource environmental carrying capacity and development potential. Subsequent policies such as the "National Forestland Protection and Utilization Planning Outline (2010–2020)" and the "Greater and Lesser Xing'an Mountains Forest Region Ecological Protection and Economic Transformation Planning (2010–2020)" created a multi-layered policy system tailored to regional characteristics. Research on these policies has shifted from single policy evaluation to assessing policy synergy and implementation effectiveness across different regional contexts.

Methodologically, research on land use efficiency in border regions has undergone several stages. Early studies primarily focused on policy description and simple evaluation indicators, while recent methods use complex analytical frameworks. Fekete and Priesmeier (2021) advanced methodological innovation by developing an integrated assessment framework for the US-Mexico border region, emphasizing coordination between cross-border resource management and environmental risk prevention. Efficiency measurement methods have undergone similar evolution, with Chang et al. (2023) applying industrial structure optimization modeling techniques to assess land use efficiency improvement mechanisms. Spatial analysis methods have become increasingly refined, as exemplified by Bazarov et al. (2021) quantitatively comparing human modification degrees on the Chinese (50%) and Russian (28%) sides of the Xingkai Lake basin. The latest methodological Frontier involves digital methods, with Wang et al. (2024) pioneering the use of deep learning techniques to identify inefficient spaces in resource-depleted cities, and Dong et al. (2021) developing integrated models to analyze connections between ecological degradation and urban expansion.

Despite these advances, three key research gaps remain. First, systematic theoretical frameworks for policy-efficiency correlations are lacking. Previous studies have focused mainly on single-dimensional policy implementation or efficiency evaluation. They offer limited exploration of interactions from a comprehensive systems perspective. Second, theoretical explanations for city type differences are insufficient. Although Zheng et al. (2022) proposed spatial conflict measurement methods, these methods have not adequately revealed the heterogeneous mechanisms of policy responses across different types of cities. Finally, theoretical understanding of the uniqueness of land use in cold-region border areas needs deepening. While Yuan et al. (2019) identified core-periphery differentiation in land use efficiency of mining cities, their analysis did not deeply examine the comprehensive impacts of climatic conditions, geopolitics, and development strategies on land use patterns in border regions.

Based on these gaps, this study attempts to fill these theoretical voids by constructing a "policy-efficiency-space" theoretical analysis framework. This framework not only proposes a dual analytical perspective of "type differentiation-spatial heterogeneity" for border region land policy implementation but also constructs a policy response theory based on urban functional positioning while developing a spatial coupling theory for cold-region border land use. Selecting China's northeastern border region as a case study holds unique value: the region's 14 border cities exhibit significant differences in functional positioning and development stages, have implemented diverse land policies, and possess a typical "three vertical and one horizontal" spatial pattern, providing an ideal sample for validating the theoretical framework.

This study focuses on three core questions: (1) the formation mechanism of spatial heterogeneity in border region land use efficiency; (2) the response mechanisms of different types of cities to land use policies; and (3) the spatial coupling mechanism between policy implementation and efficiency improvement. This study not only enriches theoretical research on land use efficiency in border regions and provides a new analytical framework for understanding policy implementation effects but also offers scientific basis for formulating

TABLE 1 Basic characteristics of study area.

Province	City/Region	Administrative level	Bordering country	City type
Heilongjiang	Mudanjiang	Prefecture-level City	Russia	Port-type
	Heihe	Prefecture-level City	Russia	Port-type
	Jiamusi	Prefecture-level City	Russia	Ecological
	Jixi	Prefecture-level City	Russia	Industrial
	Shuangyashan	Prefecture-level City	Russia	Industrial
	Yichun	Prefecture-level City	Russia	Ecological
	Hegang	Prefecture-level City	Russia	Industrial
	Daxinganling	Regional	Russia	Ecological
Jilin	Yanbian	Autonomous Prefecture	Russia, DPRK	Ecological
	Tonghua	Prefecture-level City	DPRK	Ecological
	Baishan	Prefecture-level City	DPRK	Ecological
Liaoning	Dandong	Prefecture-level City	DPRK	Port-type
Inner Mongolia	Hulunbuir	Prefecture-level City	Russia, Mongolia	Port-type
	Xing'an	League	Mongolia	Ecological

differentiated land use policies, which has important practical significance for promoting ecological civilization construction and high-quality development in China's northern border regions.

2 Materials and methods

2.1 Study area overview

The study area encompasses the northeastern border region of China. It includes eight regions in Heilongjiang Province (Mudanjiang, Jixi, Shuangyashan, Jiamusi, Hegang, Yichun, Heihe, and Daxing'anling), three regions in Jilin Province (Yanbian, Baishan, and Tonghua), two regions in Inner Mongolia Autonomous Region (Hulunbuir and Xing'an League), and Dandong City in Liaoning Province. The region borders Russia's Far East in the east, faces North Korea's North Hamgyong Province and Chagang Province across the river in the southeast, and neighbors Russia and Mongolia in the north, with a total border length of 2,682 km, forming an important border economic belt and ecological barrier zone in China's northeastern region (Sui et al., 2024) (Table 1; Figure 1).

The study area's terrain follows a "three vertical and one horizontal" spatial pattern. The eastern part is dominated by the Changbai Mountain system. This area includes ecological conservation regions such as Yanbian, Baishan, and Tonghua. Forest coverage rates reach 91.34% in Baishan and 84.54% in Yanbian. The central part consists of the Songnen Plain and Sanjiang Plain, represented by areas such as Jiamusi and Shuangyashan, which the "National Land Use Master Plan (2006–2020)" designated as important commercial grain production bases, with Jiamusi's cultivated land accounting for 77.90%. The western part is dominated by the Greater Xing'an Mountains system, designated as an important ecological functional zone according to the "Greater and Lesser Xing'an Mountains Forest Area Ecological Protection and Economic Transformation Planning (2010–2020)", forming a grassland and forest interlaced ecosystem represented by Hulunbuir, with forest coverage of 59.43% and grassland coverage of 29.56%. The northern Lesser Xing'an Mountains ("one horizontal") forms an important regional ecological barrier, typically represented by Yichun with a forest coverage rate of 87.80%. The study area has a temperate continental monsoon climate but shows significant regional differences due to topographical influences, with average annual temperatures ranging from −4°C to 5°C and annual precipitation decreasing from east to west (1,000–300 mm).

Based on development positioning and policy orientation, the study area can be divided into three functional zones. The industrial development policy-led zone includes Jixi, Shuangyashan, and Hegang, dominated by energy and raw materials industries, with the secondary industry accounting for 24%–32% of GDP in 2023. The port economy policy-guided zone includes Heihe, Mudanjiang, Dandong, and Hulunbuir, possessing 7 national-level ports and 1 temporary opening port, mainly focusing on foreign trade and service industries, with the tertiary industry exceeding 45%. The ecological protection policy-led zone includes Daxing'anling, Yichun, Yanbian, Tonghua, Baishan, Jiamusi, and Xing'an League, primarily focused on ecological resource protection, with forest coverage generally exceeding 80%.

The study area is rich in natural resources with distinct regional characteristics. In terms of water resources, Heihe City alone has an average annual surface runoff of 7.31 billion cubic meters. Mineral resources are diverse, with Dandong City possessing 50 types of minerals including gold, silver, lead, and zinc, while Jixi City's coal and graphite reserves rank among the highest in the province. Biological resources are abundant, with over 3,890 species of wild plants in the region, including 11 nationally protected species. Regional economic development showed notable differences in

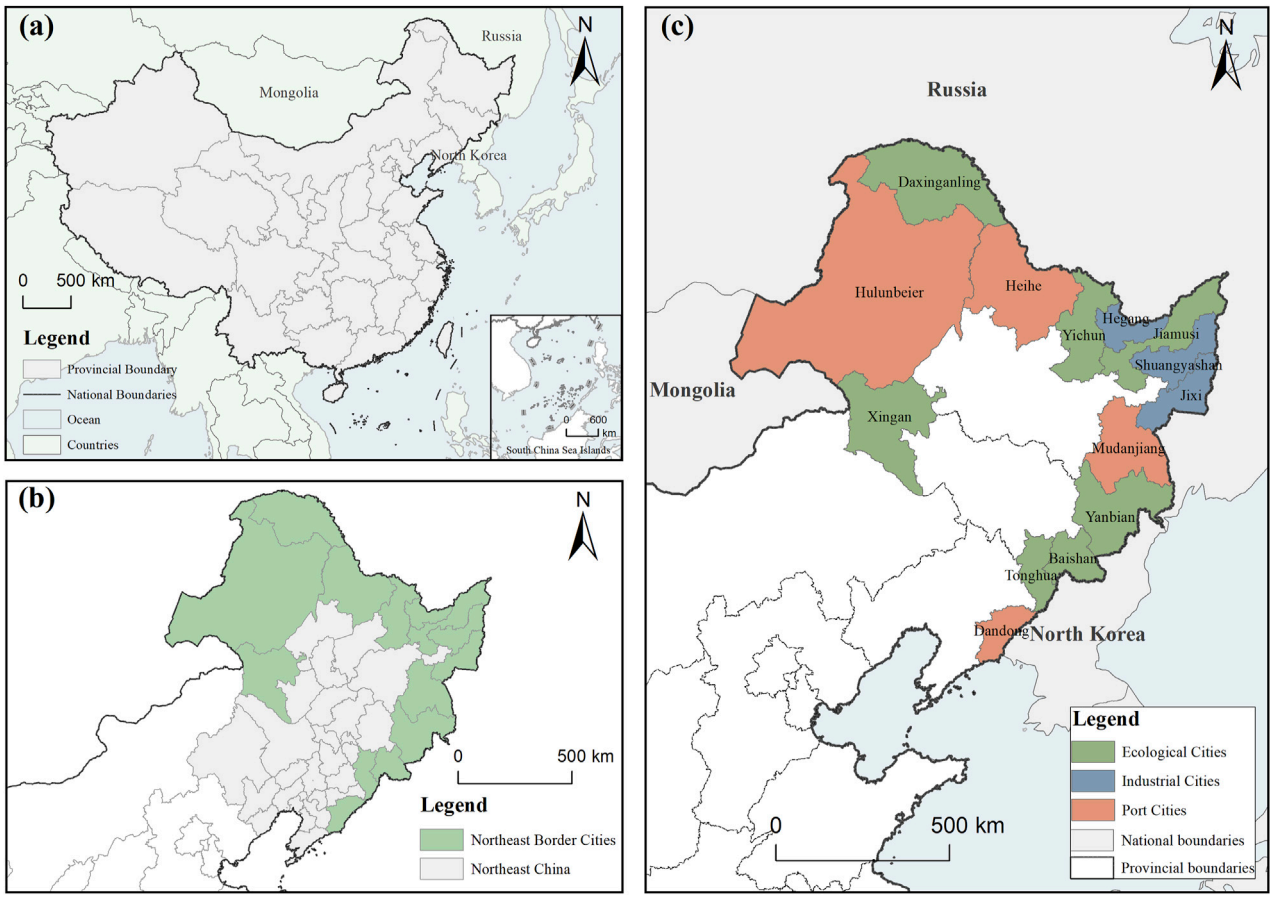


FIGURE 1
Study area in northeastern border regions of China: **(a)** Location in China; **(b)** Northeast China; **(c)** Distribution of different types of border cities and major geographical features.

2023, with *per capita* GDP ranging from 73,192 yuan in Hulunbuir City to 38,000 yuan in resource-based cities, forming a development pattern combining traditional industry, modern service industry, and ecological industry.

As an important window for China's Northeast Asian opening-up, the study area plays a crucial role in promoting regional economic cooperation and cross-border ecological protection. These border regions face dual pressures of economic transformation and ecological protection, making the relationship between land use changes and carbon emissions particularly valuable for research.

2.2 Data sources and processing

2.2.1 Study period selection rationale

First, this period marks an important turning point in China's land space control, with the implementation of significant policy documents such as the "National Main Functional Zone Planning," "National Land Use Master Plan (2006–2020)," and "Greater and Lesser Xing'an Mountains Forest Area Ecological Protection and Economic Transformation Planning (2010–2020)," which profoundly influenced land use patterns in the study area. Second, 2010–2020 was a critical period of transformation for the northeastern border region. Under the promotion of the Northeast Revitalization Strategy and the "Belt and Road" Initiative, regional land use patterns underwent significant changes. This period fully covers the implementation phase of the new round of Northeast revitalization strategy, providing an appropriate time window for policy effect evaluation. Third, statistical data for this period is relatively complete and standardized. After 2010, China's carbon emission statistical system gradually improved, with significant enhancement in the availability and reliability of city-level carbon emission data. Meanwhile, advances in land use change monitoring technology also provided more accurate spatial data support. Selecting this study period not only helps systematically evaluate policy implementation effects but also provides scientific basis for future policy optimization.

2.2.2 Land use data

This study employed the China Land Cover Dataset (CLCD) developed by Wuhan University as its primary data source (Yang and Huang, 2021). The dataset spans from 1985 to 2019, with a spatial resolution of 30 m, and was constructed based on the Google Earth Engine platform. The dataset utilized 335,709 Landsat satellite images, employing a random forest classifier combined with spatiotemporal features for classification, and implemented spatiotemporal filtering and logical reasoning for post-processing

to enhance data consistency. Validation based on 5,463 visually interpreted samples showed that the overall classification accuracy reached 80%. These characteristics make the CLCD dataset an ideal source for studying regional land use changes.

To accommodate research needs, this study selected data from three time points: 2010, 2015, and 2020. The original CLCD classification system contains nine land cover types: cropland, forest, shrub, grassland, water, snow and ice, barren, impervious surface, and wetland. Based on research objectives and regional characteristics, we reclassified the original nine classes into six categories: (1) cropland, including the original cropland class; (2) forestland, including the original forest and shrub classes, as these two types have similar ecological functions in the northeastern border region; (3) grassland, maintaining consistency with the original classification; (4) water bodies, corresponding to the original water class; (5) built-up land, corresponding to the original impervious surface class; (6) unused land, integrating the original barren, snow/ice, and wetland classes, which all represent land types with relatively limited human activity impact in the study area.

In our analysis, forestland and grassland were collectively termed as ecological land, a classification based on their shared ecosystem service functions, particularly in carbon sequestration, biodiversity conservation, and ecological security barrier construction. In policy implementation assessment, this integration helps provide a more comprehensive understanding of the overall effects of ecological protection policies. The data preprocessing included: using the Krasovsky 1940 Albers projection system for projection conversion, with central meridian set at 105°E and standard parallels at 25°N and 47°N—a configuration particularly suitable for area calculation in northeastern regions; clipping data according to administrative boundaries; and conducting spatial statistical analysis based on the ArcGIS platform.

To ensure the reliability of the reclassification results, this study employed a multi-level accuracy verification method: first, using confusion matrix methodology to assess classification accuracy, calculating overall accuracy, producer's accuracy, and user's accuracy; second, cross-validating with existing land use maps and land use change survey data; finally, selecting representative sample points within the study area for field verification, combined with visual interpretation validation using high-resolution remote sensing images (such as Google Earth historical imagery). Verification results showed that the overall accuracy of the six reclassified land use types exceeded 85%, meeting research requirements. These data provide important support for evaluating the effects of land use policy implementation and land use efficiency.

2.2.3 Carbon emission data

This study constructs a multi-level land use efficiency assessment system based on Scope 1, 2, and 3, covering carbon emission data from 14 border regions during 2010–2020. The assessment framework follows the methodological systems of the "Provincial Greenhouse Gas Inventory Compilation Guidelines" and "IPCC Guidelines for National Greenhouse Gas Inventories," with carbon emissions measured in 10,000 tons of CO_2 equivalent. The accounting scope includes direct emissions from fossil fuel combustion, industrial processes, agricultural activities, and waste treatment (Scope 1), indirect energy emissions from purchased electricity, heating, and cooling (Scope 2), and other indirect emissions in the value chain (Scope 3) (Wei et al., 2020).

Based on the above scope classification, this study designed a multi-level carbon emission accounting framework with the following specific calculation formulas:

$$C_{total} = C_{direct} + C_{energy} + C_{indirect} \quad (1)$$

Where C_{total} represents the total carbon emissions, C_{direct} represents direct emissions (Scope 1), C_{energy} represents energy indirect emissions (Scope 2), and $C_{indirect}$ represents other indirect emissions (Scope 3).

Direct emissions (Scope 1) calculation formula:

$$C_{direct} = \sum (FC_i \times EF_i) \quad (2)$$

Where FC_i is the consumption of fuel type i, and EF_i is the corresponding emission factor. This study prioritizes the use of localized emission factors provided by the "Provincial Greenhouse Gas Inventory Compilation Guidelines (Trial)", followed by industry-specific emission factors issued by the National Development and Reform Commission, and for areas lacking localized data, default values from the IPCC emission factor database are referenced.

Energy indirect emissions (Scope 2) calculation formula:

$$C_{energy} = \sum \left(EC_j \times EF_{grid,j} \right) \quad (3)$$

Where EC_j is the consumption of purchased energy type j, and $EF_{grid,j}$ is the regional power grid emission factor or heating emission factor. We adopt the official emission factors of the Northeast Power Grid to ensure the regional applicability of the calculation results.

Other indirect emissions (Scope 3) calculations mainly consider upstream and downstream emissions in the industrial chain, using the input-output analysis method:

$$C_{indirect} = \sum (IO_k \times EF_{io,k}) \quad (4)$$

Where IO_k is the input-output value of industry k, and $EF_{io,k}$ is the corresponding emission intensity factor.

In the carbon emission accounting process, this study adopted a hierarchical, multi-source emission factor selection strategy to ensure the accuracy and reliability of the calculation results. The selection of emission factors for Scope one direct emissions is primarily based on fuel type and emission activity characteristics. For fossil fuel combustion, recommended emission factors for the Northeast region from the "Provincial Greenhouse Gas Inventory Compilation Guidelines (Trial)" are adopted, with appropriate adjustments based on the actual carbon content and oxidation rate of fuels in the study area. Emissions from industrial production processes use industry-specific emission factors published in the "Enterprise Greenhouse Gas Emission Accounting Methods and Reporting Guidelines" to ensure consistency with national standards. Emission factors for agriculture, forestry, and land-use change reference the technical specifications of the National Forestry and Grassland Administration, with localized adjustments based on the climatic

conditions and soil characteristics of the study area. Waste treatment emission factors are based on IPCC guideline recommended values, considering local waste composition characteristics and treatment process differences.

For Scope two indirect emissions, purchased electricity emissions use regional grid emission factors from the Northeast Power Grid, with temporal differentiation coefficients based on power structure changes during the study period. Heating and cooling emission factors consider the characteristics of the heating energy structure in the study area and the efficiency of centralized heating systems, using the carbon emission coefficient for "Steam and Hot Water Production and Supply Industry" with transmission loss corrections. The selection of emission factors follows the priority sequence: localized emission factors provided by the "Provincial Greenhouse Gas Inventory Guidelines (Trial)" are prioritized; followed by industry-specific emission factors issued by the National Development and Reform Commission; for areas lacking localized data, default values from the IPCC emission factor database are referenced.

Data sources integrate multiple statistical systems. Energy activity data comes from the "China Energy Statistical Yearbook" and local energy balance sheets; industrial process data is sourced from the "China Industry Statistical Yearbook" and local industrial statistical reports; agriculture and forestry data is collected from the "China Agricultural Statistical Yearbook," "China Animal Husbandry Yearbook," and "China Forestry and Grassland Statistical Yearbook"; waste treatment data is from the "China Environmental Statistical Yearbook" and local environmental statistical reports; energy purchase data comes from the "China City Statistical Yearbook" and local statistical yearbooks.

Regarding accounting uncertainties, this study identified three main sources. Activity data uncertainty primarily stems from multi-departmental submission and aggregation processes of energy statistics, quality of industrial product output data reported by enterprises, and survey methods and sample representativeness of agricultural and forestry activity data. In terms of emission factor uncertainty, fossil fuel combustion emission factors have relatively low uncertainty, while agricultural, forestry, and land-use change emission factors possess higher uncertainty due to ecosystem complexity. Methodological uncertainty mainly originates from accounting boundary definition, applicability assumptions, and data aggregation.

To manage and reduce uncertainty, this study established a comprehensive data quality control system, including a three-level verification mechanism: first, cross-validation of statistical data from different sources to ensure data consistency; second, time series consistency testing to analyze the reasonableness of annual data changes; third, cross-regional comparative verification to evaluate spatial comparability of data. Through these measures, the reliability and accuracy of carbon emission accounting results were ensured.

2.2.4 Socioeconomic data

This study constructs a multi-dimensional socioeconomic indicator system covering four dimensions: economic development, population structure, technological innovation, and infrastructure. Economic development indicators include Gross Domestic Product (GDP) and its three-industry composition, fixed asset investment, and total foreign trade. Population structure indicators include permanent population, population density, and urbanization rate. Technological innovation indicators include the proportion of science and technology expenditure in fiscal expenditure and patent grants. Infrastructure indicators include energy consumption intensity (energy consumption per unit GDP) and road network density.

Data sources primarily include official data from national and local statistical systems. National-level data comes from the "China City Statistical Yearbook" and "China Energy Statistical Yearbook." Provincial data comes from the "Heilongjiang Statistical Yearbook," "Jilin Statistical Yearbook," "Liaoning Statistical Yearbook," and "Inner Mongolia Statistical Yearbook." City-level data comes from local statistical yearbooks and statistical bulletins. To ensure temporal comparability of data, this study calculates GDP and related economic indicators at constant 2010 prices to eliminate the impact of price changes. Urbanization rate is calculated based on permanent population to reflect actual urbanization levels. Foreign trade data includes total imports and exports.

To eliminate dimensional differences among different indicators, this study uses the range standardization method to process all indicators dimensionlessly, as shown in Equation 5. The formula is:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{5}$$

where X' is the standardized value, X is the original value, and $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of the indicator during the study period, respectively. The standardized indicator values all fall within the [0,1] interval, facilitating comprehensive comparison between different indicators (Ma et al., 2023).

Data quality control adopts a three-step verification process: First, using the box plot method to identify outliers, re-examining data that exceeds 1.5 times the interquartile range; Second, conducting time series consistency checks to analyze whether indicator trends are reasonable; Finally, comparing indicators horizontally among similar cities to verify spatial comparability of data. For data with discrepancies, corrections are made through consulting original statistical materials and statistical departments to ensure data accuracy and reliability.

2.2.5 Variable description and research design characteristics

Table 2 provides descriptive statistics for the main variables in this study, including land use structure variables, carbon emission variables, and socioeconomic variables at two time points, 2010 and 2020, with sample size, minimum values, maximum values, and standard deviations. From the perspective of land use structure, forest land accounts for the highest proportion in the study area (maximum 97.52% in 2010, maximum 96.87% in 2020), followed by cultivated land (maximum 77.03% in 2010, maximum 77.90% in 2020), while the proportion of construction land is relatively low (maximum 4.22% in 2010, maximum 4.76% in 2020) but shows a stable increasing trend. Carbon emission data indicate that during the 2010–2020 period, the maximum value of total carbon emissions increased from 35.772 million tons to 46.640 million tons, and the minimum value also rose from 8.028 million tons to 9.424 million tons, with significant differences between cities (standard deviation of 878.32 in 2010, increasing to 1,284.42 in 2020). Regarding

TABLE 2 Statistical analysis of land use, carbon emissions, and socioeconomic variables (2010 and 2020).

Variables	2010				2020				Unit
	Sample	Min	Max	S.D.	Sample	Min	Max	S.D.	
Land Use Structure Variables									
Cropland Proportion	14	1.33	77.03	23.24	14	1.96	77.90	23.29	%
Forest Proportion	14	17.81	97.52	25.79	14	16.27	96.87	25.69	%
Grassland Proportion	14	0.02	39.91	12.78	14	0.05	34.56	11.56	%
Water Body Proportion	14	0.28	6.59	1.66	14	0.30	6.84	1.71	%
Built-up Land Proportion	14	0.36	4.22	1.00	14	0.45	4.76	1.15	%
Unused Land Proportion	14	0.0003	0.6514	0.18	14	0.0006	0.5711	0.15	%
Carbon Emission Variables									
Total Carbon Emissions	14	802.80	3577.20	878.32	14	942.40	4664.00	1,284.42	10^4 t CO_2
Scope 1 Emissions	14	556.84	2415.72	589.90	14	587.60	3202.77	866.73	10^4 t CO_2
Scope 2 Emissions	14	154.85	610.42	128.71	14	110.60	887.89	230.92	10^4 t CO_2
Scope 3 Emissions	14	86.52	879.46	216.43	14	214.55	1,089.44	239.89	10^4 t CO_2
Socioeconomic Variables									
GDP	14	99.22	932.01	240.45	14	141.91	1,172.20	259.02	10^8 yuan
Primary Industry (%)	14	10.17	44.78	10.85	14	9.12	48.47	13.06	%
Secondary Industry (%)	14	17.12	60.09	11.72	14	12.56	33.25	6.86	%
Tertiary Industry (%)	14	24.88	50.09	7.13	14	35.00	61.69	8.52	%

socioeconomic variables, the proportion of secondary industry decreased significantly (maximum 60.09% in 2010, maximum only 33.25% in 2020), while the proportion of tertiary industry increased notably (maximum 50.09% in 2010, maximum reaching 61.69% in 2020), reflecting the industrial structure transformation trend in the study area. All statistical data are based on a sample of 14 northeastern border cities.

To ensure data quality, this study conducted systematic preprocessing of carbon emission data. Carbon emission data preprocessing included three key steps. First, activity data standardization converted activity data (such as energy consumption, industrial output) from different sources through unit conversion and standardization processing to ensure data consistency, for example, energy consumption data were uniformly converted to standard coal equivalent. Second, emission factor selection followed a three-tier system: priority was given to localized emission factors (such as region-specific research results), followed by industry-specific emission factors published by the National Development and Reform Commission, and finally IPCC default values (when the first two types of factors were unavailable). Third, for missing value processing, linear interpolation was used to supplement missing data in time series to ensure data continuity; for inter-regional data gaps, average values from similar regions were used as substitutes and noted in the uncertainty analysis.

Besides carbon emission data, the processing of land use data also required precise technical parameter settings. In terms of projection system settings, the Krasovsky 1940 Albers projection system was configured with central meridian 105°E and standard parallels 25°N and 47°N, a configuration particularly suitable for area calculations in the northeastern region. During the land classification process, functional differences of various land types in the carbon cycle were emphasized, especially classifying forestland and grassland as ecological land categories to facilitate subsequent analysis of their carbon sink functions. Additionally, all spatial analysis operations were completed using ArcGIS 10.8, ensuring consistency and reproducibility of spatial calculations.

Based on the functional positioning and policy orientation characteristics of cities in the study area, this research adopted a classification analysis method. Based on development positioning and policy orientation, the 14 border cities were divided into three categories. Industrial development policy-guided areas include Jixi, Shuangyashan, and Hegang, with main characteristics of energy and raw material industries as the dominant sectors, secondary industry accounting for 24%–32% of GDP, land use dominated by agricultural land, continuous expansion of urban construction land, and relatively high carbon emission intensity (8.14–12.48 tons/10,000 yuan). Port economic policy-guided areas include Heihe, Mudanjiang, Dandong, and Hulunbuir, characterized by national-level ports, foreign trade and service industries as the main sectors, tertiary industry proportion exceeding 45%, diversified land use structure, coordinated development of ecological land and construction land, and moderate carbon emission intensity (average 1.54 tons/10,000 yuan). Ecological protection policy-guided areas include Daxing'anling, Yichun, Yanbian, Tonghua, Baishan, Jiamusi, and

Xing'an League, primarily characterized by ecological resource protection, forest coverage generally exceeding 80%, land use dominated by forests supplemented by agricultural land, and relatively low carbon emission intensity (1.31 tons/10,000 yuan). This classification is based on comprehensive assessment of policy document analysis, land use structure characteristics, and economic development indicators, ensuring scientific validity and policy relevance.

To further explore land use efficiency differences among different types of cities, this study employed the Tukey HSD *post hoc* test method based on one-way analysis of variance. Statistical analysis results show that although the observed carbon emission intensity of industrial cities (1.72 tons/10,000 yuan) was higher than that of port cities (1.54 tons/10,000 yuan) and ecological cities (1.31 tons/10,000 yuan), these differences did not reach statistical significance ($F(2,11) = 0.655$, $p = 0.538$). The 95% confidence intervals for carbon emission intensity of each city type were: industrial cities [7.50, 12.55] tons/10,000 yuan, port cities [1.97, 7.22] tons/10,000 yuan, and ecological cities [2.17, 16.80] tons/10,000 yuan. The overlap of these confidence intervals further supports the conclusion that differences are not significant. Effect size analysis ($\eta^2 = 0.1065$) shows that city type only explains approximately 10.65% of land use efficiency variation.

This study selected 14 border cities in the northeastern region as the research sample, mainly based on the following considerations: (1) these cities constitute a complete economic belt and ecological barrier belt along China's northeastern border, with spatial continuity and integrity; (2) these cities show obvious differences in functional positioning, including industrial development-oriented, port economy-oriented, and ecological protection-oriented types, providing ideal samples for studying policy response differences across different types of cities; (3) these cities have experienced similar policy implementation backgrounds, simultaneously influenced by the "Northeast Revitalization Strategy" and the "Belt and Road Initiative", facilitating horizontal comparison of policy effects; (4) these cities have high data completeness and accessibility, especially relatively comprehensive land use change and carbon emission data during the 2010–2020 period, capable of supporting the empirical analysis of this study. This sample selection ensures both representativeness of the research and feasibility of the analysis.

2.3 Theoretical framework

2.3.1 "Border location-functional differentiation-efficiency coupling" theoretical framework

This study constructs an innovative theoretical analysis framework of "border location-functional differentiation-efficiency coupling" to systematically explain the formation mechanism of land use efficiency in border regions. Unlike traditional studies that view border regions as homogeneous entities, this framework emphasizes the heterogeneity and functional differences of border cities, revealing the formation path of spatial differences in land use efficiency.

Border location factors hold a central position in this framework. As important regions connecting different countries, border regions' land use efficiency not only relates to regional economic transformation but also affects ecological security. Fekete and Priesmeier (2021), in their study of the US-Mexico border, found that coordination between cross-border resource management and environmental risk prevention is crucial for improving land use efficiency; while Bazarov et al. (2021), comparing the Xingkai Lake basin, discovered that the degree of human modification on the Chinese side (50%) is significantly higher than on the Russian side (28%), reflecting the impact of different development paths under border location on land use patterns.

The functional differentiation dimension explains the interaction mechanism between the development positioning of border cities and policy implementation effects. Cities with different functional positioning exhibit differentiated responses to land use policies: industrial cities (such as Jixi, Shuangyashan, and Hegang) show relatively lagged land use policy implementation effects under traditional industrial inertia; port cities (such as Heihe, Mudanjiang, Dandong, and Hulunbuir) utilize their openness advantages to form efficient land use patterns; ecological cities (such as Daxing'anling, Yichun, *etc.*) form a "protection priority-efficiency synergy" development model through strict ecological protection policies. This functional differentiation not only explains regional differences in policy implementation effects but also provides a theoretical basis for differentiated policy formulation in border regions.

The efficiency coupling dimension introduces spatial connection and interaction mechanisms. Unlike traditional regional economic theory, this framework emphasizes that border regions have formed a networked development pattern with port cities as nodes and industrial chains as links. In the policy transmission process, low-efficiency regions become key areas for policy implementation through industrial connections, high-efficiency regions drive overall regional efficiency improvement through demonstration effects, and different types of cities form functionally complementary mechanisms in policy responses, constituting a spatial coupling path of "demonstration effect-diffusion mechanism-collaborative improvement." This dimension transcends traditional single-center development theory and better fits the networked development reality of border regions.

2.3.2 Theoretical mechanism of policy-efficiency relationship

How land use policies influence green utilization efficiency is one of the core questions of this study. Through review of existing literature and theoretical analysis, we have identified several key pathways and mechanisms. Land use structure optimization is the primary mechanism through which policy affects efficiency. During policy implementation, optimization of the ratio between ecological land and construction land can directly change regional carbon emission patterns. This relationship has a profound theoretical foundation—spatial economics has long focused on the impact of different land types on regional sustainable development. Empirical research also supports this view; Chang et al. (2023) demonstrated that industrial structure optimization significantly enhances land use efficiency, while Song et al. (2022) revealed the profound influence of resource endowment differences and development cycles on efficiency in border regions, especially during economic transition periods.

Spatial layout optimization constitutes another important mechanism. By adjusting urban form and industrial spatial distribution, land policies can significantly influence energy consumption patterns and carbon emission levels. Li H. et al. (2024) found in their Beijing-Tianjin-Hebei study that optimizing spatial planning can achieve carbon emission reductions of 643.42×10^4 tons; Chen et al. (2023), in their analysis of resource-based cities in Shanxi Province, pointed out that low urban compactness under traditional development models directly affects land use efficiency. These findings are highly consistent with spatial economic theories on location choice and resource allocation.

Synergistic effects between policies represent a more complex influence mechanism. Land policies at different levels and in different domains do not operate in isolation but form interactive networks. A typical example is the coordination between the "National Main Functional Zone Planning" and the "Forest Land Protection and Utilization Planning Outline (2010–2020)"—the former provides institutional guarantees for the latter through macro spatial control, while the latter improves land efficiency through specific ecological restoration measures. This policy integration produces evident multiplier effects, far exceeding the expected outcomes of single policy implementation.

The driving role of technological innovation cannot be ignored. Technology upgrades guided by land policies can indirectly but significantly improve land use efficiency. In industrial city transformation practices, digital transformation and energy structure optimization have become significant efficiency improvement pathways. Qian and Luo (2024) research confirmed that digital technology application can effectively enhance land efficiency in resource-based cities, which is particularly crucial for the transformation of border industrial cities. This technological pathway also reflects that the long-term effects of land use policies are often realized through innovation diffusion mechanisms. Understanding these mechanisms is valuable for evaluating policy effects and optimizing future policy design, and also provides a theoretical foundation for the empirical analysis in this study.

2.3.3 Theoretical explanation of spatial heterogeneity

This study breaks through the spatial homogeneity assumption in traditional regional research and constructs a heterogeneity analysis framework of "three types of cities-multiple spaces." The spatial differences in land use efficiency in border regions have complex formation mechanisms requiring multi-dimensional understanding. Traditional industrial inertia is a key factor explaining spatial heterogeneity. Border industrial cities, deeply influenced by historical development path dependency, often form high-carbon emission, low-efficiency land use patterns. The core-periphery differentiation phenomenon in mining cities' land use efficiency discovered in Yuan et al. (2019) research provides important evidence, but they did not deeply explore the comprehensive effects of climatic conditions, geopolitics, and development strategies. Our theoretical framework views industrial inertia as a fundamental explanatory variable for spatial heterogeneity, emphasizing the persistent influence of historical accumulation on current land use patterns.

Differences in location conditions also shape the spatial pattern of land use. Significant differences exist in geographic location, port distance, and transportation convenience among border region cities, directly leading to diversification of land use methods. Practice shows that port cities can often utilize location advantages to form efficient and intensive land use patterns, while geographically peripheral areas tend toward extensive use. This phenomenon is highly consistent with Turner and Pham (2015) research results on the northern border of Vietnam—port cities significantly improved land use efficiency through regional development platforms.

The unbalanced distribution of ecological resource endowments constitutes the third important dimension. The study area has formed a special spatial pattern of "three vertical and one horizontal": the eastern Changbai Mountain system and the western Greater Khingan Range system constitute key ecological barriers, providing a good ecological foundation for the local area; while the central Songnen Plain mainly undertakes agricultural production functions. These resource endowment differences directly affect policy implementation effects and efficiency performance. Mendoza-Ponce et al. (2021) research on the Guatemala-Mexico border verified the importance of ecological resource management policies, especially the significant role of zero deforestation policies in improving carbon stocks.

The differentiated positioning of regional development strategies is also an indispensable factor. Based on the "National Main Functional Zone Planning," border regions have formed a functionally diverse spatial layout: the Greater Khingan Range and Changbai Mountain regions are positioned as key ecological function zones, while some port cities are included in key development regions. This differentiated planning guides various types of cities onto different development paths, leading to spatial heterogeneity in land use efficiency. Although Zheng et al. (2022) proposed spatial conflict measurement methods, they did not fully explain the heterogeneous mechanisms of policy responses across different types of cities. By analyzing functional positioning differences, this study provides a more comprehensive theoretical perspective for explaining the spatial heterogeneity of policy responses. This multi-dimensional theoretical framework not only helps understand the complex pattern of land use efficiency in border regions but also provides a scientific basis for differentiated policy formulation.

2.4 Research methodology system

This study constructs a comprehensive "policy-efficiency-space" multi-level analysis framework, integrating quantitative and spatial analysis methods to systematically evaluate the relationship between land use policies and green utilization efficiency in border regions. This framework, based on three theoretical dimensions (border location, functional differentiation, efficiency coupling) and four mechanisms (land use structure optimization, spatial layout optimization, policy synergy, technology driving), adopts the research approach of "mechanism analysis-spatial verification-effect evaluation" to form an analytically consistent system with inherent logic.

Method selection follows these principles: First, the systemic principle suitable for complex system analysis. The land use system in border regions involves multi-dimensional interactions, requiring

methods capable of processing multi-variable relationships simultaneously. Second, the geographical principle that accounts for spatial heterogeneity. Border regions show significant spatial differences, requiring analytical methods that capture spatial patterns and regional differences. Third, the mechanistic principle focusing on policy implementation pathways. Policy influences are transmitted through multiple channels, requiring analysis of each factor's contribution and operating mechanism. Fourth, the integrative principle balancing quantitative analysis and qualitative explanation. This combines statistical significance testing with interpretation of practical policy significance, avoiding over-reliance on single indicators.

Based on these principles, this study forms three mutually supporting methodological modules: The policy implementation effect analysis module uses regional difference indices and transition matrix methods to evaluate land use structure changes, and analyzes spatial patterns through global Moran's I; the efficiency evaluation module adopts a carbon emission-based multi-level evaluation system, combining annual change rates, variation coefficients, and variance analysis methods to identify temporal-spatial characteristics; the policy effect evaluation module integrates Pearson correlation analysis, BiLISA spatial association analysis, and regression-based path analysis to reveal policy driving mechanisms, supplemented by LMDI decomposition to quantify the contribution of various factors.

The innovation of this methodological system lies in: First, it overcomes limitations of traditional single methods by combining the mechanism analysis capability of regression path analysis with the location sensitivity of spatial analysis methods; second, it achieves comprehensive land use efficiency assessment through a multi-level carbon emission accounting framework; third, it integrates quantitative statistics and spatial analysis techniques, answering not only "what" and "what differences" but also exploring "why" and "how to improve"; finally, it adopts dual perspectives of type differentiation and spatial heterogeneity, providing scientific support for differentiated policy formulation in border regions. We will detail the theoretical basis, specific operational steps, and application contexts of these methods, demonstrating how to systematically evaluate the relationship between land use policies and green utilization efficiency in border regions through multi-method integration.

2.4.1 Theoretical basis of spatial econometric methods

Spatial heterogeneity is a core characteristic in research on land use efficiency in border regions. Recent studies show that traditional spatial econometric methods face two main theoretical limitations: insufficient justification of spatial dependence assumptions and inconsistency in handling cross-border effects (Inmaculada et al., 2017). This study addresses these limitations in the following ways: First, we explicitly theorize spatial dependence based on Tobler's First Law of Geography, namely, "things closer in space are more related than things farther apart." Unlike studies that merely report spatial autocorrelation without articulating theoretical foundations (Inmaculada et al., 2017), we adopt Anselin's spatial autocorrelation theory, explicitly linking the application of global Moran's I index and BiLISA methods with spatial dependence mechanisms specific to border regions. Second, we address the cross-border specific spatial dynamics issue pointed out by Grau et al. (2018) and Daniel et al. (2023). Unlike existing studies with inconsistent analytical methods from grid units to parcel level, we adopt an integrated approach combining regional level analysis with city type differentiation analysis to more comprehensively capture spatial heterogeneity in border regions. Third, we address the model selection problem revealed by Zhao et al. (2020) and Sipos et al. (2021), which show different models (such as spatial Durbin, spatial autoregressive, and geographically weighted regression) have different advantages in parameter estimation and spatial heterogeneity capture. Our study overcomes limitations of single models by using regression-based path analysis and spatial analysis, providing a more comprehensive analytical framework.

Compared to existing research, this study offers three important innovations in theoretical framework and methodology: First, breaking through traditional spatial homogeneity assumptions to construct a differentiated border region analysis framework. Existing studies generally view border regions as homogeneous entities Bazarov et al. (2021) or rely on a single spatial scale (Mesbah et al., 2012; Xiu-Qing et al., 2022), failing to fully reveal heterogeneity among different border city types. Based on location characteristics and functional positioning, this study constructs a "border location-functional differentiation-efficiency coupling" framework, surpassing the parcel-level analysis of David and Ralph (2014) and the international comparative research of Zhao et al. (2020), providing a more comprehensive understanding of border region differences. Second, developing a multi-dimensional theoretical model of "policy tools-city types-efficiency performance" to systematically reveal policy response mechanisms of different types of cities. Unlike the spatial conflict measurement methods proposed by Zheng et al. (2022), which fail to fully reveal heterogeneous mechanisms of policy responses across different city types, our theoretical model integrates Benny and Steffen (2013) analysis of administrative boundary effects and Turner and Pham (2015) research on border region development platforms to construct a more explanatory policy response theory. Third, developing a border land use research framework integrating spatial econometric methods and causal inference. Unlike Wang et al. (2024) use of deep learning to identify inefficient spaces and Zhao et al. (2020) application of geographically weighted regression as a single method orientation, our research framework combines the mechanism analysis capability of regression path analysis with the location sensitivity of spatial analysis, and integrates temporal-spatial heterogeneity processing methods from Wenjia and Kexin (2023) to construct an integrated research architecture of "mechanism analysis-spatial verification." This innovation surpasses the methodological comparative studies of Mühlbach (2019) and Laurent and Thierry (2016), providing analytical tools more suitable for the complex realities of border regions.

2.4.2 Integration of causal inference methods

This study incorporates causal inference methods into spatial analysis, an integration inspired by recent methodological advances. Since 2020, several innovative causal inference methods have emerged in the field of land use policy evaluation, particularly Spatial Interrupted Time Series (SITS) analysis, which directly addresses the challenges of temporal-spatial heterogeneity (Wenjia and Kexin, 2023).

Our method integrates several key causal inference principles: First, we adopt a comparative framework similar to the synthetic control method (Sills et al., 2015; Laurent and Thierry, 2016), systematically selecting and weighting comparison units, using long-term pre-intervention data to evaluate policy effects. This approach is particularly suitable for border region research as it can handle cases with few treatment units. Second, we draw on insights from improved difference-in-differences methods proposed by Brantly and Tong (2023), relaxing standard parallel trend assumptions to address dynamic selection and time stationarity issues common in border regions. Third, we extract value from interdisciplinary approaches from Marcelo et al. (2018) research, which adapts epidemiological methods to land use policy evaluation for handling data limitation situations. This integration of causal inference methods enables us to move beyond simple correlation analysis into more rigorous evaluation of policy effects. In particular, we can distinguish between direct and indirect effects of policies, address potential reverse causality, and consider the influence of unobservable factors.

2.4.3 Selection basis and structural design of path analysis model

This study employs regression-based path analysis to analyze the impact pathways of land use policies on green utilization efficiency. The choice of path analysis over other statistical methods is based on three main considerations: First, path analysis can effectively reveal direct and indirect relationships among multiple variables. The process by which land use policies influence green utilization efficiency involves multiple mediating variables such as economic development, industrial structure, and energy intensity, with complex interactions among these variables. Path analysis can estimate these relationships through multiple regression analysis, thereby better understanding the transmission mechanisms of policy impacts. Second, path analysis offers flexibility in model specification and interpretative intuitiveness. Compared to complex structural equation models, regression-based path analysis has lower requirements for data distribution assumptions, making it more suitable for this study's limited sample (n = 14), while providing clear and intuitive coefficient interpretation. Third, path analysis is suitable for analyzing longitudinal data. This study spans multi-year observations from 2010 to 2020, necessitating consideration of dynamic changes in policy effects. Path analysis combined with time series data analysis can effectively track the evolution of policy impacts over time.

During the method selection process, we also considered the Geographically Weighted Regression (GWR) method. Although GWR has obvious advantages in handling spatial heterogeneity, this study focuses on the transmission mechanisms of policy impacts rather than merely identifying spatial distribution characteristics; therefore, path analysis better meets research needs. To compensate for path analysis limitations in handling spatial heterogeneity, we combine path analysis with spatial analysis methods to form an integrated research framework of "mechanism analysis-spatial verification," which can both reveal policy impact mechanisms and verify the spatial differentiation of these mechanisms.

Based on the above theoretical foundation, the path analysis model constructed in this study includes two core variable groups: policy influence factors and green utilization efficiency. Policy influence factors include eight main variables: economic development (GDP, fixed asset investment), industrial structure (proportions of three industries), technological innovation (proportion of science and technology expenditure, patent grants), energy intensity (energy consumption per unit of GDP), urbanization (urbanization rate), openness (total foreign trade), and infrastructure (road network density). These variables as independent variables directly impact green utilization efficiency as the dependent variable, which is measured through three dimensions of carbon emission intensity (Scopes 1, 2, and 3). The model employs Ordinary Least Squares (OLS) to estimate path coefficients and evaluates model fit through indicators such as R^2, adjusted R^2, F-statistic, and p-value.

Model application results show that based on cross-sectional data from 14 border cities, this study's model fits well (R^2 = 0.924, Adj. R^2 = 0.803, F (8,5) = 7.610, p = 0.0194), indicating that the selected policy driving factors can explain 92.4% of carbon emission variation. This result verifies the rationality and effectiveness of the model selection. Specific results of the path analysis will be presented in detail in Section 3.3.3, revealing the degree and direction of influence of different policy factors on land green utilization efficiency through path coefficients and their significance levels.

2.4.4 Analysis of policy implementation effects

(1) This study uses area proportion method and Regional Difference Index (RDI) to evaluate land use policy implementation effects, while employing transition matrix method to analyze land use conversion relationships during policy implementation. The Regional Difference Index is calculated as:

$$RDI = \sqrt{\frac{(S_i - S)^2}{S^2}} \tag{6}$$

where S_i is the proportion of a certain land use type in a region, and S is the average proportion of that land use type across all regions. A larger index value indicates greater difference between the region's policy implementation effect and the regional average level (Xu et al., 2020).

(2) To evaluate the spatial effects of policy implementation, the global Moran's I index is used to measure the spatial correlation of policy implementation:

$$I = \frac{n\sum\sum w_{ij}(x_i - \bar{x})\left(x_j - \bar{x}\right)}{\sum\sum w_{ij}\sum(x_i - \bar{x})^2} \tag{7}$$

where n is the number of regions, w_{ij} is the spatial weight matrix, x_i and x_j are policy effect indicators for regions i and j, and $\bar{x}$ is the mean value. A positive value indicates spatial clustering of policy effects, while a negative value indicates spatial dispersion. The index ranges from [-1,1], with values closer to ±1 indicating stronger spatial correlation (Juknelienė et al., 2021).

2.4.5 Efficiency assessment methods

This study employs a comprehensive assessment system based on carbon emission intensity to measure land green utilization efficiency. The selection of carbon emission data as the main indicator for evaluating green utilization efficiency, rather than other pollutants such as sulfur dioxide, industrial wastewater, and

PM2.5, is primarily based on the following three considerations: First, carbon emissions serve as a comprehensive indicator for measuring the sustainability of land resource utilization. Compared to single pollutant indicators, carbon emission data can more comprehensively reflect the environmental impacts of various land use methods including agricultural production, industrial activities, energy consumption, and ecosystem functions. Particularly in the context of international climate change response, carbon emissions have become a key indicator for measuring regional sustainable development levels, directly linked to global emission reduction goals. Second, carbon emissions possess clear cross-regional comparability. Unlike certain environmental indicators with significant regional specificities (such as the varying impacts of water pollution indicators in water-rich areas *versus* water-scarce areas), carbon emission impacts are global and not limited by regional conditions, helping ensure the comparability of assessment results between different types of border cities. Third, carbon emission data have higher consistency and accessibility in border regions. The carbon emission statistical system in China's northeastern border region is relatively well-established with high data quality, capable of supporting long time-series regional comparative studies. In contrast, data for other pollutants show greater differences in statistical standards and monitoring methods across different regions, making it difficult to meet the needs of cross-regional comparative research.

Based on these considerations, land use efficiency assessment employs annual average change rates and variation coefficients to measure temporal change characteristics, analyzing efficiency structural characteristics through multi-dimensional composition analysis. To analyze regional differences, one-way analysis of variance method is adopted:

$$F = \frac{MSB}{MSW} = \frac{\sum n_i (\bar{x}_i - \bar{x})^2 \Big/ (k-1)}{\sum \left(x_{ij} - \bar{x}_i\right)^2 \Big/ (n-k)} \tag{8}$$

where MSB is between-group mean square, reflecting differences between regions; MSW is within-group mean square, reflecting fluctuations within each region; n_i is the sample size of group i; $\bar{x}_i$ is the mean of group i; $\bar{x}$ is the overall mean; x_{ij} is the jth observation in group i; k is the number of groups (14 border regions in this study); n is the total sample size; $(k-1)$ is between-group degrees of freedom; $(n-k)$ is within-group degrees of freedom (He et al., 2020). The one-way ANOVA method is chosen because it can effectively test the overall significance of land use efficiency differences across regions. F-test ($p < 0.05$) is used to determine the significance level of land use efficiency differences across regions.

2.4.6 Policy effect evaluation methods

Policy effect evaluation methods include three dimensions: First, Pearson correlation coefficient is used to evaluate policy implementation effects:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y} \tag{9}$$

where x_i represents land use policy indicators, y_i represents land use efficiency indicators, $\bar{x}$ and $\bar{y}$ are corresponding means, s_x and s_y are standard deviations. The correlation coefficient matrix evaluates the association degree between different policy measures and land use efficiency, with significance tests at $p < 0.001$, $p < 0.01$, and $p < 0.05$ levels (Cheng et al., 2020).

Second, BiLISA method is used to analyze spatial correlation effects of policies:

$$I_i = \frac{(x_i - \bar{x})(y_i - \bar{y})}{s(x)s(y)} \times \sum w_{ij} \frac{\left(x_j - \bar{x}\right)\left(y_j - \bar{y}\right)}{s(x)s(y)} \tag{10}$$

where x_i and y_i are policy implementation intensity and land use efficiency values for region i, respectively, and w_{ij} is the spatial weight matrix. BiLISA analysis can identify four policy effect patterns: High-High clustering, Low-Low clustering, High-Low, and Low-High (Seemuangngam and Lin, 2024).

Finally, coupling degree analysis is used to evaluate policy synergy:

$$C = \left(\frac{U \times E}{(U+E)^2 / 4} \right)^{1/2} \tag{11}$$

where U and E are standardized policy implementation and efficiency indicators, respectively. Coupling degree $C > 0.90$ indicates high synergy, $0.70 \le C \le 0.90$ indicates moderate synergy, $C < 0.70$ indicates low synergy (Ji et al., 2020).

2.4.7 Policy driving mechanism analysis

This study employs the Logarithmic Mean Divisia Index (LMDI) decomposition method to analyze the policy driving mechanisms of land use efficiency. In the assessment of policy driving factors, this study selects energy emission intensity (energy consumption per unit of GDP) as the main infrastructure evaluation indicator, rather than solely using traditional road network density or power supply facility coverage, primarily based on the following considerations: First, energy emission intensity is a comprehensive indicator reflecting the degree of infrastructure modernization and efficient utilization. In border regions, single physical infrastructure indicators struggle to comprehensively reflect regional development levels. Energy emission intensity not only reflects the level of energy infrastructure construction but also embodies energy utilization efficiency, providing a more comprehensive assessment of the overall quality of regional infrastructure. Second, energy emission intensity has a direct intrinsic connection with land green utilization efficiency. The level of infrastructure development affects land use patterns, thereby influencing carbon emission intensity. Especially in border regions, energy infrastructure configuration significantly impacts land use efficiency. Third, data availability for energy consumption in northeastern border regions is higher than for other infrastructure indicators, capable of supporting long time-series analysis. Data selection comprehensively considers theoretical relevance and data accessibility, maximizing research feasibility while ensuring the theoretical rationality of the assessment.

The specific calculation formula is as follows:

$$\Delta C = \Delta C_{\text{gdp}} + \Delta C_{\text{str}} + \Delta C_{\text{pop}} + \Delta C_{\text{tech}} + \Delta C_{\text{int}} + \Delta C_{\text{urb}} + \Delta C_{\text{open}} + \Delta C_{\text{infra}} \tag{12}$$

where ΔC_{gdp} represents economic policy effect, ΔC_{str} represents industrial policy effect, ΔC_{pop} represents population policy effect, ΔC_{tech} represents technology policy effect, ΔC_{int} represents energy efficiency policy effect, ΔC_{urb} represents urbanization policy effect, ΔC_{open} represents opening-up policy effect, and ΔC_{infra} represents infrastructure policy effect. Each effect value is calculated as:

$$\Delta C_x = L(C_2, C_1) \times \ln(X_2/X_1) \quad (13)$$

where $L(C_2, C_1) = (C_2 - C_1)/(\ln C_2 - \ln C_1)$, C_2 and C_1 are efficiency values at end and start periods, X_2 and X_1 are policy factor values at end and start periods. Policy contribution rate is calculated as: contribution rate = (specific policy effect value/total land use efficiency change) × 100%. Effect values and contribution rates are calculated for two periods: 2010–2015 and 2015–2020, to reveal dynamic changes in policy driving mechanisms (Li Y. et al., 2024).

3 Results

3.1 Land use policy implementation and its effects

3.1.1 Policy impact on land use structure

The implementation of national land use policies has created significant regional differences and dynamic evolutionary patterns in the study area. These differences reflect policy orientations. At a deeper level, they demonstrate the comprehensive influence of regional development strategies, natural resource endowments, and historical path dependencies. In 2020, the "National Land Use General Planning (2006–2020)" and "Greater and Lesser Xing'an Mountains Forest Region Ecological Protection and Economic Transformation Planning (2010–2020)" jointly shaped the differentiated land use pattern in the study area. The high forest coverage in ecological protection policy-dominated regions—Daxing'anling (96.87%), Baishan (91.34%), and Yichun (87.80%)—is both a spatial projection of the national ecological security strategy in border regions and an institutional manifestation of regional functional positioning transformation under ecological value reassessment. The high level of ecological protection in these regions strengthens the ecological barrier function of border areas, becoming an important component of national spatial optimization. Under the guidance of agricultural policies, the distribution differences of cultivated land are significant, with plain regions such as Jiamusi (77.90%), Jixi (58.53%), and Shuangyashan (60.91%) having much higher proportions of agricultural land than other regions. This distribution pattern is both determined by natural geographical conditions and represents the institutional arrangement of the national food security strategy in spatial terms, consolidating the functional positioning of the Songnen Plain and Sanjiang Plain as major commercial grain-producing areas (Table 3).

From a temporal evolution perspective (Table 3), the land policy implementation effects during 2010–2020 exhibited differentiated characteristics adapting to regional functional positioning. Under industrial development policy orientation, urban construction land expansion was significant, such as Jixi increasing from 2.05% to 2.60%, and Shuangyashan from 1.68% to 2.16%. This expansion pattern reflects the institutional demand for construction land in resource-based cities during industrial transformation and also embodies the spatial manifestation of local development strategies against the backdrop of "land finance." Land use transition matrix analysis (Supplementary Table S1) shows that construction land expansion in these cities mainly occupied cultivated land, such as 127.88 square kilometers of cultivated land in Jixi city being converted to construction land, reflecting the adjustment mechanism of land use structure under the dual driving forces of industrialization and urbanization. In contrast, ecological protection policy-dominated regions exhibited obvious stability characteristics, such as Baishan city's forest land proportion decreasing by only 1.45 percentage points (from 92.79% to 91.34%), with changes mainly occurring between different types of ecological land. This difference highlights the institutional differences in resource allocation mechanisms and development intensity under different policy orientations, while also reflecting the restructuring role of ecological civilization construction on traditional development models.

From the perspective of inter-provincial differences, each province exhibits diverse policy implementation effects based on resource endowments and development strategies (Supplementary Figure S1). The diversified pattern in Heilongjiang Province's border regions—ecological dominance in the northern Daxing'anling (forestland 96.87%) and Yichun (forestland 87.80%), agricultural dominance in the central Jiamusi (cultivated land 77.90%) and Jixi (cultivated land 58.53%)—reflects the differentiated development strategies and resource allocation mechanisms within the province, embodying the "one province, multiple policies" approach to coordinated regional development. The unified ecological protection policy orientation in Jilin Province's three border regions (forest coverage rate 66.85%–91.34%) indicates the consistency in institutional implementation of regional ecological security strategies, strengthening the ecological barrier function of the eastern border. The differentiated pattern in Inner Mongolia Autonomous Region's two areas—Hulunbuir's "forest-grassland complex" (forestland 59.43%, grassland 29.56%) and Xing'an League's "cropland-grassland complex" (cultivated land 33.99%, grassland 34.56%)—embodies the institutional balance mechanism between grassland ecosystem and agricultural-pastoral development. Liaoning Province's Dandong City has formed a pattern primarily based on ecological protection (forestland 69.05%) supplemented by urban development (construction land 4.76%) through policy guidance, reflecting the differentiated functional positioning of border regions by a coastal open province.

The correlation between land use policy implementation effects and regional functional positioning reflects the targeted nature of policy design and implementation effectiveness. The land use structure characteristics of industrial development-oriented cities—high proportions of cultivated land (58%–61%) and continuous construction land growth—indicate that these regions are in a transitional development stage, with land use patterns influenced by both historical industrial layout and current development needs. The composite land use structure formed by port cities reflects their multi-functional positioning

TABLE 3 Changes in land use structure under different policies in northeastern border regions (2010–2020).

Province/Region	2010 (%)			2020 (%)			Change
	Forest	Cropland	Built-up	Forest	Cropland	Built-up	Built-up*
Heilongjiang							
Mudanjiang	75.62	21.94	1.47	74.25	22.90	1.85	+0.38
Heihe	63.20	33.56	0.88	61.79	34.88	1.19	+0.31
Jiamusi	17.81	77.03	2.26	16.27	77.90	2.96	+0.70
Jixi	32.15	59.14	2.05	31.88	58.53	2.60	+0.55
Shuangyashan	36.35	60.24	1.68	35.47	60.91	2.16	+0.48
Yichun	89.99	8.54	0.90	87.80	10.30	1.11	+0.21
Hegang	47.49	48.33	2.28	44.19	51.09	2.84	+0.56
Daxing'anling	97.52	1.33	0.44	96.87	1.96	0.53	+0.09
Jilin							
Yanbian	85.86	12.61	1.10	84.54	13.34	1.49	+0.39
Tonghua	65.83	31.25	2.23	66.85	29.78	2.71	+0.48
Baishan	92.79	5.65	0.91	91.34	6.43	1.17	+0.26
Inner Mongolia							
Hulunbuir	58.95	9.21	0.36	59.43	9.29	0.45	+0.09
Xing'an League	28.48	29.30	1.26	28.72	33.99	1.72	+0.46
Liaoning							
Dandong	68.25	25.38	4.22	69.05	24.25	4.76	+0.54

* Change in Built-up area shows the percentage point change from 2010 to 2020. Other land use types (grassland, water, and unused land) are not shown but account for the remaining percentage.

and institutional choices seeking balance between border economic cooperation and ecological security. The high forest proportion in ecological protection-dominated cities embodies the profound influence of the ecological priority concept on land policies and the restructuring effect of national ecological security strategies on regional development paths.

Land use transfer matrices further reveal differences in land use change mechanisms under different policy orientations (see Supplementary Table S1). Under industrial development policies, cities mainly expand construction land by occupying cultivated land (such as 127.88 square kilometers of cultivated land in Jixi city being converted to construction land), reflecting the institutional bias in land resource allocation and economic growth pressure during industrialization processes. The economical and intensive characteristics of ecological protection policy-dominated cities (such as only 52.25 square kilometers of cultivated land being converted to construction land in Baishan city) embody the reshaping effect of green development concepts on land use patterns. This differentiated pattern of land use change is both a spatial mapping of regional development stage differences and an institutional manifestation of resource optimization allocation mechanisms under different policy orientations, providing an important perspective for understanding the spatial heterogeneity of policy effects.

3.1.2 Spatial pattern of policy implementation

The spatial distribution of land use in the study area is influenced by both industrial (Guo et al., 2023). The implementation effect of ecological protection policies is reflected in the spatial distribution of forestland. As shown in Figure 2, forestland demonstrates significant spatial clustering, mainly distributed in ecological corridor zones such as the Greater Xing'an Mountains, Lesser Xing'an Mountains, and Changbai Mountain areas, forming a "three-mountain connected" ecological security pattern in the northeastern border region. The distribution of cropland under agricultural development policy guidance shows evident regional concentration, mainly concentrated in the Songnen Plain and Sanjiang Plain regions, particularly forming concentrated continuous agricultural production areas in regions such as Jiamusi and Shuangyashan. The implementation of grassland ecological protection policies has resulted in grassland being mainly distributed in the Hulunbuir grassland region, showing unique spatial continuity. Built-up land under urban development policies, although occupying a relatively small proportion, shows significant expansion tendencies around major cities, with spatial distribution showing evident point-clustering characteristics.

We evaluated spatial effects of policy implementation using the global Moran's I index method (Equation 7). The analysis results (Supplementary Table S2) reveal that different land use types show

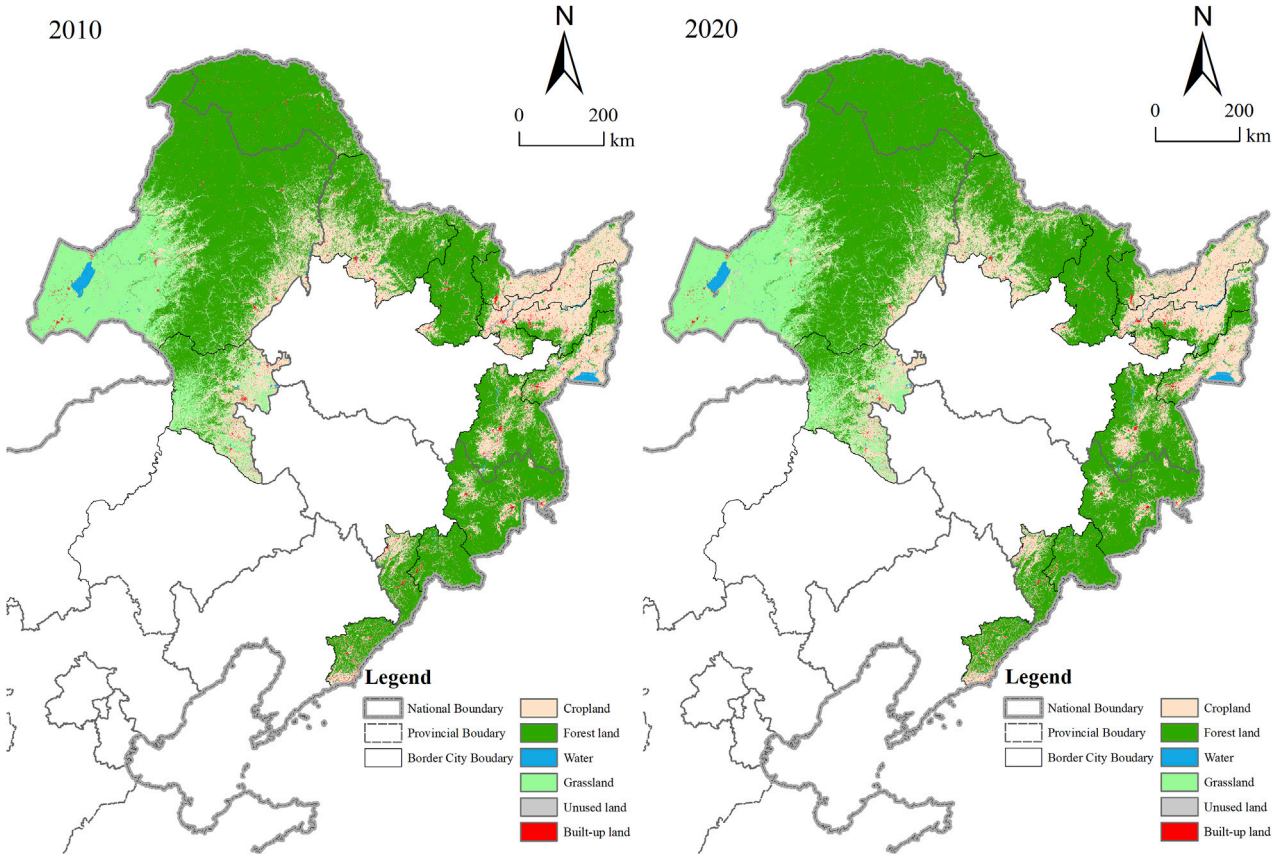


FIGURE 2
Spatial distribution of land use policy implementation effects in northeastern border regions (2010–2020).

distinct policy response characteristics. Statistical significance testing of Moran's I indices reveals spatial autocorrelation characteristics in the land use pattern of border regions. In 2020, the implementation of agricultural land policies resulted in significant clustering of cultivated land (Moran's I = 0.441, $p < 0.05$), while the effects of grassland protection policies are reflected in the high clustering of grassland (Moran's I = 0.661, $p < 0.001$). The Z-score for grassland reached 4.237, far exceeding the critical value of 1.96, indicating highly significant positive spatial autocorrelation at the 95% confidence level. These results clearly confirm that the spatial distribution of cultivated land and grassland is not random but influenced by common topographical conditions, historical development patterns, and policy orientations, forming a spatial pattern of "similar value clustering."

In contrast, ecological protection policies have promoted a balanced distribution of forestland, with spatial autocorrelation test results for forest land (Moran's I = 0.249, $p > 0.05$) indicating that its distribution pattern shows no significant difference from the random distribution hypothesis. In-depth analysis of local indicator results shows that although overall spatial autocorrelation is not significant, local regions (such as the Daxing'anling-Yichun area) have still formed high-value clustering areas for forestland. This characteristic of "overall dispersion, local clustering" reflects the spatial targeting and regional adaptability of forest protection policies. The implementation characteristics of urban development policies are embodied in the weak spatial correlation of construction land (Moran's I = 0.247, $p > 0.05$), reflecting a decentralized urban development model. Although overall spatial autocorrelation is not significant, there is a high-value aggregation phenomenon of construction land in the eastern border region, while the western region is dominated by low-value clustering. This statistically significant spatial differentiation pattern provides an objective basis for evaluating policy implementation effects.

Comparing policy implementation effects between 2010 and 2020 (Figure 2), spatial differences in land use changes can be observed. The impact of ecological protection policies has resulted in forestland changes mainly occurring in marginal transition zones, primarily involving policy adjustments with cultivated land; grassland protection policies have ensured the stability of grassland spatial distribution, mainly concentrated in eastern Inner Mongolia; while urban development policies have guided the orderly expansion of construction land along transportation arteries and central urban areas. This policy effect is also supported by spatial autocorrelation indices, with the Moran's I statistic for cultivated land increasing from 0.433 ($p = 0.015$) in 2010 to 0.441 ($p = 0.013$) in 2020, indicating enhanced spatial clustering reaching statistical significance. This transition confirms the gradually strengthening spatial synergy effect of regional agricultural policy orientation. The Moran's I value for grassland in 2020 (0.661)

slightly increased compared to 2010 (0.651), reflecting the enhanced effect of grassland protection policies.

The spatial distribution characteristics of unused land and water bodies embody the differentiation of policy implementation. Unused land exhibits stronger spatial dependence (Moran's I = 0.319, $p < 0.001$), mainly concentrated in eastern Inner Mongolia, reflecting the implementation focus of land remediation policies. The spatial distribution of water bodies is relatively scattered (Moran's I = 0.036, $p > 0.1$), mainly distributed in strips along major rivers. The spatial distribution patterns of these two land uses remained stable during 2010–2020, reflecting the sustained effect of protection policies.

By comparing the spatial autocorrelation significance test results of different land types, the spatial differentiation effect of policy interventions can be identified: regions with the most significant ecological protection policy effects (grassland protection areas) exhibit the highest spatial autocorrelation coefficient (0.661) and statistical significance ($p < 0.001$); while urban development areas, although showing obvious spatial clustering, have not yet formed statistically significant overall autocorrelation, reflecting the relative dispersion and regional differentiation of urbanization processes. This evolution of spatial patterns reflects the full consideration of natural conditions and effective response to socioeconomic development needs during the implementation of land policies in the study area. Particularly in the urban development process, spatial control of construction land expansion has achieved notable results, mainly confined to the periphery of existing towns without causing significant damage to ecological space, which can be verified by the stability of forestland spatial patterns, reflecting the continuous improvement of land use efficiency.

Further in-depth analysis reveals complex socioeconomic and institutional driving mechanisms behind this spatial pattern of land use policy implementation. The significant spatial clustering of cultivated land and grassland *versus* the relative dispersion of construction land and forestland reflects the interaction process between differentiated policy tools and regional characteristics. Specifically, cultivated land clustering under agricultural land policy orientation mainly stems from historically formed agricultural production specialization and pursuit of economies of scale; Heilongjiang Province's Songnen Plain and Sanjiang Plain have formed concentrated contiguous major grain-producing areas, institutionally prioritized and protected by the "National Land Use General Planning." The high clustering of grassland (Moran's I = 0.661) reflects the requirement for integrity protection of the eastern Inner Mongolia grassland ecosystem, with relevant ecological compensation policies reinforcing this spatial pattern. In contrast, the relative evenness of forestland distribution aligns with the policy concept of the "Greater and Lesser Xing'an Mountains Forest Region Ecological Protection and Economic Transformation Planning," which emphasizes overall ecosystem protection rather than local priority protection. The dispersion of urban construction spatial patterns embodies the strategic choice of balanced development in border regions and policy orientation toward small town construction. This spatial differentiation is not only a result of natural conditions and historical inertia but also a spatial mapping of differences in policy tool selection, implementation intensity, and control methods, reflecting the spatial coordination mechanism of multiple policy objectives in the regional sustainable development process.

3.1.3 Regional differences in policy response

Different land use policy orientations have caused significant regional differences. Regional Difference Index analysis results show (Supplementary Table S3) that RDI values calculated using Equation 6 reflect the spatiotemporal differentiation of land policy implementation effects. Under agricultural policy orientation, Jiamusi City shows the highest cropland difference index (1.504 in 2020), significantly higher than the study area's average level. Hulunbuir City, dominated by grassland protection policies, shows prominent performance in grassland difference index (5.053), reflecting the significant effect of grassland ecological protection policies. Regarding forest protection, Daxing'anling region (0.598) and Yanbian Prefecture (0.395) show relatively stable difference indices, while Jiamusi City (0.732) shows relatively higher values, reflecting regional differences in forest protection policy implementation intensity.

From the temporal evolution of policy implementation, grassland protection policy implementation shows significant effects. In 2020, the grassland difference indices of Hulunbuir City (5.053) and Xing'an League (6.077) were significantly higher than other regions. Compared to 2010 (5.076 and 6.104 respectively), these two regions maintained relatively stable difference indices, indicating continuous effective implementation of grassland ecological protection policies. Regarding urban development policies, built-up land difference indices show an overall convergence trend, such as Dandong City decreasing from 1.737 in 2010 to 1.420 in 2020, reflecting the gradual effect of regional coordinated development policies, with urban construction becoming more balanced.

Box plot analysis (Supplementary Figure S2) further reveals the characteristics of inter-provincial policy implementation differences. Heilongjiang Province adopts differentiated land policies, resulting in the largest internal differences, particularly evident in cropland proportion. Within this, agriculture policy-led Jiamusi (77.90%) and ecological protection policy-led Daxing'anling (1.96%) constitute the upper and lower quartile extreme points respectively, forming an "agriculture-forest" composite policy pattern. Jilin Province implements unified ecological protection policies, with forest proportions in its three regions maintaining high levels (66.85%–91.34%) and showing small box height, reflecting policy orientation consistency.

The radar chart (Figure 3) clearly demonstrates policy implementation characteristics of different types of regions. Cities under industrial development policies formed a structure dominated by cropland (56.84%) with relatively high built-up land proportion (2.53%). Cities guided by port economy policies show a balanced composite pattern, with moderate forest proportion (66.13%) and coordinated proportions of built-up land (2.06%) and water bodies (1.06%). Cities dominated by ecological protection policies prominently show a forest-led (67.48%) and cropland-supplemented (24.81%) structure, with the lowest unused land proportion (0.0855%), reflecting higher land use efficiency. This type differentiation reflects high consistency between policy implementation effects and regional functional positioning.

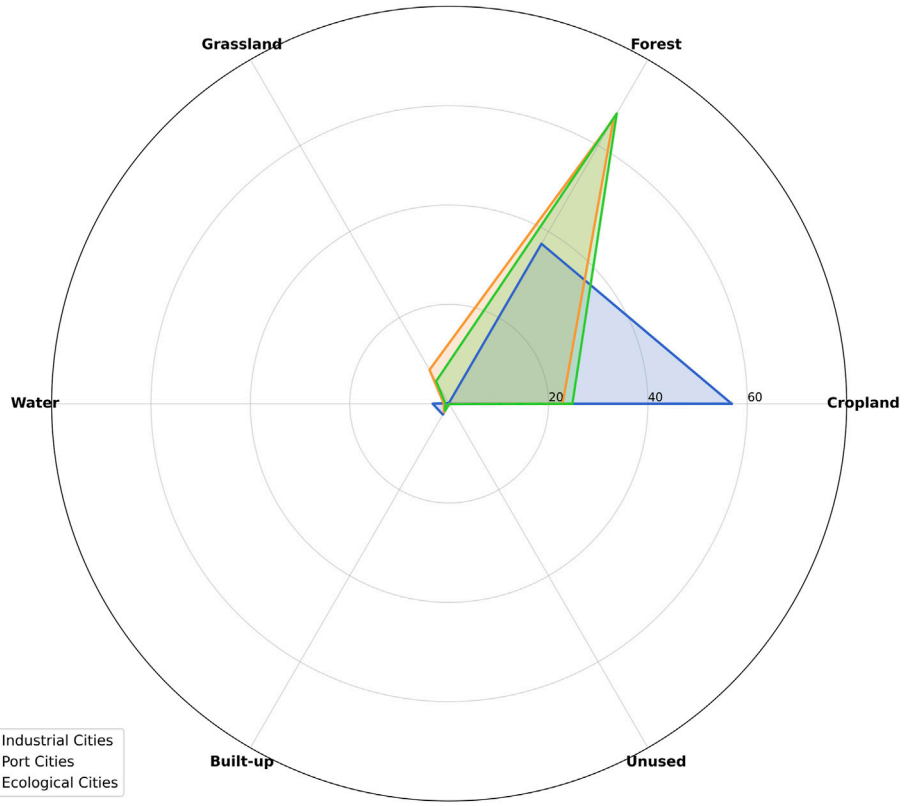


FIGURE 3
Land use patterns by city type under different policy implementation (2020).

This type differentiation not only reflects the high degree of alignment between policy implementation effects and regional functional positioning but also reveals deeper socioeconomic and institutional driving mechanisms. The differences in land use patterns among the three types of cities presented in the radar chart (Figure 3) are essentially the result of the combined effects of urban functional positioning, economic development stages, and regional collaboration mechanisms.

The structure of industrial cities dominated by cultivated land (56.84%) with a relatively high proportion of construction land (2.53%) reflects the natural geographical conditions and historical agricultural foundation of these cities located in plain areas, while also relating to industrial layout during the planned economy period. Resource-based economic structures have limited the diversified development of land use methods, forming characteristics of coexisting agricultural and industrial land. Particularly for resource-depleted cities like Jixi, facing dual challenges of industrial upgrading and spatial restructuring during transformation, land use policies more often shoulder the functions of stabilizing employment and ensuring livelihoods.

The "diversified" land use structure of port cities reflects their transitional economic development stage and multi-functional positioning, with cross-border economic cooperation reshaping land spatial organization, and policy implementation focusing more on balancing development and openness. The "forestland-dominated, cultivated land-supplemented" pattern of ecological cities embodies the restructuring of regional development paths by national ecological security strategies, with ecological compensation mechanisms and regional interest coordination mechanisms having a key impact on policy implementation effects. From the inter-provincial comparison of regional difference indices (Supplementary Figure S2), internal policy differences within Heilongjiang Province's border regions are most significant, reflecting its diversified functional positioning and complex governance system; while the uniformity of Jilin Province's border regions embodies the institutional effects of regional coordinated development strategies. These differentiated characteristics indicate that successful land use policies need to fully consider regional historical paths, development stages, and functional positioning, achieving an organic unity of "adaptation to local conditions" and "coordinated development" in policy design and implementation processes.

3.2 Land green utilization efficiency: spatiotemporal analysis

3.2.1 Temporal trends in land use efficiency

Carbon emission intensity, as an important indicator for assessing land green utilization efficiency, reflects the spatiotemporal evolution characteristics of land use efficiency in the study area. Based on the land use efficiency assessment results (Supplementary Table S4), the total carbon emissions calculated by Equation 1 for the 14 border regions increased from 373.56 million

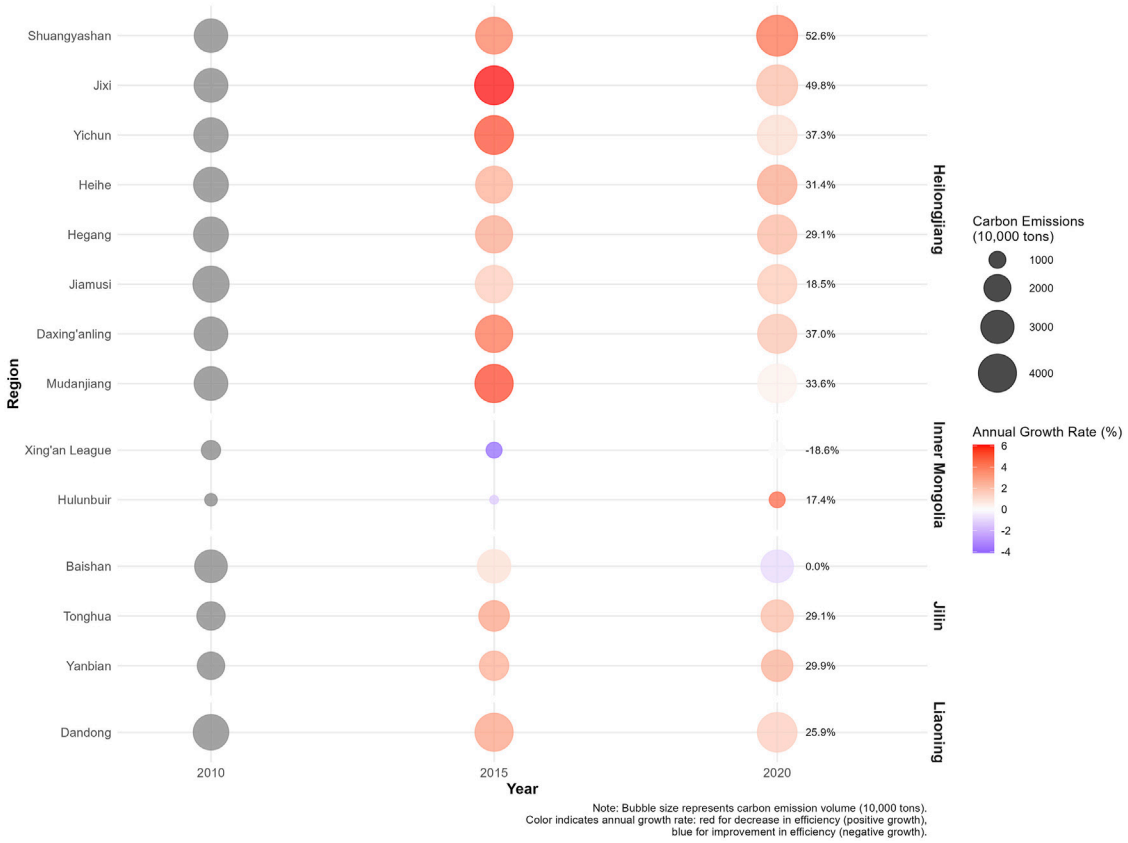


FIGURE 4
Changes in land use efficiency in northeastern border regions (2010–2020).

tons in 2010 to 495.54 million tons in 2020, an increase of 32.65%, indicating that the overall land use efficiency needs improvement. There are significant differences in land use efficiency across regions. For instance, carbon emissions in Jixi City increased from 31.11 million tons in 2010 to 46.60 million tons in 2020, an increase of 49.79%, reflecting a decline in land use efficiency. In contrast, Inner Mongolia Autonomous Region showed relatively higher land use efficiency, with carbon emissions in Hulunbuir City increasing only from 8.028 million tons to 9.424 million tons, an increase of 17.39%.

Different regions within the study area demonstrate unique efficiency change patterns. Taking Hulunbuir City as an example, its carbon emissions achieved a decrease during 2010–2015 (from 8.028 million tons to 7.469 million tons), reflecting improved land use efficiency, but showed a slight increase during 2015–2020 (rising to 9.424 million tons), forming a "V-shaped" change trend, reflecting the impact of land policy adjustments during regional development. In contrast, Dandong City shows relatively stable land use efficiency characteristics, with its carbon emission proportion showing a slight downward trend (from 9.24% in 2010 to 8.77% in 2020), reflecting continuous improvement in intensive land use levels.

To more intuitively display the dynamic change characteristics of land use efficiency, this study constructs a bubble chart (Figure 4). Bubble size reflects the absolute level of land use efficiency, while color depth indicates the rate of efficiency change. During 2010–2015, most regions showed declining trends in land use efficiency, manifested as bubbles showing obvious red color and increased size, with Jixi City showing the fastest efficiency decline at an annual growth rate of 6.11%. Entering 2015–2020, the trend of land use efficiency improvement gradually emerged, with bubble colors generally becoming lighter, some regions even showing light blue, reflecting the gradual emergence of positive effects from land use policies.

These temporal evolution characteristics of land use efficiency not only reflect changes in statistical data but also embody deeper socioeconomic transformation processes. The decline in carbon emissions in Hulunbuir City from 2010 to 2015 (from 8.028 million tons to 7.469 million tons) is closely related to its industrial structure adjustment, particularly the increase in tertiary industry proportion and energy structure optimization, reflecting institutional innovation in this region actively responding to the national low-carbon development strategy. In contrast, the rapid growth of carbon emissions in Jixi City (with an annual average growth rate of 6.11%) embodies institutional barriers to the transformation of resource-based cities, including resistance to state-owned enterprise reform, policy implementation deviations caused by employment pressure, and imperfect technological innovation systems. This difference simultaneously reflects imbalances in regional innovation capabilities and differences in policy implementation effectiveness, revealing that institutional design for coordinated regional development needs to place

greater emphasis on adaptation to local conditions and precise policy implementation.

3.2.2 Structural characteristics of land use efficiency

The assessment of land use efficiency in the study area requires not only attention to the overall level but also in-depth analysis of its structural characteristics to reveal the underlying socioeconomic transformation mechanisms and institutional driving factors. Based on the multi-dimensional analysis of carbon emission composition (Supplementary Table S5), direct emissions (Scope 1) calculated by Equation 2 from land use activities dominate the carbon emissions in the study area. In 2020, the proportion of Scope 1 emissions across regions was generally between 61% and 70%, indicating that land use efficiency is mainly influenced by fossil energy consumption and industrial production processes. This emission structure characteristic reflects the deep-rooted heavy industrial foundation and relatively traditional energy utilization patterns in Northeast China, as well as the institutional resistance in regional industrial structure transformation.

Different types of cities exhibit significant differences in efficiency structure, revealing the profound impact of urban functional positioning on resource utilization patterns. Industrial cities (Jixi, Shuangyashan, and Hegang) have land use efficiency dominated by industrial activities, characterized by high Scope one emission proportions (average 67.01%) and high energy consumption calculated by Equation 3 (Scope two average 15.01%). This structural characteristic originates from the heavy industry-oriented spatial layout and resource-intensive production methods formed during the planned economy period, reflecting the dual challenges of technological upgrading and institutional innovation faced by resource-based cities during industrial transformation. Port cities (Heihe, Mudanjiang, Dandong, and Hulunbuir) have formed more efficient land use patterns, with relatively low proportions of Scope one emissions (average 65.96%), but higher indirect emissions from service industries calculated by Equation 4 (Scope three average 18.99%). This structural characteristic embodies the effectiveness of economic structure optimization achieved by port cities under the promotion of opening-up policies, and also reflects the reshaping effect of modern service industry development on land use patterns, demonstrating the institutional dividends of the national border opening strategy.

From an inter-provincial comparison perspective (Supplementary Figure S3), regional differences in efficiency structure reflect the dual influence of local governance models and resource endowments. The land use efficiency structure in Heilongjiang Province's border regions is relatively homogeneous, with coefficient of variation calculation results showing that in 2020, the proportions of Scope 1, 2, and 3 emissions were 0.05, 0.21, and 0.19 respectively. This homogeneity stems from integrated industrial policies and energy planning at the provincial level, embodying the institutional effects of unified regional market construction. In contrast, significant differences in land use efficiency exist between the two border regions of Inner Mongolia Autonomous Region, with Hulunbuir City and Xing'an League differing by 2.78 percentage points in the proportion of Scope 1 emissions, reflecting the spatial heterogeneity of local autonomy and adaptability in the land use policy implementation process, while also highlighting the practical paths of differentiated development strategies.

The regional differences in energy consumption dimension (Scope 2 emissions) and industrial development dimension (Scope 3 emissions) of land use efficiency further reveal the diversity of development path choices. In 2020, Shuangyashan City's Scope 2 emissions accounted for 19.04%, significantly higher than the study area average; while Xing'an League was only 11.69%, reflecting institutional environment differences in energy infrastructure construction and energy structure adjustment across different regions. From a temporal evolution perspective, the degree of dependence on purchased energy has been continuously increasing, such as the proportion of Scope 2 emissions in Mudanjiang City rising from 10.12% in 2010 to 18.45% in 2020, indicating that regional energy integration strategies are reshaping the association mechanism between land use and energy consumption, promoting the formation of more intensive and efficient energy utilization patterns.

In terms of industrial development dimension, efficiency structure changes are closely associated with industrial transformation policies. In 2020, Yichun City had a relatively high proportion of Scope 3 emissions (24.7%), embodying the institutional innovation effectiveness of transition from traditional forestry economy to ecological service economy; while the Daxing'anling region was relatively low (16.3%), reflecting path dependency of industrial development under strict ecological protection policies. During 2010–2020, the land use optimization trends of some ecological cities—such as the increase in Scope 3 emissions proportion in Yanbian Prefecture from 15.77% to 20.92%—indicate that service-oriented industrial policies have become the core driving force for land use pattern transformation in these regions, embodying the synergistic effects of industrial upgrading and spatial restructuring under the Northeast Revitalization Strategy. These structural differences and their evolutionary characteristics not only reflect the differences in land use efficiency improvement strategies across different types of regions but also reveal the interactive mechanism between institutional change and technological innovation in the regional development process. With the deepening advancement of ecological civilization construction and implementation of carbon peaking and carbon neutrality strategies, the proportions of Scope 2 and Scope 3 will further increase, especially in ecological cities, a trend presaging that land use patterns in border regions are undergoing profound institutional transformation, forming greener and lower-carbon development models.

3.2.3 Spatial patterns of land use efficiency

The spatial pattern of land use efficiency demonstrates significant clustering and gradient distribution characteristics (Han et al., 2019) (Figure 5). In terms of carbon emission intensity, regional land use efficiency generally shows a "high west-low east" spatial pattern. In 2020, eastern regions including Jixi City (46.600 million tons), Shuangyashan City (46.640 million tons), and Dandong City (43.440 million tons) formed a low-efficiency cluster zone; while western regions including Hulunbuir City (9.424 million tons) and Xing'an League (9.456 million tons) demonstrated characteristics of highly efficient utilization.

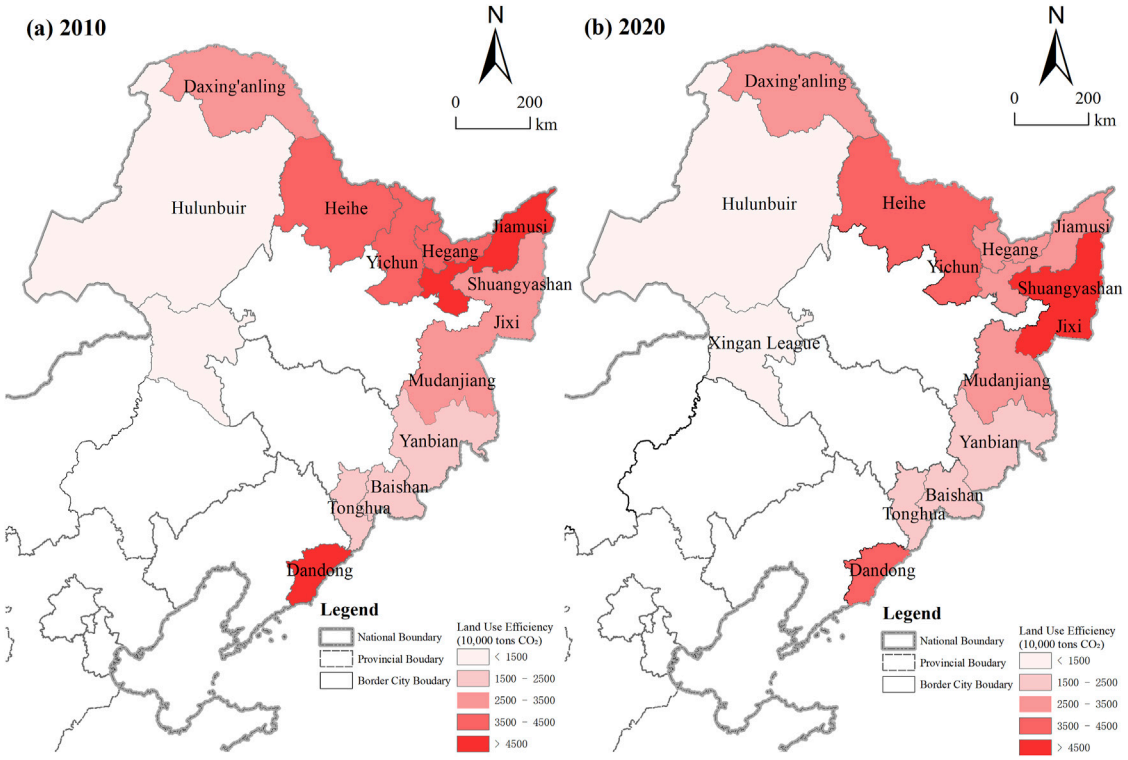


FIGURE 5
Spatial pattern of land use efficiency in northeastern border regions during different periods: **(a)** 2010; **(b)** 2020.

Further verification of this spatial differentiation pattern comes from spatial clustering characteristics of land use efficiency (Supplementary Table S6). In 2020, eastern Heilongjiang Province formed a significant low-efficiency cluster (H-H), with Jixi City ($p = 0.022$), Shuangyashan City ($p = 0.018$), Yichun City ($p = 0.014$), and Hegang City ($p = 0.004$) all showing significant spatial positive correlation. From spatial autocorrelation analysis of land use efficiency, ecological cities show relatively independent efficiency characteristics. Western regions including Hulunbuir City and Xing'an League maintain relatively stable high-efficiency utilization patterns ($p > 0.08$), demonstrating the unique land use patterns of ecological cities.

From the temporal evolution of land use efficiency, the study area's spatial pattern has undergone partial adjustments. During 2010–2020, Jiamusi City's land use efficiency characteristics underwent significant changes, transforming from a non-significant state in 2010 ($p = 0.056$) to low-efficiency clustering in 2020 ($p = 0.002$), indicating strengthened correlation with surrounding regions in its land use patterns. Meanwhile, port cities demonstrated relatively independent efficiency characteristics, with cities like Heihe and Mudanjiang consistently maintaining non-significant spatial correlation (2020 p-values of 0.220 and 0.110 respectively).

Different provinces demonstrate differentiated spatial clustering characteristics in land use efficiency. Border regions in Heilongjiang Province show the most significant spatial correlation in land use efficiency, with five regions showing significant spatial autocorrelation in 2020. In comparison, border regions in Jilin Province demonstrate more independent efficiency characteristics ($p > 0.05$), while Inner Mongolia Autonomous Region maintains relatively stable high-efficiency utilization patterns ($p > 0.08$), reflecting spatial heterogeneity in land use policy implementation effects. This spatial distribution pattern and clustering characteristics of land use efficiency reflect both the influence of regional natural endowments and historical development paths, as well as differences in border region land use policy implementation. Particularly, the formation of low-efficiency clusters in eastern regions is closely related to traditional industrialization paths and extensive urban development, providing important basis for formulating differentiated land use optimization strategies.

Behind this spatial distribution pattern and clustering characteristics of land use efficiency lie complex socioeconomic, historical development, and institutional driving mechanisms. The "high in the west, low in the east" efficiency spatial pattern reflects the differential influence of regional industrial evolution paths. The formation of low-efficiency clustering areas in the eastern region, represented by Jixi and Shuangyashan, stems from the historical inertia of resource-led industrialization; long-term resource dependence has not only shaped an industrial structure dominated by heavy industry but also formed a high-carbon emission technological path dependency. The spatial autocorrelation in these regions is significant ($p < 0.05$), indicating that low-efficiency characteristics have a strong regional contagion effect, which is closely related to industrial association networks and regional resource flow patterns. In contrast, the high-efficiency characteristics of the western region are related to its development path integrating into the grassland ecological economic system; the industrial models developed by

Hulunbuir and Xing'an League based on ecological resource advantages have effectively avoided high-carbon lock-in effects.

From a temporal evolution perspective, the phenomenon of Jiamusi City transitioning from a non-significant state to low-efficiency clustering (p decreasing from 0.056 to 0.002) reveals the profound impact of position changes in the regional industrial division system on land use efficiency. The spatial independence exhibited by port cities embodies the reshaping role of open economies on regional development paths, with relatively loose industrial spatial associations enabling them to escape the influence range of regional low-efficiency clustering. Behind inter-provincial differences lies the spatial heterogeneity of regional governance systems; the significant spatial association of Heilongjiang Province's border regions stems from its integrated regional planning system and similar industrial development stages; while the independence characteristics of Jilin Province's border regions reflect its unique development positioning and relatively self-contained governance model. The implications of this spatial pattern for policy formulation are that improving regional land use efficiency requires breaking existing spatial dependencies, promoting spatial transmission of efficient land use models through establishing cross-regional innovation networks and green technology diffusion mechanisms, achieving coordinated regional development.

3.2.4 Regional differences in efficiency

Significant provincial differences and type differentiation characteristics exist in land use efficiency in the study area, and this spatial heterogeneity may be closely related to regional development paths, industrial structure characteristics, and resource endowment conditions. In terms of carbon emission intensity, one-way analysis of variance (Equation 8) results (Supplementary Table S7) show that Heilongjiang Province's border regions have relatively high carbon emissions, with an average total of 43.621 million tons in 2020, significantly higher than other provinces. This may be related to the historically formed resource-intensive industrial structure and traditional energy utilization patterns in this region, reflecting historical remnants of heavy industrial layout during the planned economy period. Notably, the carbon emission intensity in this region decreased from 0.88 tons/10,000 yuan in 2010 to 0.68 tons/10,000 yuan in 2020, a reduction of 22.73%. This improvement trend coincided with industrial adjustment policies and technological updating measures implemented in recent years, but more evidence is needed to determine specific causal relationships. Border regions in Inner Mongolia Autonomous Region have relatively low total carbon emissions, only 9.44 million tons in 2020, with a carbon emission intensity of 0.11 tons/10,000 yuan. This efficiency difference may be associated with its industrial structure characteristics and natural resource endowment conditions.

From an urban type perspective, the three types of cities exhibit differentiated characteristics in land carbon emission efficiency. Industrial cities (Jixi, Shuangyashan, Hegang) have relatively high *per capita* carbon emissions, maintained at a level of 1.00 tons/person in 2020, with no significant change during 2010–2020. This stability may reflect structural challenges faced in the transformation process of resource-based economies, including insufficient industrial diversification and slow technological updating. Port cities (Heihe, Mudanjiang, Dandong, Hulunbuir) have lower *per capita* emissions at 0.46 tons/person, with carbon emissions per unit of GDP at 1.54 tons/10,000 yuan. The data indicate that these cities are dominated by service industries, with a statistical association between their land use patterns and lower carbon emission intensity. Ecological cities are at an intermediate level, with *per capita* emissions of 0.95 tons/person in 2020 and an emission intensity of 1.31 tons/10,000 yuan, which may be related to their need to balance the dual goals of ecological protection and economic development.

Time series data show differences in efficiency improvement degrees among different types of cities during 2010–2020. Industrial cities had the smallest reduction in carbon emission intensity (8.51%), while port cities (12.50%) and ecological cities (13.82%) showed relatively larger improvements. These differences may be related to industrial structure characteristics, technological application levels, and policy implementation environments of various types of cities, but this association does not necessarily imply a direct causal relationship. Determining specific causal mechanisms requires further empirical research, especially targeted policy effect assessments.

The relationship between efficiency and economic development shown in Figure 6 further highlights the potential association between development models and land use efficiency. Industrial cities such as Jixi City (57.238 billion yuan, 8.14 tons/10,000 yuan) and Shuangyashan City (49.394 billion yuan, 9.44 tons/10,000 yuan) have relatively high carbon emission intensities, which may be associated with industrial structures dominated by resource extraction and heavy industry; while port city Hulunbuir (117.220 billion yuan, 0.80 tons/10,000 yuan) has a lower carbon emission intensity, possibly reflecting different resource utilization patterns of a service-dominated economy. Differences also exist among cities of the same type, such as the carbon emission intensity of industrial city Hegang (12.48 tons/10,000 yuan) being higher than that of Jixi City (8.14 tons/10,000 yuan), suggesting that individual city characteristics (such as resource endowments, development stages, and management capabilities) may explain efficiency performance better than simple type classification.

Based on the above analysis, we propose the following specific, operational policy recommendations:

For industrial cities, research results indicate that this type of city has the highest carbon emission intensity and the smallest improvement margin. We recommend implementing targeted technological innovation incentive measures, such as establishing special technological transformation funds, providing over 50% financial support for energy efficiency improvement projects; establishing a differentiated emission rights trading system, setting stricter emission reduction targets for high-carbon intensity industries; developing tax incentive policies for high-energy-consuming enterprises, such as reducing corporate income tax by 30% for enterprises achieving energy consumption reductions of more than 15%.

For port cities, data shows that this type of city already has relatively high land use efficiency. We recommend supporting their further development of service industry advantages while promoting these experiences to other types of cities: establishing a service industry development experience sharing platform in border regions, regularly organizing technical exchanges between

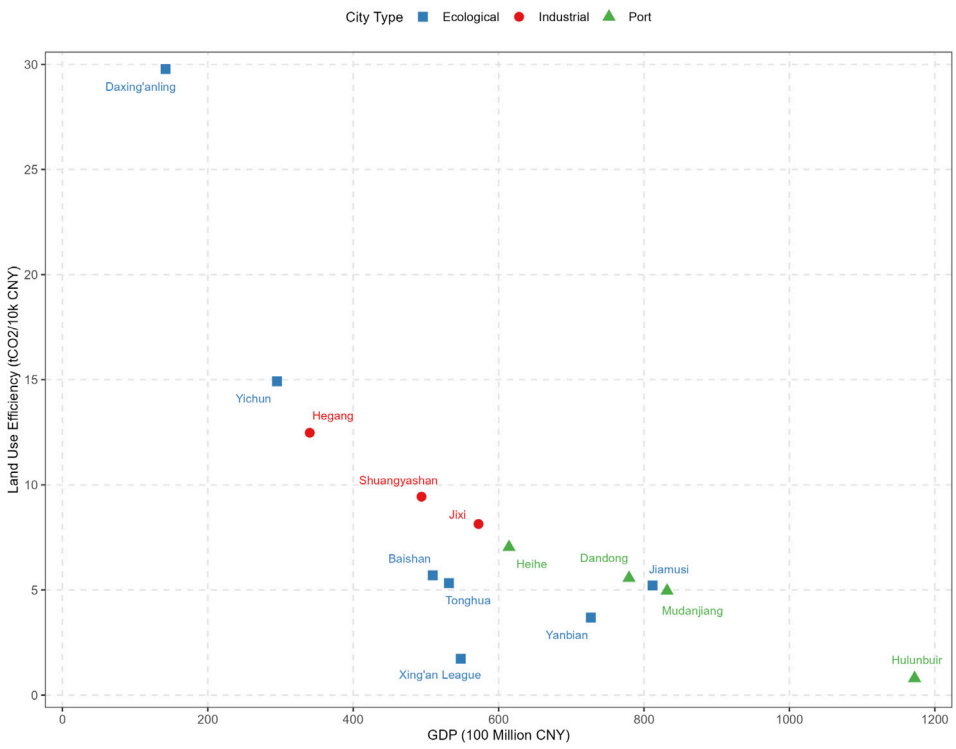


FIGURE 6
Relationship between economic development and land use efficiency across different types of cities (2020).

different types of cities; strengthening intelligent upgrading of port infrastructure, such as digital customs clearance systems, to improve land use efficiency; policy support should not simply favor port cities while neglecting industrial cities, but should allocate resources according to efficiency improvement potential.

For ecological cities, we recommend developing economic activities consistent with ecological positioning on the basis of ecological protection: developing ecological value transformation mechanisms, such as establishing carbon sink trading platforms to convert ecological protection into economic benefits; designing ecological tourism franchise auction systems to balance development and protection; formulating quantitative ecological service industry development targets, such as increasing the proportion of service industries to 60% by 2030.

The above recommendations are based on empirical data analysis of different types of cities, proposing differentiated measures targeting their respective characteristics, rather than simply favoring one type of city. Implementation of these policies needs to consider local specific conditions and establish dynamic evaluation mechanisms, adjusting policy tool combinations in a timely manner to achieve continuous improvement in land use efficiency in border regions.

3.3 Policy effects on land use efficiency

3.3.1 Policy response analysis

To evaluate land use policy effects, this study analyzes the correlation between different land use types and land use efficiency (with carbon emissions as indicators), deeply revealing the socioeconomic driving mechanisms and institutional effects behind policy implementation. Research results show significant differences in the impact of different land use types on land use efficiency, reflecting spatial heterogeneity in the matching degree between policy tool selection and regional characteristics. Analysis results using the Pearson correlation coefficient method (Equation 9) indicate (Table 4) that in 2020, the proportion of cultivated land use showed a significant negative correlation with land use efficiency ($r = 0.377$, $p < 0.05$), with the strongest association with energy consumption-related efficiency indicators ($r = 0.509$, $p < 0.01$). This phenomenon indicates that agricultural production methods have a negative impact on land use efficiency, rooted in insufficient regional agricultural modernization levels, low intensification degrees, and institutional inertia of energy-intensive agricultural production models. Particularly in the Northeast region, the high dependence of large-scale mechanized agriculture on fossil energy has led to a positive feedback mechanism between cultivated land expansion and carbon emission growth. The implementation effects of forestland policies have not yet been fully manifested, with weak correlation with land use efficiency (r between −0.154 and 0.134, $p > 0.05$), indicating that the ecological benefits of existing forestland policies need enhancement. This weak correlation reveals the dual challenges of lag in forestland carbon sink functions and insufficient institutional incentives, while also reflecting that the ecological system service values of forestry have not yet been fully incorporated into regional development evaluation systems.

Grassland policies exhibit the most significant effects, with correlation coefficients with land use efficiency in

TABLE 4 Correlation analysis between land use types and land use efficiency.

Land use type	2010				2020			
	Total	Scope 1	Scope 2	Scope 3	Total	Scope 1	Scope 2	Scope 3
Cropland	0.442**	0.459**	0.159*	0.447**	0.377*	0.362*	0.509**	0.223
Forest	−0.043	−0.072	0.213	−0.105	0.006	0.013	−0.154	0.134
Grassland	−0.787***	−0.760***	−0.752***	−0.674***	−0.852***	−0.840***	−0.752***	−0.804***
Water	0.332*	0.312*	0.247	0.349*	0.356*	0.382*	0.282	0.251
Built-up	0.458**	0.485**	0.145	0.448**	0.367*	0.369*	0.359*	0.286
Unused	−0.656***	−0.638***	−0.665***	−0.526**	−0.723***	−0.710***	−0.645***	−0.679***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.
All correlation coefficients are Pearson correlation coefficients.

2020 reaching −0.852, −0.840, −0.752, and −0.804 respectively (all $p < 0.001$). This strong correlation may be related to the efficient carbon sink function of grassland ecosystems and the systematic institutional arrangements of grassland protection policies, especially the grassland ecological compensation mechanism and grazing prohibition and rotation policies implemented in Inner Mongolia Autonomous Region, forming a governance system combining protection incentives and regulatory constraints. This policy effect persisted throughout 2010–2020, highlighting the important role of grassland ecosystems in enhancing regional land use efficiency, while also embodying successful practices of regionally differentiated ecological protection strategies. The effects of water body management policies are relatively limited, showing significant impacts only in terms of overall efficiency (r = 0.356, $p < 0.05$) and direct utilization efficiency (r = 0.382, $p < 0.05$), reflecting insufficient integration of water resource management policies with carbon reduction targets, and institutional construction for regional coordinated governance of water and soil resources still needing improvement.

Urban construction land policies show dynamic changes, embodying the evolutionary characteristics of land use policies during urbanization processes. The correlation between this type of land and land use efficiency decreased from 0.458 ($p < 0.01$) in 2010 to 0.367 ($p < 0.05$) in 2020, indicating an improvement in land intensive utilization levels. This weakening correlation is closely related to the strengthened spatial control after the implementation of the "National Land Use General Planning (2006–2020)," especially the total amount control and incremental restriction policies for construction land implemented in the Northeast region, effectively curbing extensive urban expansion patterns. In terms of energy utilization efficiency, the correlation increased from 0.145 ($p > 0.05$) in 2010 to 0.359 ($p < 0.05$) in 2020, reflecting optimization trends in land use patterns during urbanization processes, closely related to institutional promotion of smart city construction and green infrastructure investment, embodying the transformation of urban spatial governance concepts from scale expansion to quality improvement.

Unused land remediation policies continue to show effectiveness, reflecting institutional innovation in land resource integration and optimal allocation. In 2020, it maintained significant positive correlations with all land use efficiency indicators, with correlation coefficients of −0.723, −0.710, −0.645, and −0.679 respectively (all $p < 0.001$). Behind this continuously enhanced policy effect is the institutionalized operation of land remediation system projects and continuous innovation in technical methods, especially the desertification prevention and control, wetland restoration, and abandoned land reclamation projects implemented in the study area, which not only enhance land productivity but also strengthen carbon sink capacity, forming a win-win situation of ecological improvement and efficiency enhancement.

The hierarchy of policy effects that can be intuitively observed from the heat map (Figure 7) profoundly reflects the ecological function differences of different land types and spatial variation in policy intervention intensity. Grassland and unused land policies show the most significant effects (deep blue regions), benefiting from the relatively concentrated spatial distribution and clear policy intervention objectives of these two land types, ensuring coordination and execution effectiveness of policy implementation; the impacts of cultivated land and construction land policies are relatively moderate (light red regions), reflecting that these two land types are regulated by multiple-objective policies, with certain tensions between economic development and environmental protection goals; the effects of forestland and water body policies are not sufficiently evident (near-white regions), embodying that the ecological service functions of these two land types have not been fully transformed into economic value, with incentive mechanisms in policy design still needing strengthening. This multi-level policy effect reveals the importance of matching land use policies with regional characteristics, providing a scientific basis for formulating more targeted and coordinated land policy systems, while also establishing an evidence-based analytical framework for evaluating policy implementation effects.

3.3.2 Spatial coupling of policy implementation

The implementation effects of land use policies are reflected in the spatial coupling relationship between land use patterns and their efficiency. Research results show that the study area exhibits complex spatial coupling characteristics between land use and efficiency levels. Results from the BiLISA (Bivariate Local Indicators of Spatial Association) analysis method (Equation 10) show (Figures 8a,b) that the implementation effects of construction land policies underwent significant changes during 2010–2020. In

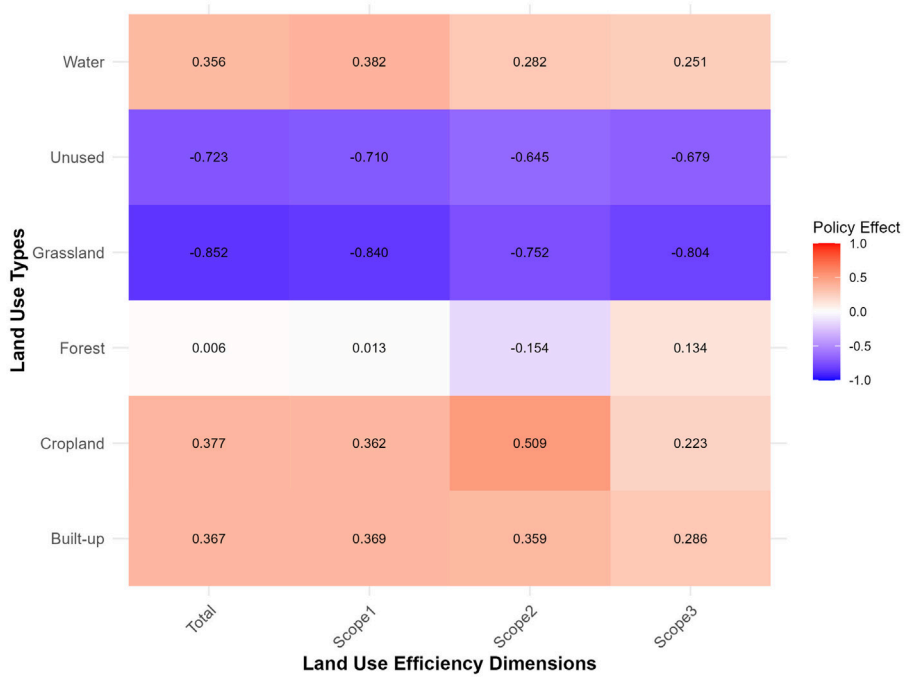


FIGURE 7
Correlation analysis between land use types and land use efficiency (2020).

2010, Hegang City showed high-high clustering, indicating that intensive construction land development led to decreased land use efficiency; while Yichun City exhibited low-high outlier characteristics, reflecting that its land-saving utilization policies failed to effectively improve land use efficiency. By 2020, only Shuangyashan City maintained high-high clustering characteristics, indicating the gradual emergence of land use policy effects in improving land use efficiency.

The implementation effects of ecological land policies show spatial differentiation (Tan et al., 2022) (Figures 8c,d). In 2010, Xing'an League's ecological protection policy effects were significant, showing high-low outlier characteristics, achieving a positive combination of high ecological land proportion and high land use efficiency; while policy effects in the eastern study area varied, with Yichun City showing high-high clustering and Hegang City showing low-high outlier characteristics. By 2020, Jiamusi and Shuangyashan showed poor ecological land policy effects, both transforming to low-high outliers, indicating that ecological space protection and land use efficiency improvement failed to progress synergistically.

Using the coupling degree measurement method (Equation 11) to further evaluate land use policy implementation effects (Table 5), the analysis results show significant regional differences (Huang et al., 2024). In 2020, border regions in Heilongjiang Province showed strong policy synergy, with Jiamusi City (0.979), Jixi City (0.946), and Shuangyashan City (0.908) all achieving high-level coupling. In contrast, the Daxing'anling region showed weaker policy synergy (coupling degree 0.400), indicating that its land use patterns and efficiency improvement goals have not yet achieved good coordination.

From the temporal evolution of policy implementation, different types of cities show differentiated characteristics. Industrial cities maintain stable policy synergy, with cities like Jixi and Shuangyashan consistently maintaining coupling degrees above 0.9. Port cities show significant improvement in policy effects, particularly Hulunbuir City, whose policy synergy improved from a low level (0.000) in 2010 to a high level (0.908) in 2020. Among ecological cities, Yanbian Prefecture and Tonghua City consistently maintain good policy synergy effects, achieving balance between land use efficiency and ecological protection. The formation and evolution of this spatial coupling pattern reflect both achievements and challenges in the study area's land use policy implementation process, providing important basis for optimizing the land use policy system and enhancing policy implementation effects.

The formation and evolution of this spatial coupling pattern not only reflects the achievements and challenges in the process of advancing land use policy implementation in the study area but also more deeply embodies the combined effects of regional development stages, governance capabilities, and industrial transformation paths. Behind the high-level coupling in Heilongjiang Province's border regions (Jiamusi 0.979, Jixi 0.946, Shuangyashan 0.908) are long-term accumulated institutional dividends and policy coordination mechanisms.

During the implementation of the Northeast Revitalization Strategy, these regions have achieved positive interactions between resource allocation and efficiency improvement by establishing coordination mechanisms between industrial and land policies, manifested as coupling degrees continuously maintained at high levels. The stability of policy coordination in industrial cities reflects their high emphasis on land use efficiency during transformation, despite facing dual pressures of resource depletion and industrial transformation, but maintaining relatively

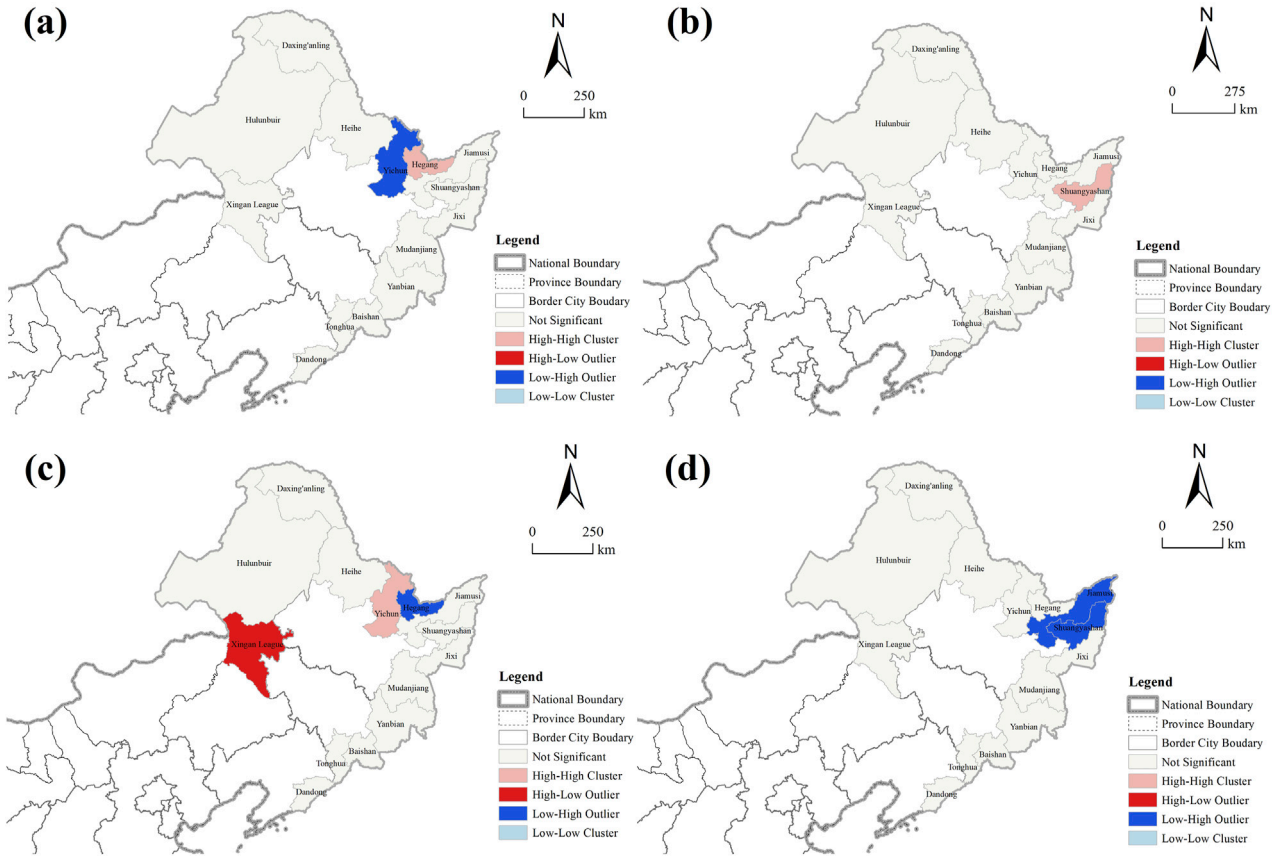


FIGURE 8
Spatial coupling analysis of policy implementation in border regions (2010–2020): **(a)** Built-up land policy effects in 2010; **(b)** built-up land policy effects in 2020; **(c)** ecological land policy effects in 2010; **(d)** ecological land policy effects in 2020.

high coupling degrees through strengthening the systematization of policy implementation.

Port cities, especially Hulunbuir's significantly improved policy coordination (from 0.000 to 0.908), embody the institutional innovation effectiveness of border opening and regional collaboration under the "Belt and Road" Initiative; the improvement of cross-border cooperation mechanisms has created new coupling paths for land use policies and efficiency enhancement. The sustained high coupling of ecological cities such as Yanbian Prefecture and Tonghua City indicates that coordination mechanisms for protection and development under the background of ecological civilization construction have formed institutionalized operation modes.

In contrast, the low coupling degree in the Daxing'anling region (0.400) reflects potential conflicts between ecological protection intensity and economic development needs, requiring further optimization of balance mechanisms between ecological compensation and local development in institutional design. The spatial differences in policy coupling degrees reveal that successful land use policy implementation needs to simultaneously consider the matching degree between regional development stages and functional positioning, establishing dynamic policy adjustment mechanisms to achieve coordinated evolution of policy orientation and regional needs, which is of key significance for enhancing overall land use efficiency in border regions.

3.3.3 Policy driving mechanisms

Land use efficiency changes are influenced by multiple policy factors (Liu et al., 2022). LMDI decomposition analysis (Equations 12, 13) shows significant differences in the impact degrees of different driving factors. Based on the LMDI decomposition method, this study evaluates policy effects from eight aspects: economic scale, industrial structure, population scale, technological progress, energy intensity, urbanization, opening-up, and infrastructure. Analysis results show (Table 6) significant differences in policy responses across different regions during two periods (2010–2015 and 2015–2020). Among these factors, economic development policy had the most significant impact during 2010–2015, with land use efficiency in Heihe City (410.68%), Yanbian Prefecture (368.64%), and Tonghua City (316.48%) being greatly affected. During 2015–2020, the regulatory effects of economic policies began to emerge, with land use efficiency improving in Hulunbuir City (−132.74%) and Tonghua City (−586.59%), reflecting effective regulation of economic development patterns by land use policies.

Industrial and energy policies show continuous effects in improving land use efficiency. During 2015–2020, industrial structure adjustment policies achieved positive effects in most regions, such as Xing'an League (−669.26%) and Jiamusi City (−124.29%) showing significant improvements in land use efficiency. Energy utilization policy effects were particularly

TABLE 5 Spatial coupling of land use policy implementation effects.

Province	Region	Coupling degree			Type		
		2010	2015	2020	2010	2015	2020
Heilongjiang	Mudanjiang	0.914	0.885	0.900	High	Medium	Medium
	Heihe	0.722	0.743	0.753	Medium	Medium	Medium
	Jiamusi	0.968	0.975	0.979	High	High	High
	Jixi	0.975	0.951	0.946	High	High	High
	Shuangyashan	0.945	0.936	0.908	High	High	High
	Yichun	0.740	0.688	0.723	Medium	Low	Medium
	Hegang	0.981	0.976	0.974	High	High	High
	Daxing'anling	0.339	0.386	0.400	Low	Low	Low
Jilin	Yanbian	0.942	0.950	0.949	High	High	High
	Tonghua	0.998	0.999	1.000	High	High	High
	Baishan	0.904	0.897	0.866	High	Medium	Medium
Inner Mongolia	Hulunbuir	0.000	0.000	0.908	Low	Low	High
	Xing'an League	0.948	0.746	0.696	High	Medium	Low
Liaoning	Dandong	0.993	0.998	0.999	High	High	High

Coupling degree classification: Low ($C < 0.70$), Medium ($0.70 \leq C \leq 0.90$), High ($C > 0.90$).
Coupling degree ranges from 0 to 1, where higher values indicate stronger coupling relationships.

evident during 2010–2015, with significant improvements in land use efficiency in Heihe City (−926.99%) and Jiamusi City (−890.88%), demonstrating the policy effectiveness of energy structure optimization.

To further reveal the influence mechanisms and action pathways of policy factors on land use efficiency, this study constructed a policy impact network model using regression-based path analysis. As shown in Figure 9, the path analysis results display direct influence relationships between eight policy factors and land green utilization efficiency. The model fits well (R^2 = 0.924, Adj. R^2 = 0.803, F (8,5) = 7.610, p = 0.019), indicating that these policy factors can explain 92.4% of carbon emission variation in the study area.

From the perspective of policy impact pathways (Figure 9), energy efficiency policies (−6452.09, $p < 0.01$) and industrial transformation policies (−4664.92, $p < 0.01$) are the two most important routes for enhancing land use efficiency, both showing highly significant negative influences, indicating that optimizing energy structure and industrial structure can effectively suppress carbon emissions and improve land use efficiency. Urbanization policies (58.91, $p < 0.05$) and openness policies (15.71, $p < 0.1$) exhibit positive influences on land use efficiency, suggesting that urbanization processes and increased openness may increase carbon emissions in the short term. Infrastructure policies (3321.78, $p < 0.1$) also show positive effects, reflecting the promoting role of infrastructure construction on carbon emissions at the current stage. In contrast, the influences of technological innovation policies (−1.12, $p > 0.05$), population policies (8.76, $p > 0.05$), and economic scale policies (−0.42, $p > 0.05$) on land use efficiency are all non-significant.

Overall, both LMDI decomposition and path analysis results indicate that energy intensity optimization and industrial structure adjustment constitute the dominant pathways for enhancing land green utilization efficiency. The differential responses of cities in the study area to different policies reflect the important influences of city types, development stages, and resource endowments in the policy implementation process. This complex policy response pattern provides important references for optimizing land use policy systems and improving policy implementation precision.

3.3.4 Analysis of policy synergy effects

The improvement of land use efficiency not only stems from the implementation effects of single policies but more deeply embodies the synergistic effects of multi-level policies and the complex institutional interaction mechanisms behind them. Research results indicate that policy coordination is significantly correlated with the enhancement of land green utilization efficiency in border regions, with its action mechanisms involving multiple dimensions such as policy integration, institutional innovation, and governance coordination. The synergistic complementarity between the "National Land Use General Planning (2006–2020)" and the "Greater and Lesser Xing'an Mountains Forest Region Ecological Protection and Economic Transformation Planning (2010–2020)" typically demonstrates the institutional connection mechanism between national strategies and regional planning: the former constructs a rigid spatial control framework through land use regulation and indicator allocation, forming institutional boundaries for regional development; the latter provides flexible implementation paths through differentiated ecological restoration measures, achieving precise implementation of policy objectives. This institutional innovation model of "rigid control + flexible

TABLE 6 Policy effects and driving mechanisms of land green utilization efficiency in border regions (%).

Province	Region	Period	Policy effect contribution (%)							
			Eco	Ind	Pop	Tech	Ene	Urb	Open	Infr
Heilongjiang	Mudanjiang	2010–2015	162.03	−7.85	−1.27	264.38	−387.48	21.91	−461.56	210.97
		2015–2020	−1,538.04	146.15	−855.49	−1876.37	1925.74	546.88	1,319.86	82.99
	Heihe	2010–2015	410.68	−16.33	−25.03	1,131.50	−926.99	414.43	−1,449.20	592.69
		2015–2020	223.32	30.37	−194.05	246.93	−170.19	49.19	−206.44	−12.22
	Jiamusi	2010–2015	551.33	−27.70	−109.44	1,042.32	−890.88	194.76	−1984.95	456.31
		2015–2020	2.27	−124.29	−82.88	−589.55	−278.90	119.74	8.90	190.50
	Jixi	2010–2015	69.15	−8.91	−13.80	256.73	−217.20	5.03	−446.43	187.84
		2015–2020	98.10	1.47	−186.65	−70.65	−105.07	113.97	346.82	−11.25
	Shuangyashan	2010–2015	44.20	15.70	6.57	247.00	−399.28	−50.02	−307.23	448.17
		2015–2020	59.33	−18.40	−95.64	−75.28	−98.21	77.37	−586.90	1.13
	Yichun	2010–2015	78.52	−12.47	−17.20	532.55	−387.35	−25.58	−636.09	451.45
		2015–2020	299.82	91.62	−578.72	−1,389.67	−105.90	145.53	177.73	79.34
	Hegang	2010–2015	40.20	−2.84	−17.23	653.00	−492.46	3.15	606.56	628.66
		2015–2020	216.29	42.46	−155.21	84.13	−246.32	14.17	221.72	23.29
	Daxing'anling	2010–2015	141.46	−8.50	−44.26	998.63	−147.92	3.91	1,112.84	−10.66
		2015–2020	50.84	78.75	−153.79	−611.45	−89.95	−3.01	−2747.11	24.04
Jilin	Yanbian	2010–2015	368.64	27.58	−19.28	−125.39	−382.18	41.15	−223.33	63.40
		2015–2020	−152.77	9.02	−32.90	727.73	194.80	−8.72	109.30	108.42
	Tonghua	2010–2015	316.48	9.70	−323.87	582.37	−448.24	59.22	−211.62	82.09
		2015–2020	−586.59	53.88	−74.45	185.49	469.73	133.77	−502.26	72.46
	Baishan	2010–2015	229.36	12.04	−123.58	520.92	−388.83	32.72	−136.35	29.57
		2015–2020	−135.43	51.56	−39.16	−338.24	263.09	40.55	−161.32	14.00
Inner Mongolia	Hulunbuir	2010–2015	−745.30	−18.86	10.77	−1,350.29	415.19	−18.73	515.42	−243.70
		2015–2020	−132.74	1.93	−52.48	135.35	169.18	13.85	70.66	72.21
	Xing'an League	2010–2015	−312.35	−18.49	4.23	−1,089.03	355.70	−45.42	−1,487.97	−77.18
		2015–2020	3039.63	−669.26	−4321.85	42,903.33	11,178.15	4923.33	−53544.07	6710.74
Liaoning	Dandong	2010–2015	200.49	17.84	−17.58	671.59	−230.12	56.79	−28.01	166.77
		2015–2020	−291.50	48.43	−39.33	−158.67	200.47	59.24	−679.07	61.35

A positive value indicates that the factor promotes carbon emissions growth, while a negative value indicates that the factor inhibits carbon emissions growth.

implementation" provides a governance framework for the overall improvement of land use efficiency in border regions.

Policy synergy effects exhibit significantly differentiated characteristics among cities of different functional types, reflecting the complex interactive relationship between institutional environments and regional characteristics. In ecological cities, policy coordination forms a multi-level protection system centered on ecological values, promoting overall strengthening of ecological functions. The high forestland coverage rate of 96.87% in the Daxing'anling region is not only a result of strict land use control but more an institutional product of the combined effects of ecological compensation mechanisms, environmental governance responsibility systems, and resource monitoring systems. The maintenance of high ecological land proportions in Baishan City (91.34%) and Yichun City (87.80%) benefits from the coordinated advancement of ecological red line control and industrial transformation policies, forming an institutional balance between protection and development. The significant 13.82% reduction in carbon emission intensity in these regions during 2010–2020 not only verifies the synergistic effect of ecological protection policies but also embodies the institutionalization process of the development concept that "lucid waters and lush mountains are invaluable assets."

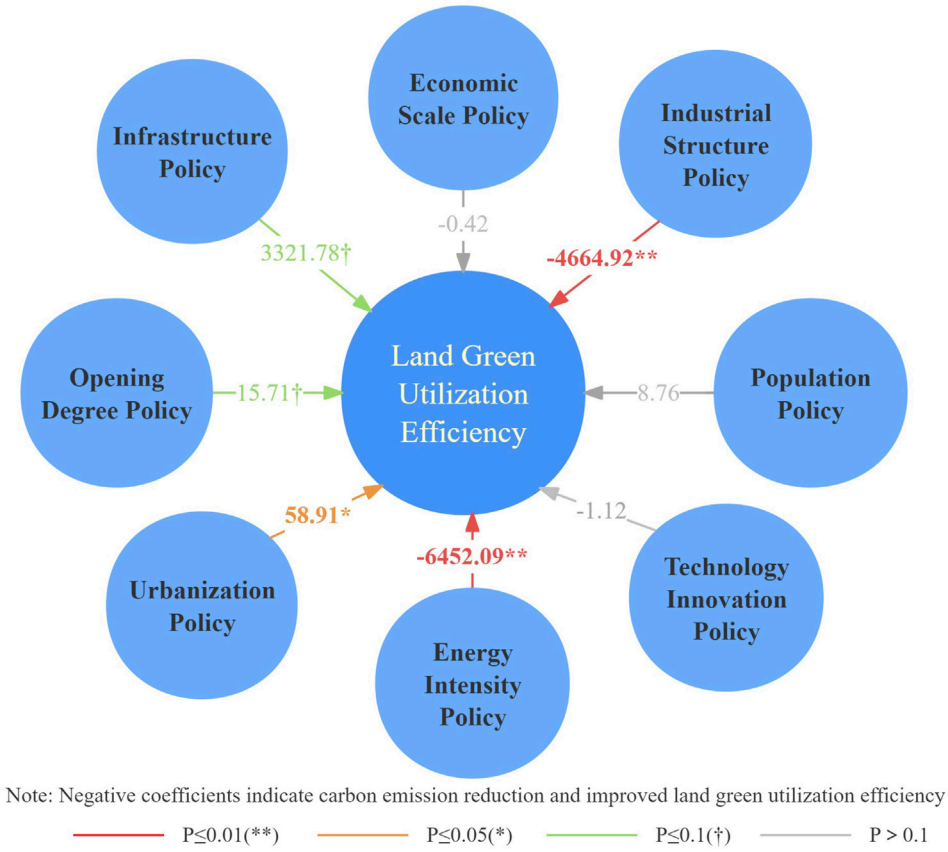


FIGURE 9
Analysis of the impact pathway of land use policy on green utilization efficiency.

Port cities demonstrate typical pathways of policy coordination promoting spatial optimization and functional enhancement. The low carbon emission intensity of this type of city (average 1.54 tons CO_2/10,000 yuan) originates from high coordination between opening policies and spatial planning, forming a functionally intensive spatial organization model centered on ports. Particularly, Hulunbuir City's practice indicates that effective connection between regional opening strategies and industrial layout optimization policies creates a mechanism for coordinated advancement of ecological protection and economic development. This city's achievement of efficient land use while maintaining a relatively high GDP level (117.220 billion yuan) reflects institutional coordination among port economic zone development planning, ecological function zoning, and industrial access policies, displaying the innovation effectiveness of "multiple plans integration" in spatial governance.

Although industrial cities face greater transformation pressure, policy coordination has explored differentiated development paths for them. The relatively low land use efficiency of this type of city (8.14–12.48 tons CO_2/10,000 yuan) is an institutional legacy of historical industrial layout and resource-dependent development models, but the coordinated implementation of industrial structure adjustment (−4664.92, $p < 0.01$) and energy efficiency improvement (−6452.09, $p < 0.05$) policies has begun to reshape their development trajectories. This transformation process is essentially an institutional innovation process of multi-departmental policy coordination—energy transition policies provide technical support, industrial upgrading policies create market space, and spatial restructuring policies optimize resource allocation, forming a complementary and mutually promoting policy combination, exploring a new path of "reduced-quantity development, quality and efficiency improvement" for resource-based cities.

The differentiated performance of policy synergy effects in the study area reveals the deep institutional logic of land use governance. The significant positive correlation between policy coordination degree and land use efficiency indicates that effective land governance requires the construction of multi-level, cross-departmental coordination mechanisms to achieve precise matching of policy objectives, implementation tools, and regional characteristics. This coordination mechanism not only needs complementarity in policy design but also coordination in the execution process and consistency in evaluation feedback, forming an institutional framework of "unified objectives, clear division of labor, and shared responsibilities." The practice of improving land use efficiency in border regions enlightens us that successful regional governance models should fully consider differences in regional functional positioning and development stages, constructing flexible and differentiated policy systems under the national strategic framework, stimulating endogenous dynamics of regional development through institutional innovation, and achieving long-term goals of green high-quality development.

4 Discussion

4.1 Analysis of spatial heterogeneity in land use efficiency

Our findings reveal significant spatial heterogeneity in border region land use efficiency. This heterogeneity manifests at three levels: differences between city types, regional gradient distribution patterns, and spatial clustering characteristics. First, different types of cities show significant efficiency differences. Industrial cities demonstrate relatively low land use efficiency, with carbon emission intensity reaching 8.14–12.48 tons CO_2/10,000 yuan, reflecting land use efficiency issues under traditional industrial development models. Taking Jixi City as an example, its carbon emission intensity reached 8.14 tons CO_2/10,000 yuan in 2020, with land use dominated by industrial land and continuous expansion of construction land (increasing by 127.88 square kilometers during 2010–2020). In contrast, port cities demonstrate higher land use efficiency, with average carbon emission intensity of only 1.54 tons CO_2/10,000 yuan. Exemplified by Hulunbuir, while achieving a GDP of 117.220 billion yuan, it achieved higher utilization efficiency through optimized land use structure.

Second, land use efficiency shows evident regional gradient characteristics. The study area overall shows a "high west-low east" spatial pattern. Western regions, represented by Hulunbuir (9.424 million tons) and Xing'an League (9.456 million tons), demonstrate higher land use efficiency; while eastern regions form a low-efficiency cluster centered on Jixi (46.600 million tons) and Shuangyashan (46.640 million tons). This gradient distribution is closely related to regional industrial layout and development paths: western regions have formed a "forest-grassland composite" high-efficiency utilization model leveraging ecological resource advantages; eastern regions show relatively lower land use efficiency influenced by traditional industrial layout.

Third, spatial clustering effects are significant. Spatial autocorrelation analysis shows that eastern Heilongjiang Province has formed a significant low-efficiency cluster (H-H), with Jixi City ($p = 0.022$), Shuangyashan City ($p = 0.018$), Yichun City ($p = 0.014$), and Hegang City ($p = 0.004$) all showing significant spatial positive correlation. This clustering phenomenon reflects the mutual influence of land use patterns between neighboring regions. In contrast, border regions in Inner Mongolia Autonomous Region maintain relatively independent high-efficiency utilization characteristics, demonstrating spatial heterogeneity.

Several mechanisms contribute to this spatial heterogeneity: the industrial inertia of traditional manufacturing bases, the locational advantages of port cities, variations in ecological resource endowments, and different orientations of regional development strategies (Li et al., 2020). The industrial inertia of traditional industrial bases leads to slow improvement in land use efficiency, reflecting the profound influence of historical development paths; port cities achieve efficient land use leveraging opening-up advantages, demonstrating the importance of locational condition differences; regions rich in ecological resources more easily form efficient land use patterns, indicating the key role of resource endowments in spatial heterogeneity formation; differentiated orientation of regional development strategies further strengthens this spatial heterogeneity.

These findings have important implications for optimizing regional land use policies. Research shows that policy formulation needs to fully recognize spatial heterogeneity characteristics, avoiding "one-size-fits-all" policy implementation models. For low-efficiency clusters, special policy interventions should be adopted to improve land use efficiency. Meanwhile, the demonstration effects of high-efficiency regions should be fully leveraged to promote regional coordinated development through experience promotion and policy synergy. Based on this, when formulating land use optimization strategies, spatial heterogeneity characteristics should be fully considered to implement differentiated policy measures.

4.2 Analysis of land use policy improvement effects

Research results show that land use policies oriented towards industrial transformation and ecological protection significantly improved land use efficiency (Ge and Liu, 2021). Through driving force analysis, energy intensity (−6452.09, $p < 0.05$) and industrial structure (−4664.92, $p < 0.01$) are identified as two key pathways for improving land use efficiency, reflecting the significant effect of industrial transformation policies. During 2015–2020, most regions improved land use efficiency through industrial layout optimization, with particularly significant improvement effects in Xing'an League (−669.26%) and Jiamusi City (−124.29%). This improvement was mainly achieved through two pathways: optimizing land use structure through industrial upgrading and improving intensive land use levels through industrial spatial reorganization.

Ecological cities in the study area achieved steady improvement in land use efficiency through strict land use control and ecological space protection, with carbon emission intensity decreasing by 13.82% during 2010–2020. Energy efficiency policies also showed significant effects, with land use efficiency significantly improving in Heihe City (−926.99%) and Jiamusi City (−890.88%) during 2010–2015. In contrast, urbanization policy (58.91, $p < 0.05$), opening-up policy (15.71, $p < 0.1$), and technological innovation policy (−1.12, $p > 0.05$) had relatively limited effects.

These findings have three important implications for improving land use policies:

First, implement differentiated policies, formulating personalized land use strategies for different types of cities, particularly addressing the efficiency gap between industrial cities (8.14–12.48 tons CO_2/10,000 yuan) and port cities (average 1.54 tons CO_2/10,000 yuan), prioritizing support for low-carbon efficient industrial layout under the framework of the "National Land Use Master Plan (2006–2020)."

Second, adhere to ecological protection priority, drawing on implementation experiences from the "Greater and Lesser Xing'an Mountains Forest Area Ecological Protection and Economic Transformation Planning (2010–2020)," maintaining high forest coverage rates through strict land use control and ecological compensation mechanisms.

Finally, promote intensive and efficient utilization, adopting differentiated measures for different types of cities, particularly

focusing on green transformation of traditional industries in industrial cities to improve output efficiency per unit of land.

4.3 Policy response differences among different types of cities

Different types of cities in the study area show significant differences in their responses to land use policies, reflecting the correlation characteristics between urban functional positioning and policy implementation effects (Qu et al., 2020). These differentiated responses provide important basis for formulating precise land use policies.

Industrial cities (Jixi, Shuangyashan, Hegang) demonstrate evident policy transformation pressure. These cities show relatively low land use efficiency, with carbon emission intensity maintaining high levels of 8.14–12.48 tons CO_2/10,000 yuan. In terms of policy response, these cities prioritize efficiency improvement through technological upgrading, but improvements are slow due to constraints from existing production capacity. Land use structure adjustment faces considerable resistance, as evidenced by Jixi City's conversion of 127.88 square kilometers of cropland to construction land during 2010–2020. Although industrial transformation policy effects gradually emerged during 2015–2020 with some cities showing improved land use efficiency, transformation costs in key areas such as energy structure optimization remain high.

Port cities (Heihe, Mudanjiang, Dandong, Hulunbuir) show stronger policy adaptability. These cities average carbon emission intensity of 1.54 tons CO_2/10,000 yuan, significantly lower than industrial cities. Their policy response mainly manifests in fully utilizing port advantages to develop modern service industries, forming high-efficiency development models. Land use structure shows diversified characteristics, meeting urban development needs while maintaining ecological functions. The implementation of opening-up policies further promoted industrial structure optimization, driving continuous improvement in land use efficiency, exploring a new path of green development for border regions.

Ecological cities (Daxing'anling, Yichun, *etc.*) emphasize protection-oriented policy responses. While maintaining ecological functions, these cities achieved steady improvement in land use efficiency. Through strict implementation of ecological protection policies, these cities generally maintained forest coverage above 80%, and achieved synergy between ecological protection and efficiency improvement through developing eco-friendly industries. Innovative ecological compensation mechanisms effectively balanced protection and development relationships, enabling these cities to achieve the most significant improvement in land use efficiency, with carbon emission intensity decreasing by 13.82% during 2010–2020.

These differentiated policy responses have important implications for optimizing regional land use policies. First, differentiated land policy systems need to be established based on city types: industrial cities should accelerate technological upgrading and promote green transformation of traditional industries; port cities can further leverage service industry advantages to explore high-efficiency, low-carbon development models; ecological cities need to strengthen institutional guarantees for ecological protection and innovate green development paths. Second, policy synergy should be emphasized, promoting complementary advantages and linked development between different types of cities. Finally, dynamic assessment mechanisms should be established to timely adjust policy implementation directions and continuously improve policy execution efficiency. Future policy optimization should focus on policy specificity and synergy, flexibly adjusting policy tool combinations according to city characteristics while strengthening policy coordination between cities to construct new patterns of regional coordinated development. This will not only help improve individual cities' land use efficiency but also promote overall sustainable development in border regions.

4.4 Theoretical implications

Based on empirical analysis of China's northeastern border region, this study develops a theoretical framework of 'border location-functional differentiation-efficiency coupling', systematically explaining the formation mechanisms of land use efficiency in border regions (He et al., 2024). The innovation of this theoretical framework is reflected in three aspects:

First, the research breaks through the limitations of traditional land use theory that views border regions as homogeneous entities, constructing a differentiated analysis framework based on location characteristics and functional positioning. Empirical research finds that border regions' land use efficiency is closely related to their development stages and locational conditions. This finding enriches the theoretical connotation of border region land use efficiency, providing new perspectives for understanding regional differences.

Second, the study constructs a multi-dimensional theoretical model of 'policy tools-city types-efficiency performance'. This model breaks through traditional single policy evaluation models, systematically revealing differentiated response mechanisms of different types of cities to land policies. Research shows that industrial cities have relatively low land use efficiency due to existing production capacity constraints; port cities achieve efficiency improvements through regional cooperation; ecological cities form a 'protection priority-efficiency synergy' development model. This theoretical model provides a new analytical framework for understanding policy effects.

Third, the study developed a "multi-center-networked" regional land use efficiency theory. By introducing dimensions of spatial heterogeneity and functional complementarity, the research found that border regions have formed a networked development pattern with port cities as nodes and industrial chains as links. In the policy transmission process, the study identified a "demonstration effect-diffusion mechanism-collaborative improvement" spatial coupling path: low-efficiency areas become policy implementation focus areas through industrial linkages; high-efficiency areas promote overall regional efficiency improvement through demonstration effects; and different types of cities form functional complementary mechanisms in policy responses.

These theoretical innovations have important implications for land use research: they construct a comprehensive theoretical framework for studying land use efficiency in border regions; develop a policy effect evaluation theory based on city types; and

enrich regional collaborative development theory. Future research could deepen theoretical innovation in the following directions: exploring long-term evolutionary mechanisms of land use efficiency in border regions; studying cross-border regional policy coordination mechanisms; and analyzing adaptation mechanisms of land use efficiency in border regions under climate change.

4.5 Policy implications

Spatial heterogeneity characteristics require the formulation of differentiated policy systems. Research shows that land use efficiency varies significantly among different types of cities, with industrial cities' carbon emission intensity (8.14–12.48 tons/10,000 yuan) significantly higher than that of port cities (average 1.54 tons/10,000 yuan), consistent with international experience. Fekete and Priesmeier (2021), in their study of the US-Mexico border region, found that coordination between cross-border resource management and environmental risk prevention is crucial. Therefore, traditional "one-size-fits-all" policies can hardly adapt to regional development needs, and precise land policies should be formulated based on urban functional positioning. For industrial cities, research results indicate that this type of city has the highest carbon emission intensity and the smallest improvement margin, so targeted technological innovation incentive measures should be implemented, such as: establishing special technological transformation funds, providing over 50% financial support for energy efficiency improvement projects; establishing a differentiated emission rights trading system, setting stricter emission reduction targets for high-carbon intensity industries; developing tax incentive policies for high-energy-consuming enterprises, such as reducing corporate income tax by 30% for enterprises achieving energy consumption reductions of more than 15%.

Industrial transformation and energy structure optimization are key pathways for enhancing land use efficiency. Empirical analysis shows that energy intensity (−6452.09, $p < 0.05$) and industrial structure (−4664.92, $p < 0.01$) are the main factors affecting land use efficiency. Qian and Luo's (2024) research found that digital transformation significantly enhances land use efficiency in resource-based cities. This means that policy focus should be placed on promoting traditional industry upgrading and optimizing energy utilization structures. Especially for industrial cities, carbon emission intensity in land use processes needs to be reduced through technological innovation and clean energy promotion. Simultaneously, cultivation of emerging industries should be accelerated to promote industrial structure transformation toward low-carbon, high-efficiency directions. For port cities, data shows that this type of city already has relatively high land use efficiency. We recommend supporting their further development of service industry advantages while promoting these experiences to other types of cities: establishing a service industry development experience sharing platform in border regions, regularly organizing technical exchanges between different types of cities; strengthening intelligent upgrading of port infrastructure, such as digital customs clearance systems, to improve land use efficiency; policy support should not simply favor port cities while neglecting industrial cities, but should allocate resources according to efficiency improvement potential.

Establishing regional coordinated development mechanisms is crucial. Research finds that land use efficiency exhibits significant spatial clustering characteristics, with the eastern region forming a low-efficiency clustering area centered on Jixi (46.600 million tons) and Shuangyashan (46.640 million tons). Wang and Xiao (2023), in their study of the Laotian border, found that the degree of cross-border cooperation affects land use efficiency. Turner and Pham (2015), in their study of the northern Vietnamese border, verified the importance of regional development platforms. This spatial pattern indicates the need to establish cross-regional policy coordination mechanisms, leveraging the demonstration and driving role of high-efficiency regions. For ecological cities, we recommend developing economic activities consistent with ecological positioning on the basis of ecological protection: developing ecological value transformation mechanisms, such as establishing carbon sink trading platforms to convert ecological protection into economic benefits; designing ecological tourism franchise auction systems to balance development and protection; formulating quantitative ecological service industry development targets, such as increasing the proportion of service industries to 60% by 2030.

Policy support for green development needs further strengthening. Empirical research shows that coordination between environmental policies and economic policies is crucial for enhancing land use efficiency. Angelstam et al. (2020) study of Finnish-Russian border experiences indicates that differences in environmental policies can lead to significant efficiency differences. This requires improving green finance policies to support enterprise technological transformation; innovating land management systems to enhance resource allocation efficiency; improving environmental regulatory systems to strictly implement ecological red lines. Finally, strengthening international cooperation and experience exchange is of great significance. Bazarov et al. (2021) comparative study of China-Russia border regions found significant differences in land use methods between the two countries, providing important references for policy optimization. The above recommendations are based on empirical data analysis of different types of cities, proposing differentiated measures targeting their respective characteristics, rather than simply favoring one type of city. Implementation of these policies needs to consider local specific conditions and establish dynamic evaluation mechanisms, adjusting policy tool combinations in a timely manner to achieve continuous improvement in land use efficiency in border regions.

4.6 Research limitations and future directions

4.6.1 Methodological and data limitations

The current research faces several methodological limitations worth considering. First, although the study establishes significant correlation between policy implementation and land use efficiency, causal inference remains challenging. Regression-based path analysis, while helpful in revealing relationships, relies on several key assumptions that may not be fully satisfied in complex socioeconomic systems. Path analysis assumes linear relationships between variables, but in reality, there may be non-linear relationships or threshold effects between policies and land use

efficiency, for example, certain policy measures may need to reach specific intensities before effects become apparent. The model also assumes that causal flow is unidirectional (from policy to efficiency), while ignoring possible reverse causality (high-efficiency regions may more easily implement certain policies) or circular causal relationships. Additionally, although we attempt to include various policy factors, the possibility of omitted variable bias cannot be completely ruled out—certain unmeasured factors may simultaneously affect policy implementation and efficiency performance, leading to biased estimation results.

Path analysis also assumes that error terms are independent of each other, but in regional economic research, error terms from different equations may be correlated, especially when multiple factors are affected by common external shocks. At the same time, the model assumes that observations between different cities are mutually independent, while spatial dependencies may exist among border region cities, which is why we combine the use of spatial analysis methods. Nevertheless, spatial analysis methods themselves also face limitations, especially Moran's I and BiLISA, which, while effective in identifying spatial clustering patterns, are sensitive to outliers and boundary definitions, and assume stability of spatial relationships, which may not hold true in the diverse geographical environments of the study area. Finally, the specific specification of the path model (assumed causal chains between variables) has a certain subjectivity, and different model specifications may lead to different estimation results. We constructed the current model based on theoretical frameworks but cannot exclude other possible causal pathways. Future research could adopt geographically weighted regression or spatial panel models to more comprehensively capture spatial heterogeneity.

The LMDI decomposition method, though powerful in identifying driving factors, assumes that various factors are independent of each other, while in reality, these factors may be interrelated in complex ways. For example, technological progress and industrial structure optimization often occur simultaneously and influence each other, making their independent effects difficult to determine. This method also struggles to capture dynamic feedback mechanisms between variables, such as how decreases in energy intensity might, in turn, affect industrial structure; these complex interactions are difficult to fully present in a static decomposition framework.

The carbon emission data used in this study has inherent uncertainties. Although calculations follow IPCC guidelines and national emission factors, carbon accounting at the city level in border regions faces unique challenges. Cross-border economic activities may lead to carbon leakage issues, with emissions belonging to local production potentially partially transferred to the other side of the border. Moreover, the availability and quality of activity data from different regions and sectors vary, potentially affecting the comparability of efficiency assessments. While the land use classification method is based on the CLCD dataset with 80% accuracy, it inevitably includes classification errors. Reclassifying the original nine land cover types into six types may lead to information loss, especially in complex landscape transition zones such as urban-rural interfaces. Additionally, the 30-m spatial resolution may not fully capture fine land use changes in urban areas, potentially affecting the accuracy of construction land assessment in rapidly developing port cities.

4.6.2 Research design limitations

This study focuses on 14 border cities in northeastern China, which, while providing a comprehensive perspective for this specific region, limits the generalizability of research findings to other border regions of China. The southwestern border (adjacent to Vietnam, Laos, and Myanmar) or northwestern border (adjacent to Central Asian countries) regions of China operate under different geographical, climatic, and socioeconomic conditions, potentially leading to different policy response patterns. The 2010–2020 study period, while capturing important policy implementation phases, may be insufficient to fully observe the long-term effects of ecological protection policies, which typically take decades to fully manifest. Moreover, this period coincides with specific macroeconomic conditions and national policy priorities, which may not persist in the future, potentially affecting the temporal stability of identified relationships.

An important limitation of this study is the assumption of relatively uniform policy implementation within similar city types. In reality, the intensity and effectiveness of policy implementation may vary significantly due to differences in local governance capabilities, fiscal resources, and socioeconomic conditions. For example, ecological protection policies may be implemented with varying degrees of stringency in different ecological cities, leading to changes in efficiency responses not captured in the type analysis. Significant seasonal variations in the Northeast region represent another limitation. winter heating demands significantly increase energy consumption and carbon emissions, while summer growing seasons enhance carbon absorption. These seasonal effects are not decomposed in the current annual analysis, potentially affecting land use efficiency assessment, especially when comparing regions with different seasonal patterns.

4.6.3 Application generalization and future prospects

Applying the results of this study to other regions requires careful consideration of contextual factors. The research findings may be most applicable to border regions with similar development stages, industrial structures, and geographical characteristics to northeastern China. For example, findings regarding industrial city transformation challenges may apply to resource-based border regions facing similar industrial transformation pressures in the Russian Far East, parts of Eastern Europe, or Central Asia. The policy effects identified by the research, particularly the significant impacts of energy intensity (−6452.09, $p < 0.05$) and industrial structure (−4664.92, $p < 0.01$) on land use efficiency, may apply to similar regions. However, application should consider local conditions, including resource endowments, economic development stages, institutional environments, and cross-border relationships. Regions with different industrial histories, economic structures, or relationships with neighboring countries may exhibit different policy response patterns.

Based on these limitations, future research could develop in several promising directions: First, future research could further expand from path analysis to adopting complete structural equation models (SEM), quasi-experimental designs, or synthetic control methods to strengthen causal inference in policy effect assessment. These methods help isolate policy impacts from

other confounding factors, providing more robust evidence for policy effectiveness. Second, developing multi-dimensional evaluation systems incorporating additional environmental indicators beyond carbon emissions, such as water pollution, soil degradation, and biodiversity loss, would provide more comprehensive assessments of land green utilization efficiency. Third, extending the time series range would better capture the cumulative effects of ecological protection policies and reveal potential non-linear relationships between policy implementation and efficiency improvement. Fourth, strengthening cross-border comparative analysis, especially comparisons between Chinese border cities and corresponding cities in neighboring countries, would provide valuable insights into how different governance systems affect land use efficiency in geographically connected regions. Finally, incorporating climate change adaptation into the analytical framework would enhance understanding of how land use efficiency in border regions responds to increasing climate change, which is particularly important for cold-region borders that may experience significant climate-related changes. These future research directions would not only address the limitations of the current study but also provide a more comprehensive understanding of how land use policies in diverse border regions globally can effectively promote sustainable development.

5 Conclusion

This study systematically analyzes land use policy implementation effects and land green utilization efficiency in northeastern China's border regions. Our main findings include: Land use patterns show significant spatial heterogeneity. Industrial cities demonstrate lower land green utilization efficiency (8.14–12.48 tons CO_2/10,000 yuan). In contrast, port cities maintain higher utilization efficiency (average 1.54 tons CO_2/10,000 yuan). These research findings are highly consistent with international experiences: Angelstam et al. (2020)'s research verified spatial heterogeneity of land use efficiency in border regions, Turner and Pham (2015)'s research supports the development model of port cities, and Bazarov et al. (2021)'s comparative study of China-Russia borders confirmed the differences in policy implementation effects. Land use policies play an important role in improving land green utilization efficiency. The research found that land use policies oriented towards industrial transformation and ecological protection significantly improved land use efficiency, with energy intensity (-6452.09, $p < 0.05$) and industrial structure (-4664.92, $p < 0.01$) as key inhibiting factors. Different types of cities show significant differences in their responses to land use policies: industrial cities focus on improving efficiency through technological upgrading, but improvements are slow due to existing production capacity constraints; port cities leverage service industry advantages to form relatively efficient land use patterns; ecological cities achieve continuous improvement in land use efficiency through strict ecological protection policies and industrial ecological transformation.

This study achieved innovative results in theoretical, methodological, and practical aspects. At the theoretical level, it proposed an innovative framework of 'border location-functional differentiation-efficiency coupling', developed a policy effect theory based on city types, and constructed a multi-center networked regional development theory. At the methodological level, it innovatively constructed a multi-level efficiency assessment system, developed policy effect assessment methods based on city types, and proposed spatial coupling degree measurement methods for policy coordination. At the practical level, it systematically revealed the type difference characteristics of land use efficiency in border regions, identified different policy response patterns across city types, and provided scientific basis for formulating differentiated land use policies.

Future research should focus on the following directions: First, in the context of digital transformation, exploring the influence mechanisms of smart city construction on land use efficiency in border regions, especially how digital technologies improve green utilization efficiency through optimizing land resource allocation and management models; Second, in response to challenges brought by climate change, studying adaptive strategies for land use in border regions, particularly focusing on differentiated impacts of extreme weather events on land use efficiency across different types of cities; Third, strengthening research on long-term effect assessment of land use policies, optimization of policy synergy, and cross-border regional policy coordination mechanisms. These research directions will not only deepen theoretical understanding of land green utilization efficiency in border regions but also provide scientific basis for sustainable land development under the challenges of digital transformation and climate change.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: The data analyzed in this study are primarily from publicly available repositories: For land use data, the China Land Cover Dataset (CLCD) is accessible through the Earth Big Data Science Engineering Data Sharing Platform of the Chinese Academy of Sciences, which requires login via China Science and Technology Cloud Pass system (http://data.casearth.cn). For carbon emission and socioeconomic data, we used publicly available statistical yearbooks including China Energy Statistical Yearbook, China Industry Statistical Yearbook (both available from the National Bureau of Statistics), and Provincial Statistical Yearbooks (Heilongjiang, Jilin, Liaoning, Inner Mongolia) accessible through provincial statistical bureaus' websites. The processed datasets and analysis results generated during this study are available from the corresponding author upon reasonable request.

Ethics statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and the institutional requirements.

Author contributions

XF: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Visualization, Writing – original draft. LZ: Funding acquisition, Project administration, Supervision, Validation, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Hasan Bilgehan Makineci,
Konya Technical University, Türkiye
Jie Zhao,
Linyi University, China
Junyi Chen,
Kunming University of Science and Technology, China
Shaohua Zhang,
Yunnan Normal University, China

*CORRESPONDENCE
Yu Lin,
2022165107@stu.sdjzu.edu.cn
Xuya Zhang,
zhangxy@caep.org.cn

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Revealing the impact of urbanization on landscape ecological risk: a case study of the lower reaches of the Yangtze River, China

Yatong Guo[1], Wei Wang[2], Xitang Zhang[3], Chun Liu[4,5], Youxiao Wang[6], Wenqi Chen[6], Xucong Wan[6], Xinyu Zhang[6], Yu Lin[6]*, Xuya Zhang[7]* and Yaohui Liu[5,6]

[1]Shandong Communication Administration, Jinan, China, [2]Jinan Emergency Management Technical Service Center, Jinan, China, [3]Shandong Sports Lottery Administration Center, Jinan, China, [4]School of Computer Science and Technology, Chongqing University of Posts and Telecommunications, Chongqing, China, [5]Chongqing Big Data Collaborative Innovation Center, Chongqing, China, [6]School of Surveying and Geo-Informatics, Shandong Jianzhu University, Jinan, China, [7]Chinese Academy of Environmental Planning, Beijing, China

Cities along the lower reaches of the Yangtze River (CLRYR) have highlighted human-land conflicts with their rapid urban expansion. Fully assessing the landscape ecological risk (LER) of the region and its response in the context of urbanization is of great significance for regional sustainable development. To address this issue, this study explores the spatiotemporal evolution of LER in CLRYR from the perspective of "production-living-ecological" space (PLES), and evaluates the decoupling status of urbanization processes and LER in different cities, aiming to provide scientific reference for policymakers. The results indicate that the mean LER value increased from 0.2508 in 2000 to 0.2573 in 2020, with an increase in LER fluctuations. From a spatial distribution perspective, the proportion of medium risk is the highest, consistently above 30%; The lowest risk proportion is less than 3%. From 2000 to 2020, the Moran's I values for LER in the CLRYR were 0.4773, 0.4014, 0.3326, 0.2462, and 0.4779, respectively, indicating a significant positive correlation. Through decoupling model analysis, it was found that only Wuxi, Suzhou, and Changzhou achieved strong decoupling between economic growth and LER between 2010 and 2020. The findings of this study provide an important scientific basis for a deeper understanding of the complex relationship between urbanization and ecological risks in CLRYR and also lay a theoretical foundation for promoting the implementation of green development strategies in the region.

KEYWORDS

landscape ecological risk, urbanization, Tapio decoupling model, spatial autocorrelation analysis, standard deviation ellipse

1 Introduction

In recent years, there has been a significant surge in the urban population and the proliferation of cities and towns, concurrent with rapid economic development (China, 1994; Yi et al., 2021; Yu, 2021). Urbanization has conferred numerous benefits upon populations, including enhanced material living standards and the fulfillment of diverse cultural needs (Zhu et al., 2023). However, the traditional urbanization model in its early stages was predominantly fueled by land finance and industrialization. This approach led to an irrational spatial distribution and inefficient utilization of regional land, placing significant pressure on ecosystems and giving rise to numerous associated risks, both direct and indirect (Li, Zhou, and Yi, 2022; Xu et al., 2021). Effective avoidance, active adaptation, and comprehensive management of ecological risks first require a scientific and accurate assessment of ecological risks in a specific region (Cao and Shen, 1991).

Landscape ecological risk (LER) assessment can reveal the potential adverse outcomes resulting from the interaction between landscape patterns and ecological processes under the influence of natural or human factors (Zhang et al., 2024; Qian et al., 2022). In recent years, the means of LER assessment have been diversified, and the results are of great practical significance for the development of risk mitigation strategies and the allocation of limited resources, which has become one of the hot topics in ecology and geography (Peng et al., 2015; Fagiewicz, 2014). Special attention should be paid to the fact that land, as a macro-representation of the surface landscape, carries the dual importance of human activities and ecosystem functions (Xu and Yang, 2024). LER assessment, grounded in landscape patterns, identifies land use change as the causal factor and constructs a regional-scale LER model using landscape pattern indexes (Du et al., 2023; Li et al., 2020; Wang W. et al., 2023; Zeng et al., 2022). This approach can effectively illustrate the influences of anthropogenic disturbances on landscape structure, functions, and processes within a specific region, providing a comprehensive evaluation of LER across multiple scales. Ai et al. (2022), Wang et al. (2021a), Ju et al. (2021) evaluated LER and gave possible corresponding measures for land use in different character areas of islands, nature reserves, and peninsulas, respectively. Gao et al. (2022) used the PLUS model to simulate land use in Nanjing 2025 under multiple scenarios and assessed LER under multiple scenarios through a comprehensive indicator system.

To address spatial incoherence in land use, China introduced the concept in 2012 of creating intensive and efficient production areas, suitable living environments, and ecologically pristine spaces characterized by scenic landscapes (Wang et al., 2022; Huang et al., 2024)—termed as "production-living-ecological" space (PLES). This initiative aims to achieve harmonious coexistence between humanity and nature (Wu et al., 2021). The introduction of the PLES concept, structured around distinct land use functions, has spurred the emergence of related research findings (Zhang and Li, 2022; Liu C. et al., 2024; Zhang, Zheng, and Qin, 2023; Zhang S. et al., 2022). Wang J. et al. (2023), Zhang R. et al. (2022) analyzed land pattern changes and their drivers from a PLES perspective. Wang et al. (2022) assessed the spatiotemporal dynamics of ecosystem service values in the Dongliao Basin and revealed the mechanisms of its response to changes in PLES. However, research integrating LER with PLES perspectives remains relatively sparse. In contrast to studies focusing solely on land use types, an approach rooted in PLES can effectively demonstrate the holistic nature and distinctions among production, living, and ecological spaces, thereby enhancing the spatial portrayal of land use functionalities (Liang et al., 2022).

During urbanization, there exists a reciprocal influence and constraint between urban development and the ecological environment (Zhao et al., 2017). On one hand, various pollutants generated during urbanization can damage the ecological environment, leading to ecological challenges. Conversely, the degradation of the ecological environment can impede the pace of urbanization. The harmonious development of urbanization and the ecological environment is crucial for achieving sustainable development in cities and regions. Presently, research predominantly concentrates on LER conditions and their spatiotemporal variations in specific locales such as watersheds, provinces, and mining areas. However, there is limited exploration regarding the specific interplay between these factors and urban development. Thus, the adoption of the "decoupling" theory aids in precisely describing the correlation between urbanization levels and LER. Coined initially by the Organization for Economic Co-operation and Development (OECD) towards the close of the previous century, the "decoupling" concept delineates the process of disentangling economic growth from environmental stresses (Kong et al., 2021). In 2005, Tapio expanded on the concept of "decoupling elasticity" derived from decoupling theory, advancing an elasticity decoupling model (Tapio, 2005). Compared with the OECD decoupling model, Tapio's theory is characterized by its enhanced objectivity and accuracy. It underscores absolute decoupling scenarios and further distinguishes between weak and strong decoupling scenarios depending on the elasticity coefficients and accordingly (Yang and Li, 2023).

The cities along the lower reaches of the Yangtze River (CLRYR) are located in the central core of the Yangtze River Delta, renowned as China's most economically dynamic region and a prominent example of rapid urbanization (Tan et al., 2021). Against the background of rapid socio-economic development, the region faces significant challenges of landscape fragmentation and escalating human-land conflicts (Yang et al., 2022). Owing to their distinctive geographical placement, the ecological condition of these cities exerts a direct impact on the ecosystem of the Yangtze River Basin. Therefore, CLRYR was chosen as the study area to quantitatively evaluate its LER and comprehensively investigate the correlation between urbanization levels and LER. These findings will hold significant practical implications for enhancing land resource management, safeguarding ecosystem stability and security, and fostering harmonious coexistence between humanity and nature. They will serve as a scientific foundation for pursuing sustainable development in the CLRYR region and provide a theoretical framework for exploring the interplay between societal development and natural ecosystems.

The subsequent structure of this study unfolds as follows: Section 2 provides a brief overview of the current situation and the supporting data within the study area. Section 3 outlines the methodological framework and theoretical principles that underpin this study. Section 4 presents the analysis of the results, offering a comprehensive assessment of the functional spatial changes in the

CLRYR area from the perspective of PLES, alongside an exploration of the spatiotemporal dynamics of LER. This section also examines the region's urbanization development and analyzes its interconnected relationship with LER. In Section 5, suggestions for the development of CLRYR were proposed and the limitations of this study were discussed. Finally, Section 6 summarizes the main findings of this study.

2 Study area and data sources

2.1 Study area

The Yangtze River, the largest river in China, has a total length of over 6,300 km. Originating from Tanggula Mountain in Qinghai Province, the mainstream flows from west to east through 11 provincial administrative regions and finally flows into the East China Sea on Chongming Island in Shanghai (Liu L. et al., 2023). The main channel of the Yangtze River flows from west to east, encompassing numerous tributaries and characterized by distinctive geographical features and considerable developmental opportunities (Kong et al., 2019). The Yangtze River region encompasses three major urban agglomerations in China, with particular emphasis on the downstream Yangtze River Delta region, which holds a crucial role in China's economic advancement. Known for its high economic activity, urbanization rate, and innovation capacity, it ranks among the nation's leaders in these aspects and occupies a strategic position in China's comprehensive modernization and opening-up efforts. Nevertheless, the region grapples with significant challenges related to land use conflicts, and the ecological health directly impacts the broader Yangtze River Basin ecosystem.

Therefore, this study mainly focuses on cities in the CLRYR region covered by the Yangtze River Delta (as shown in Figure 1), including Shanghai City; Anqing, Chizhou, Tongling, Ma'anshan, and Wuhu in Anhui Province; as well as Nanjing, Zhenjiang, Yangzhou, Taizhou, Changzhou, Nantong, Wuxi, and Suzhou in Jiangsu Province. The downstream area features a blend of hills and plains that are conducive to agriculture and habitation. It is the longest and most mature area for land development and utilization in the Yangtze River Basin.

2.2 Data sources

The research object of this study is 14 cities located in CLRYR and the research period is from 2000 to 2020. This study mainly relies on land use data and statistical yearbook data for analysis. The land use data, which is the basis for constructing the LER model, is derived from the China multi-period land use dataset (CNLUCC) from the resource and environmental science data platform (http://www.resdc.cn/). This dataset employs a two-level classification system. At the first level, it categorizes land into six types: cropland, forest, grassland, water, built-up land, and unused land. Subsequently, the second level refines these categories into 25 types based on the initial classifications. Based on the secondary classification criteria and the differentiation between land use functions and land use types, drawing on existing research results (Deng and Yang, 2021; Li and Wu, 2022), a connection table between the PLES structure and land use types is established (as shown in Table 1). To investigate the spatiotemporal dynamics of LER amidst urbanization, this study references prior research and data comprehensiveness to select pertinent urbanization assessment indicators. These indicators are chosen based on the four principal dimensions of population, spatial configuration, economic development, and societal factors (Yi et al., 2024; Geng and Han, 2020). The statistical yearbook data spanning 2000 to 2020 from each city constitute crucial foundational data for constructing this indicator framework.

3 Methodology

The technical approach comprises several key components, outlined in Figure 2. Firstly, based on the reclassification tool in ArcGIS software, land use data is reclassified according to three functional categories: production, living, and ecological spaces. This facilitates analysis of the spatiotemporal evolution and transitions among different functional land types. Secondly, a grid-based approach divides the study area into equal-sized fishing net units, enabling the classification of land use data into units for risk assessment. The landscape ecological risk index (LERI) for each unit is computed using an assessment model, and the spatial distribution of LER across the CLRYR area from 2000 to 2020 is derived through kriging interpolation. Concurrently, specific spatiotemporal assessments of LER within each city are conducted using mean statistics and Moran's I. Subsequently, multidimensional indicators are selected to construct an urbanization assessment system for evaluating urbanization levels. Moreover, the migration of the center of gravity and standard deviation ellipse (SDE) are employed to illustrate changes in the urbanization direction of CLRYR. Finally, by analyzing the ratio of LERI change rates to urbanization change rates, the study assesses the decoupling relationship between urbanization and ecosystems, proposing targeted ecological protection measures accordingly.

3.1 LER assessment model

The LER value quantifies the resistance of an area to external disturbances. A higher LER indicates lower resistance to disturbances, and conversely. According to the principles of landscape ecology, the minimum unit for evaluation should be 2–5 times the average patch area. Considering the average patch size and characteristics of the study area, the CLRYR region was divided into 4,029 risk units using the ArcMap fishing net tool, with each unit measuring 5 km × 5km (Li S. et al., 2024). Finally, using Fragstats and Excel software, the LER assessment model was constructed based on the area ratio of land use types, landscape interference index, and landscape vulnerability index (as shown in Equation 1) (Kang et al., 2024):

$$LERI_k = \sum_{i=1}^{n} \frac{A_{ki}}{A_k} \cdot I_i \cdot V_i \quad (1)$$

where A_{ki} represents the total area of the i-th landscape type in the k-th risk unit, and A_k is the total area of the k-th risk unit; The

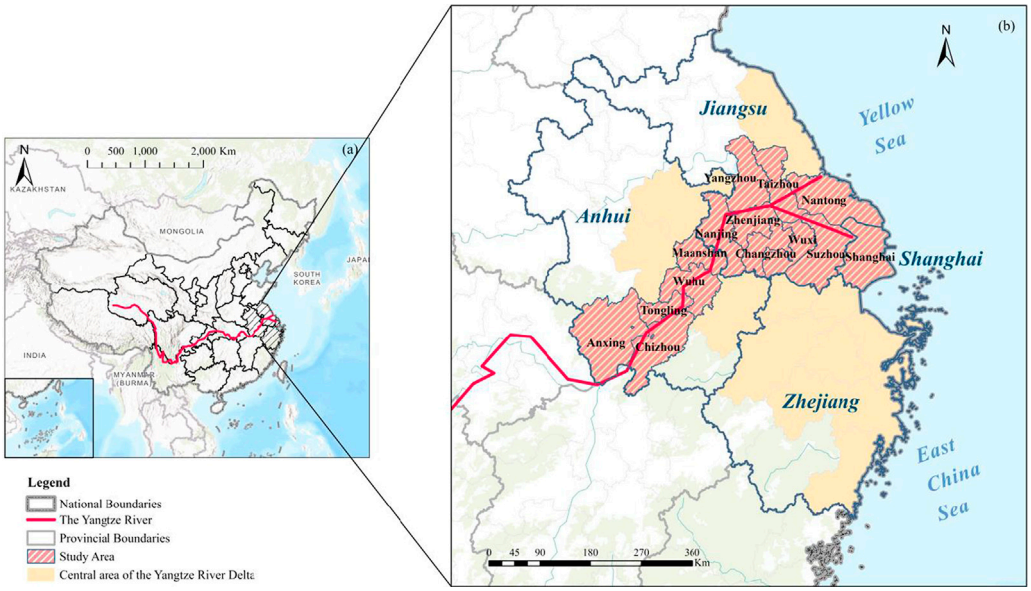


FIGURE 1
The geographical location of the study area.

TABLE 1 PLES classification system of the CLRYR.

Primary classification	Secondary classification	Land use type
Production space	Agricultural production space	Paddy fields, dry land
	Industrial production space	Other construction sites such as factories, mines, quarriesetc.
Living space	Urban living space	Townsite
	Rural living space	Rural settlements
Ecological space	Forest ecological space	Woodland, shrubland, open woodland, and other woodland
	Grassland ecological space	High-cover grassland, medium-cover grassland, and low-cover grassland
	Water ecological space	River canals, lakes, reservoirs and ponds, permanent glacial snowfields, mudflats, and beaches
	Other ecological spaces	Unutilized land such as marshland

calculation formulas for the landscape interference index (I_i) and landscape vulnerability index (V_i) are as follows.

3.1.1 Landscape interference index (I_i)

The calculation principle of landscape interference index can be found in Equations 2–5:

$$I_i = a \cdot F_i + b \cdot S_i + c \cdot D_i \quad (2)$$

$$F_i = \frac{n_i}{A_i} \quad (3)$$

$$S_i = \frac{\sqrt{\frac{n_i}{A}}}{2P_i} \quad (4)$$

$$D_i = \frac{M_i + N_i + 2P_i}{4} \quad (5)$$

Where a, b, and c are the weights of the landscape fragmentation index (F_i), landscape separation index (S_i), and landscape dominance index (D_i). Based on previous research results (Ran et al., 2022; Li et al., 2020), the weights a, b, and c are set to 0.5, 0.3, and 0.2, respectively; n_i is the number of i type patches; A_i represents the total area of the i type of landscape; A is the total area; P_i is the ratio of i type patch area to total area; M_i represents the ratio of risk units in the i type of landscape to the total number of risk units; N_i is the ratio of the number of patches of type i to the total number of patches (Li, et al., 2024; Wang et al., 2023).

3.1.2 Landscape vulnerability index (V_i)

The landscape vulnerability index reflects the sensitivity of different landscape types to external disturbances, where higher values indicate greater vulnerability. Referring to the results of existing studies (Du et al., 2023), this study assigns weights to eight land use types, which are urban living space, rural living space, forest ecological space, grassland ecological space, agricultural production space, water ecological space, industrial production space, and other ecological space in ascending order. By normalizing the weights using the arctangent function, the

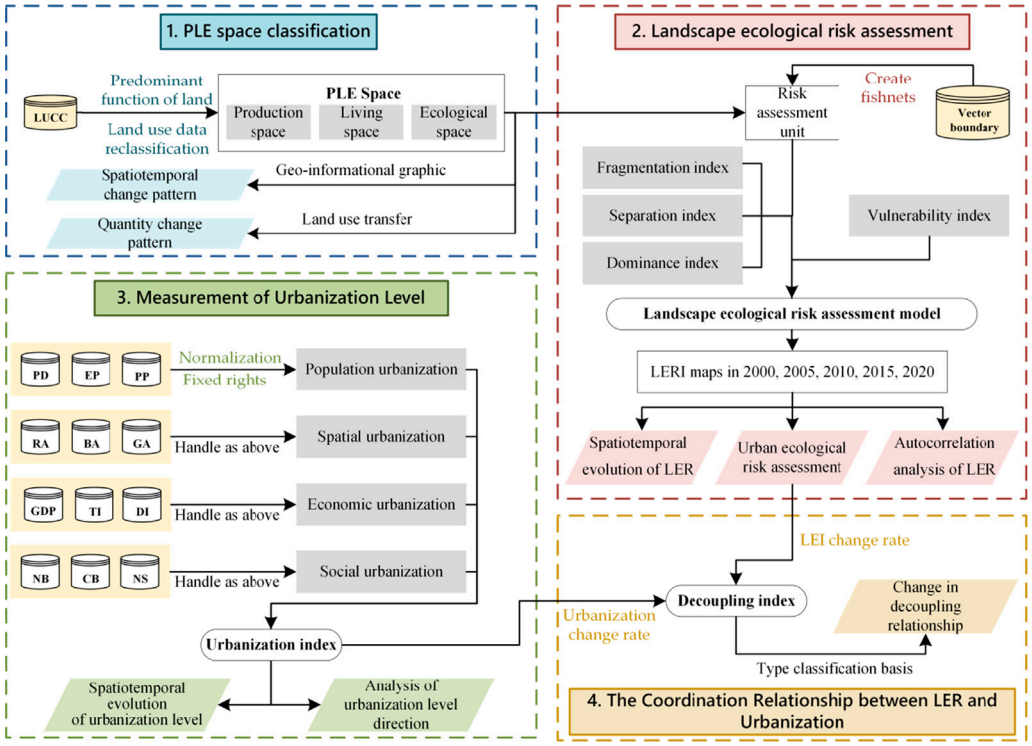


FIGURE 2
The workflow of this study.

vulnerability indexes were obtained as 0.5000, 0.7048, 0.7952, 0.8440, 0.8743, 0.8949, 0.9097, and 0.9208, respectively. The calculation principle of landscape vulnerability index can be found in Equation 6:

$$V_i = \frac{2\,arctan(x_i)}{\pi} \tag{6}$$

Where x_i represents the weight of each landscape type.

3.2 Urbanization level evaluation system

The entropy value method provides an objective approach by calculating entropy weights for each indicator, thereby effectively quantifying and assessing the significance and impact of various indicators (Wang et al., 2021b). Hence, this study adopts Shannon's entropy concept to develop an urbanization index system tailored for the CLRYR area, with the resulting weights of each index presented in Table 2. Given that the selected indicators vary in scale and units but are all positively oriented, standardization is necessary before weight calculation. The standardized formula is shown in Equation 7.

$$x_{ij}^{'} = \frac{x_{ij} - min\left(x_{ij}\right)}{max\left(x_{ij}\right) - min\left(x_{ij}\right)} \tag{7}$$

Where x_{ij} is the j-th ($j = 1, 2, 3, \ldots, m$) evaluation index value for the i-th ($i = 1, 2, 3, \ldots, n$) evaluation object; $x_{ij}^{'}$ represents the corresponding positive normalized value; $max\,(x_{ij})$ and min (x_{ij}) are the corresponding maximum and minimum values, respectively.

To avoid extreme values of the weights, such as 0 and 1, the normalized indicator values are shifted, i.e., the overall normalized value is made to add 0.0001 before the subsequent weights are calculated (as shown in Equation 8):

$$x_{ij}^{''} = x_{ij}^{'} + 0.0001 \tag{8}$$

Calculate the proportion of the j-th index in the i-th year (as shown in Equation 9):

$$p_{ij} = \frac{x_{ij}^{''}}{\sum_{i=1}^{n} x_{ij}^{''}} \tag{9}$$

Calculate the information entropy of the j-th index (as shown in Equation 10):

$$e_j = -\frac{1}{ln\,n}\sum_{i=1}^{n}\left(p_{ij} \cdot ln\,p_{ij}\right) \tag{10}$$

Calculate urbanization index (as shown in Equation 11):

$$U_i = w_i \cdot x_{ij}^{''} = \frac{1 - e_j}{\sum_{i=1}^{n}\left(1 - e_j\right)} \cdot x_{ij}^{''} \tag{11}$$

Where p_{ij} is the weight of the i-th evaluation object under the j-th evaluation index; e_j is the entropy value with the range [0, 1]; w_i represents the entropy weight; U_i is the final urbanization value.

TABLE 2 The evaluation index system for the urbanization of CLRYR.

Target layer	Subsystem	Weight	Indicator layer	Weight
Urbanization	Population urbanization (PU)	0.2274	Population density (PD)-People per square kilometer	0.0671
			Employed personnel (EP)-10000 people	0.0826
			Permanent population (PP)-10000 people	0.0777
	Spatial urbanization (SPU)	0.1866	Per capita road area (RD)-m^2	0.0506
			Built-up area (BA)-km^2	0.1075
			Per capita park green area (GA)-m^2	0.0285
	Economic urbanization (EU)	0.1684	Per capita regional gross domestic product (GDP)-Yuan per person	0.0599
			Proportion of tertiary industry output value (TI)-%	0.0288
			Per capita disposable income of urban residents (DI)-Yuan	0.0797
	Social urbanization (SOU)	0.4176	Number of beds in health institutions (NB)-10000	0.1110
			Total collection of books in public libraries (CB)-1,000 volumes, items	0.2233
			Number of schools (NS)	0.0833

3.3 Spatial autocorrelation

In this study, global Moran's I was employed to evaluate the spatial correlation across the entire CLRYR region, aiming to identify any global spatial clustering phenomenon (Liu et al., 2023a). Concurrently, local spatial autocorrelation analysis was utilized to examine spatial correlation within specific regions, providing further insights into local spatial clustering patterns (Liu Y. et al., 2024).

3.4 SDE method

SDE is a statistical tool used to accurately characterize the spatial distribution of study elements (Lefever, 1926). In this study, the parameters such as coordinates of the center of the ellipse, azimuth, and the standard deviation of the long and short semi-axes are employed to reflect the spatial change trend of the urbanization level in the CLRYR. The specific calculation formula can be found in the reference (Zhang Y. et al., 2022).

3.5 Tapio decoupling model

In this study, the tapio decoupling model was introduced to analyze the relationship between urbanization level and LER in the CLRYR region, to measure the resilience of LER to change in the urbanization process, i.e., the degree of decoupling between the two. The method is based on the ratio of the rate of change in LER to the rate of change in urbanization level, termed the decoupling index, to quantitatively describe this relationship (Dong et al., 2021). Based on the value of the decoupling index and its positive and negative situations, the type of decoupling state and its trend can be determined (Kong et al., 2019). The specific formulas and classification criteria of the model are shown in Equation 12 and Table 3, respectively.

$$\omega = \frac{r_{LERI}}{r_{UI}} = \frac{(LERI_{end} - LERI_{start})/LERI_{start}}{(UI_{end} - UI_{start})/UI_{start}} \quad (12)$$

Where ω represents the decoupling index; r_{LERI} and r_{UI} are the rate of change of LERI and Urbanization index (UI), respectively; $LERI_{end}$ and UI_{end} denote the end values of the two; $LERI_{start}$ and UI_{start} are the initial values of the two, respectively.

4 Results

4.1 The spatiotemporal distribution of PLES

Land use types are the product of the interaction between human activities and natural environmental factors, reflecting the impact of human social activities on ecosystems. This study explores the spatiotemporal evolution law of land use in CLRYR from the perspective of PLES from 2000 to 2020 in terms of spatial distribution (as shown in Figure 3), quantity structure (as shown in Figure 4) and type transfer (as shown in Figure 5). The production space forms a wide distribution in the eastern part of CLRYR, which is the dominant area of PLES. In the secondary production space, agricultural production areas notably exceed industrial zones. Nevertheless, there has been a declining trend in the agricultural production space over the years, while the industrial production space shows a corresponding increase. The living space exhibits a radial distribution pattern, primarily concentrated near the Yangtze River coast, with a noticeable trend of outward expansion. This expansion is particularly pronounced in Shanghai, where the concentration of living space is most prominent. Guided by national policies, the extent of each ecological space type remained relatively stable from 2000 to 2020. Forest and grassland ecological spaces predominated during this period concentrated notably in Anqing, Chizhou, and Tongling. Water ecological space was primarily observed along the main branches and tributaries of the Yangtze River, as well as in areas surrounding Taihu Lake.

TABLE 3 Types of decoupling states.

Decoupled model state		r_{LERI}	r_{UI}	ω
Negative decoupling	Expansive negative decoupling	+	+	$\omega \geq 1.2$
	Strong negative decoupling	+	-	$\omega < 0$
	Weak negative decoupling	-	-	$0 \leq \omega \leq 0.8$
Decoupling	Weak decoupling	+	+	$0 \leq \omega \leq 0.8$
	Strong decoupling	-	+	$\omega < 0$
	Recessive decoupling	-	-	$\omega \geq 1.2$
Coupling	Expansive coupling	+	+	$0.8 < \omega < 1.2$
	Recessive coupling	-	-	$0.8 < \omega < 1.2$

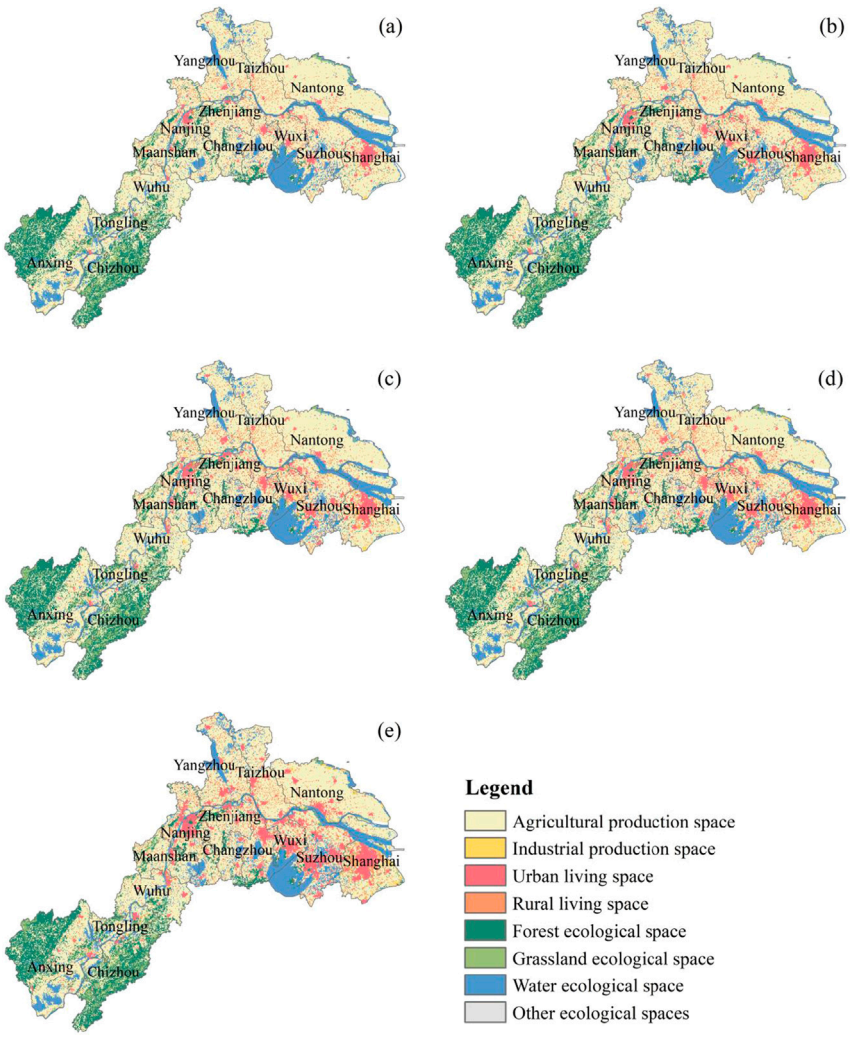


FIGURE 3
Spatial distribution of PLES in CLRYR region in 2000 **(a)**, 2005 **(b)**, 2010 **(c)**, 2015 **(d)**, and 2020 **(e)**.

Using GIS spatial analysis techniques, we computed the land use transfer matrix for PLES classification maps annually from 2000 to 2020, quantitatively exploring changes between each land use type, depicted in Figure 5. Regarding the types of transfers both into and out of various categories, the complexity has increased notably from 2000 to 2020, particularly accelerating between 2015 and 2020. In quantitative terms, the number of transfers of each type rose from 2015 to 2020, with the transfer of

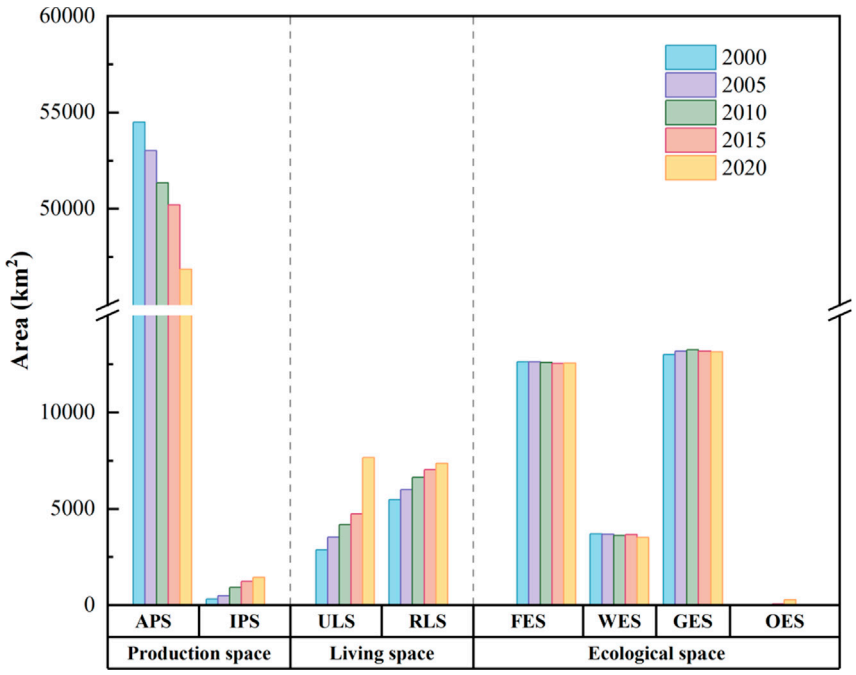


FIGURE 4
Area changes of each PLES type. Note: APS, IPS, ULS, RLS, FES, WES, GES, and OES represent agricultural production space, industrial production space, urban living space, rural living space, forest ecological space, water ecological space, grassland ecological space, and other ecological spaces, respectively.

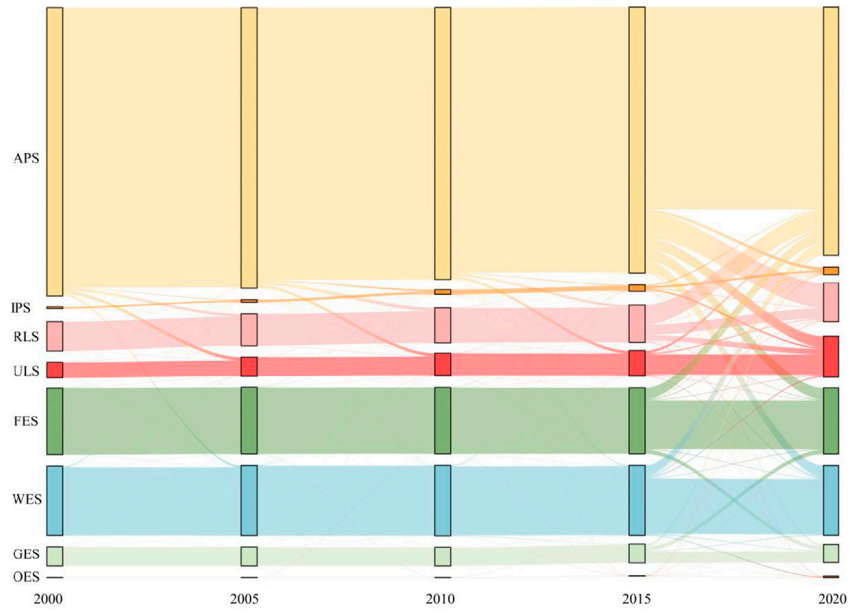


FIGURE 5
Change matrix PLES in CLRYR from 2000 to 2020.

agricultural production space to living space being more obvious. This trend underscores the accelerated urbanization within the CLRYR, driven by substantial demands for land resources for urban development. Collectively, these shifts illustrate the rapid urbanization and restructuring of PLES within the CLRYR region over the past two decades, with significant implications for local development strategies, resource management, and social stability.

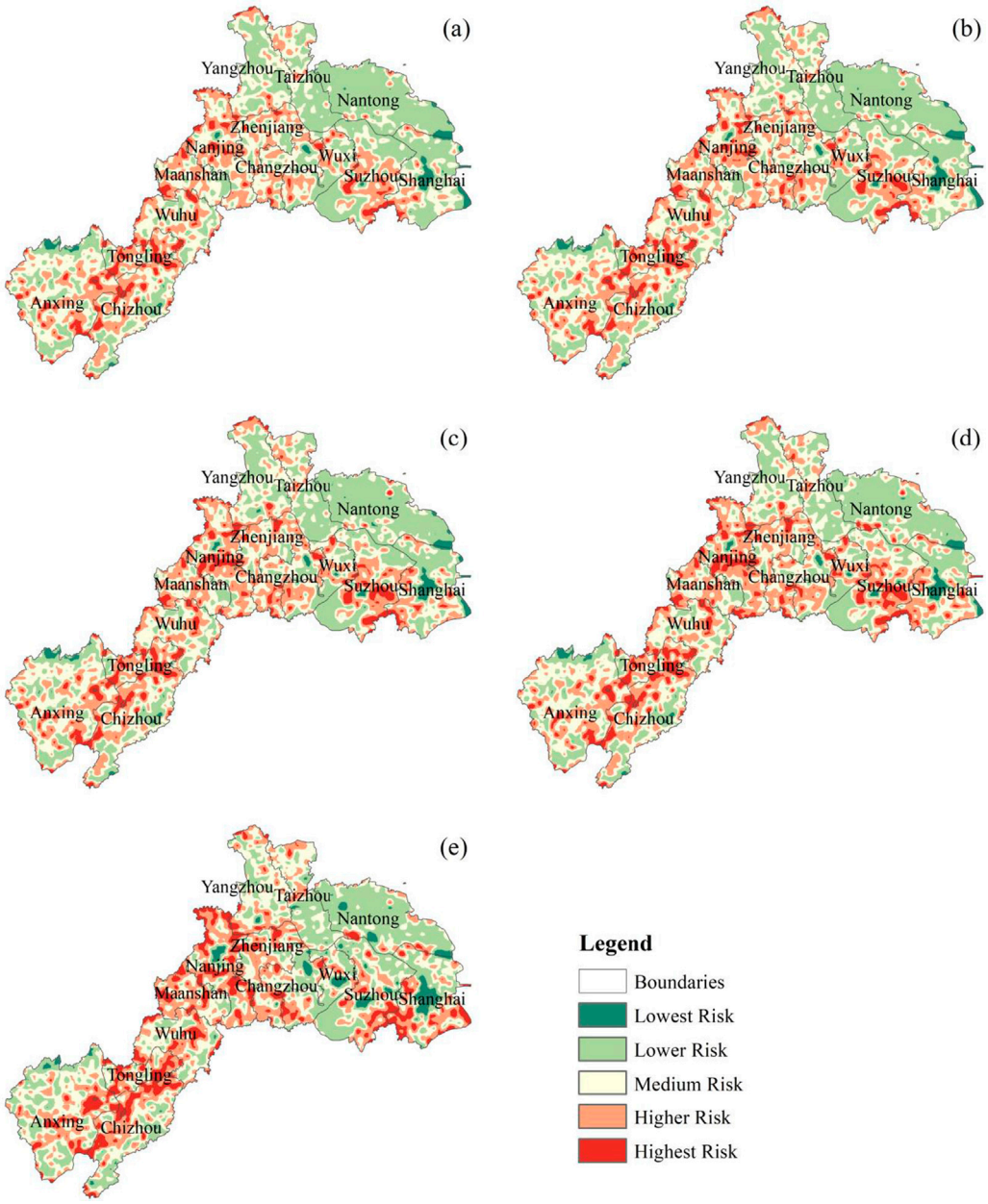


FIGURE 6
Distribution of LER levels in the CLRYR region in 2000 **(a)**, 2005 **(b)**, 2010 **(c)**, 2015 **(d)**, and 2020 **(e)**.

4.2 The spatiotemporal dynamics of LER

4.2.1 LER characteristics of the CLRYR region

To explore the heterogeneity of LER within the CLRYR, this study adopts the establishment of risk units to evaluate the risk of the whole. The results show that the mean LER value within the region from 2000 to 2020 is 0.2508, 0.2524, 0.2547, 0.2576, and 0.2573 in order. The LER of the CLRYR region shows a slightly increasing trend and is more stable from 2015 to 2020. Based on the 2000 LERI, the natural breaks method was used to classify five risk levels: [0, 0.1901] for lowest risk, (0.1901, 0.2362] for lower risk, (0.2362, 0.2670] for medium risk, (0.2670, 0.3053] for higher risk, and (0.3053, 0.4897] for highest risk. In this way, the spatial distribution of LER levels from 2000 to 2020 (as shown in Figure 6) and the area proportion of each level (as shown in Figure 7) were obtained. In the spatial distribution of LER levels in the CLRYR region, regions categorized as lower risk, medium risk, and higher risk predominate. Specifically, higher risk areas are mainly located in several cities in the southwestern part of the study area, whereas lower risk is primarily centered in Nantong City in the northeastern part. Over time, there has been varying growth in the proportion of lowest and highest risk areas: lowest risk areas are notably concentrated in cities such as Shanghai, Nanjing, Nantong, Suzhou, Changzhou, and Anqing, whereas highest risk areas have expanded annually from their initial base and are dispersed among multiple cities.

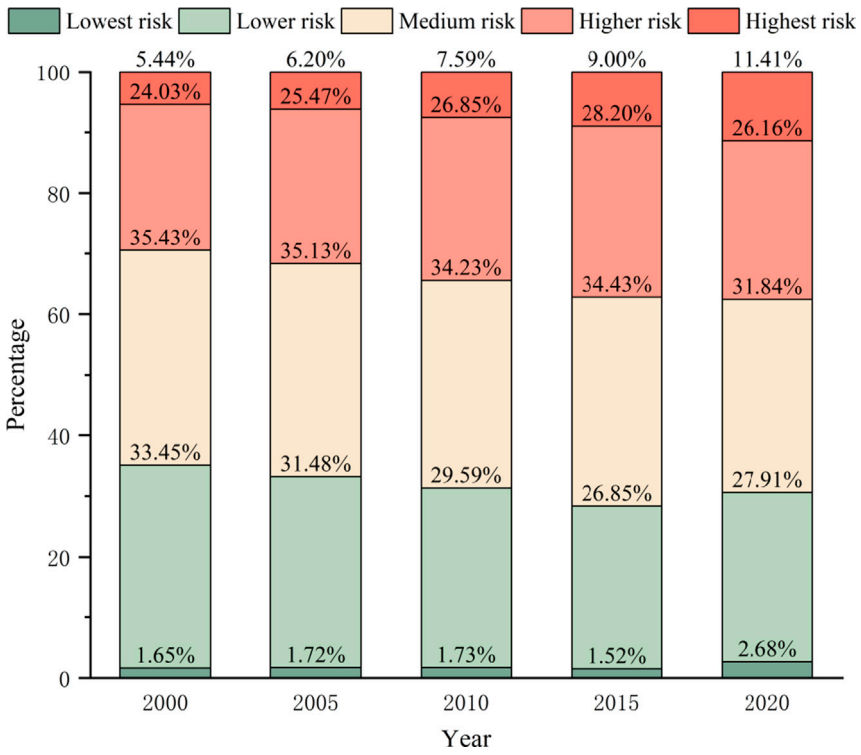


FIGURE 7
The proportion of areas with different LER levels.

4.2.2 Comparison of LER in various cities in CLRYR

The overall spatial distribution of LER does not sufficiently capture the disparities in LERI among different cities. Consequently, this study undertook a detailed analysis of LER across these cities, aiming to delineate their spatial distributions, and trends, and provide a foundational framework for formulating effective management and control strategies tailored to varying risk levels. Through a statistical examination of the mean LERI in each city, the study identified a general upward trend in LER across most cities (as shown in Figure 8). For example, Tongling, Wuhu, Ma'anshan, and Chizhou in Anhui Province, as well as Zhenjiang, Nanjing, Yangzhou, Taizhou, and Nantong in Jiangsu Province and Shanghai, exhibited consistent annual increases in the LERI. Conversely, certain cities maintained relatively stable LER levels, exemplified by Anqing City in Anhui Province, possibly influenced by regional environmental protection policies and urban development strategies. Moreover, specific cities experienced periods of decreased LER, including Changzhou, Wuxi, and Suzhou in Jiangsu Province, observed particularly in 2020, indicative of the efficacy of localized ecological restoration and environmental management initiatives.

4.2.3 Spatial autocorrelation analysis

To explore the spatial distribution pattern of LER from 2000 to 2020 in CLRYR, this study analyzed its spatial autocorrelation. Table 4 illustrates that the autocorrelation analysis of LER from 2000 to 2020 in CLRYR passed the significance test, and the global Moran's I of 0.4733, 0.4014, 0.3326, 0.2462, and 0.4779 were all greater than 0 indicating that the spatial showed significant positive autocorrelation. Over time, Moran's I showed a decreasing and then increasing trend, reflecting the dynamic evolution of the clustering effect of LER in the region. From 2000 to 2020, the clustering effect of the spatial distribution of LER decreased, followed by a resurgence to its peak in 2020. To further explore the spatial clustering characteristics of LER, local spatial autocorrelation analysis was conducted.

Figure 9 depicts the local indicators of spatial association (LISA) clustering map of LER from 2000 to 2020. The findings highlight Wuhu as consistently demonstrating high-high agglomeration, indicating persistent spatial clustering of LER in the region over the entire period. In response to the current situation where land use in Wuhu is mainly based on agricultural production space, it is urgent to strengthen the protection and efficient utilization of cropland, and strictly limit the occupation of cropland by the urbanization process. Therefore, measures should be taken to optimize the land use structure and ensure the sustainability of agricultural land and its compatibility with ecological functions. In addition, by increasing green space coverage and constructing ecological corridors, the urban ecological environment can be effectively improved, ecosystem service functions can be enhanced, landscape fragmentation can be reduced, and the connectivity and stability of regional ecosystems can be improved. In contrast, cities situated near the Yangtze River estuary, such as Nantong and Shanghai, predominantly exhibit low-low agglomeration characteristics, suggesting sustained

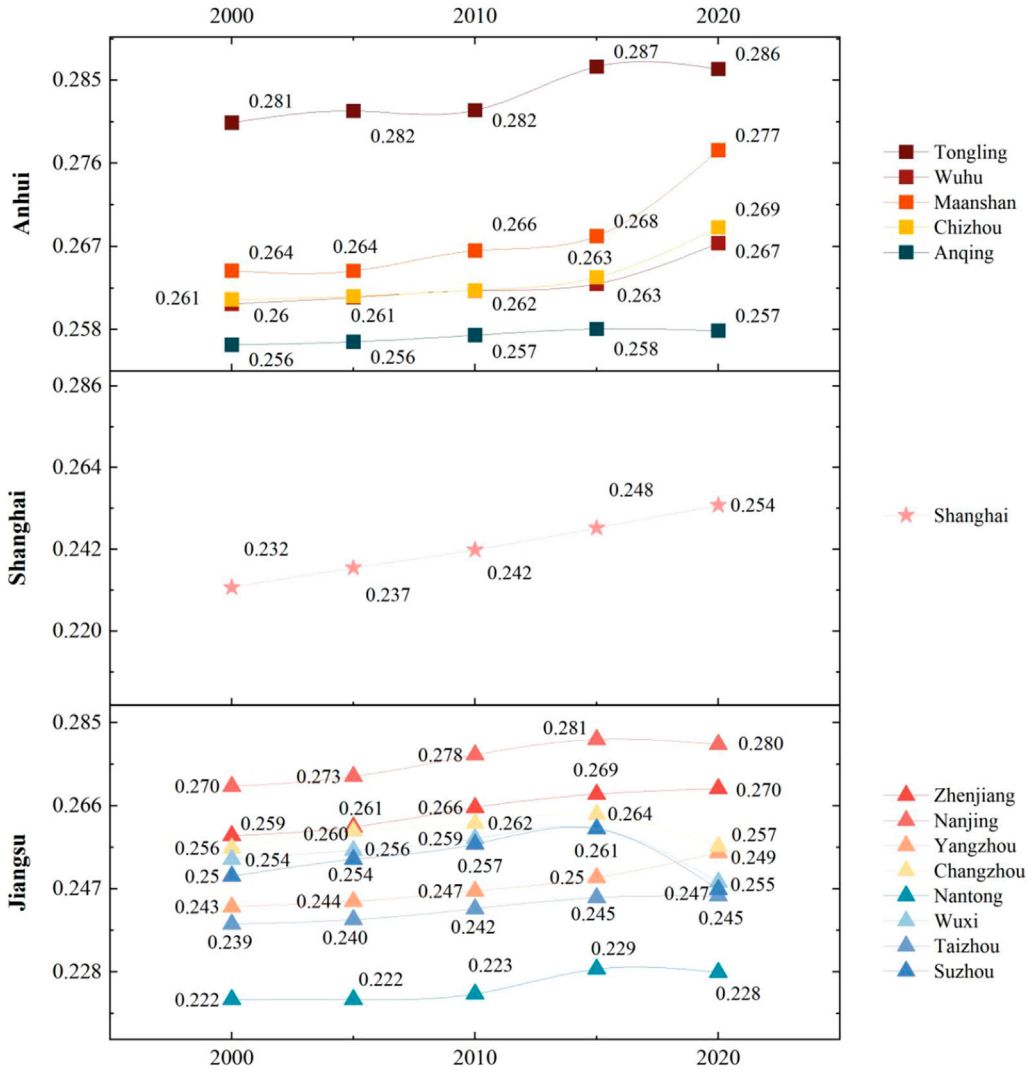


FIGURE 8
LERI values of 14 cities in the CLRYR region from 2000 to 2020.

TABLE 4 Moran's I result for LERI in CLRYR region.

Index	2000	2005	2010	2015	2020
I	0.4773	0.4014	0.3326	0.2462	0.4779
p-value	0.0025	0.0081	0.0221	0.0722	0.0028
Z	3.0241	2.6496	2.2800	1.7980	2.9848

stability in ecological risk within these areas. It is noteworthy that the occurrence of low-high agglomeration was uniquely observed in Anqing in 2015, whereas high-low agglomeration was noted in Suzhou. This shift may be attributed to local environmental policies, shifts in economic structures, and natural geographic factors. The implementation of ecological restoration measures in Anqing from 2000 to 2020 contributed to stabilizing LER levels in that area, contrasting with neighboring cities where LER continued to increase. This dynamic underscores the low-high agglomeration pattern of Anqing distinct in LER during the specified period. Conversely, in regions like Suzhou, known for its picturesque landscapes and thriving tourism economy, the enhancement of LER may correlate closely with robust economic activities. Economic development typically coincides with urbanization and extensive infrastructure projects, factors that could potentially amplify the accumulation and dissemination of LER.

4.3 The response of LER in the context of CLRYR urbanization

4.3.1 Evolution of the spatiotemporal dynamics of the level of urbanization in the CLRYR region

The comprehensive evaluation of the urbanization level of the CLRYR region from 2000 to 2020 could reveal the characteristics of the spatial distribution of the urbanization process in the CLRYR region and its trends in different years. The results in Figure 10 show that the spatial urbanization index (SPUI), economic urbanization index (EUI), and UI of all cities show a

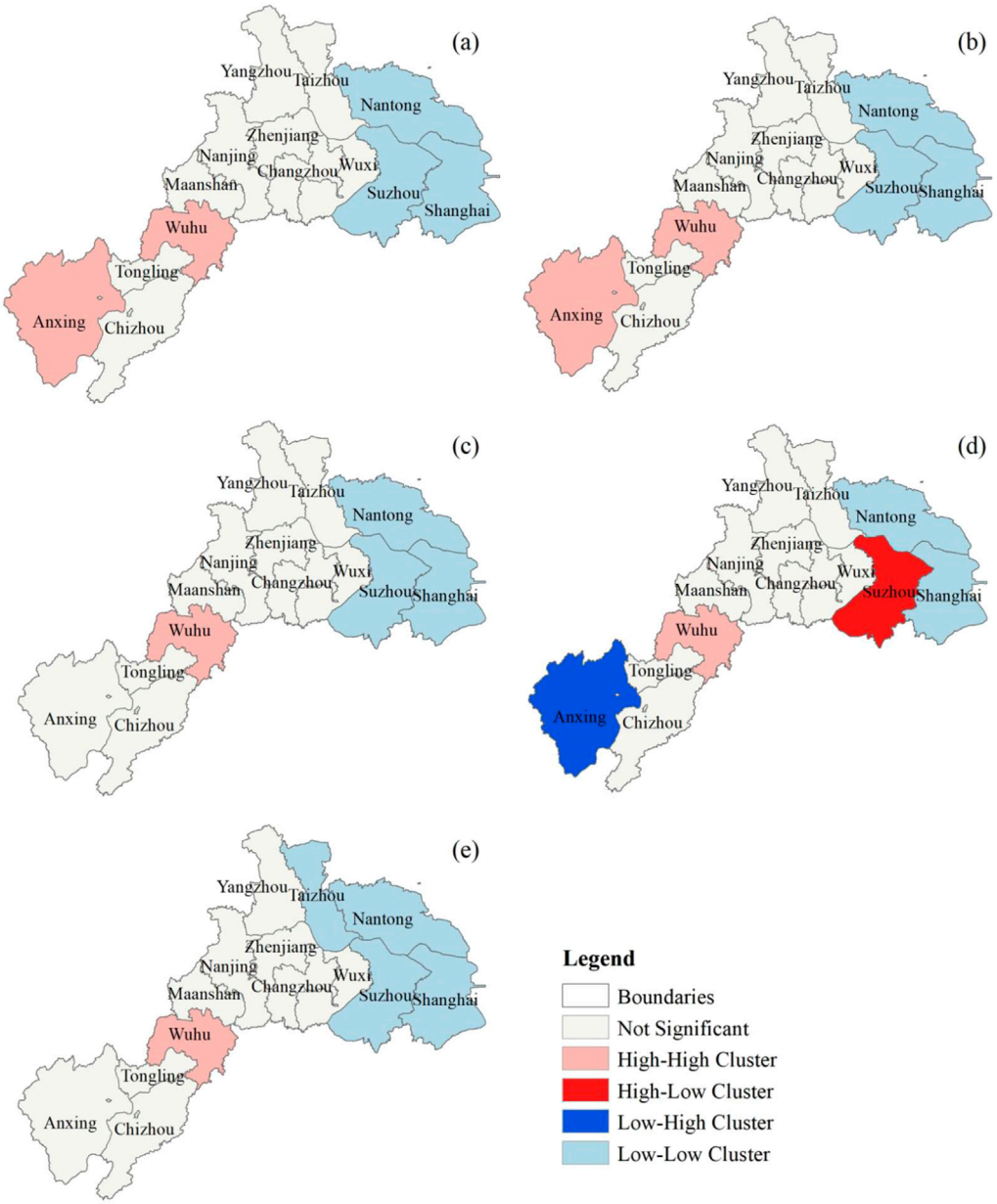


FIGURE 9
Spatial autocorrelation of LERI in 2000 **(a)**, 2005 **(b)**, 2010 **(c)**, 2015 **(d)**, and 2020 **(e)**.

steady increase year by year, albeit with a few cities experiencing declines in population urbanization index (PUI) and social urbanization index (SOUI). The sudden epidemic in 2019 (Liu et al., 2023b) caused a serious impact in all aspects, especially the employment-population was seriously affected, resulting in a decline in PUI in most cities. Compared with the period from 2000 to 2010, the increment of cities with rising PUI between 2010 and 2020 is significantly smaller. Based on the raw statistical yearbook data, certain components of the SOUI exhibit consistent growth, such as the number of beds in health institutions and the total library collections across cities. However, China's policies on school consolidation and the reduction of rural schools have led to varying declines in the number of schools, particularly elementary schools, annually across different cities. Consequently, this has resulted in diverse changes in each city's SOUI. Nevertheless, overall urbanization levels in the region continue to ascend steadily.

Utilizing the quantile method to categorize the comprehensive index of urbanization development in CLRYR and its four subsystem indexes, each of which was segmented into five levels, which in turn led to the spatial visualization results (as shown in Figure 11). Figure 11 reveals that cities situated near the mouth of the Yangtze River, particularly centered around Shanghai, exhibit higher urbanization levels, with urbanization levels gradually decreasing towards the west in 2000 compared to the east. The spatial distribution illustrates a progressive increase in urbanization

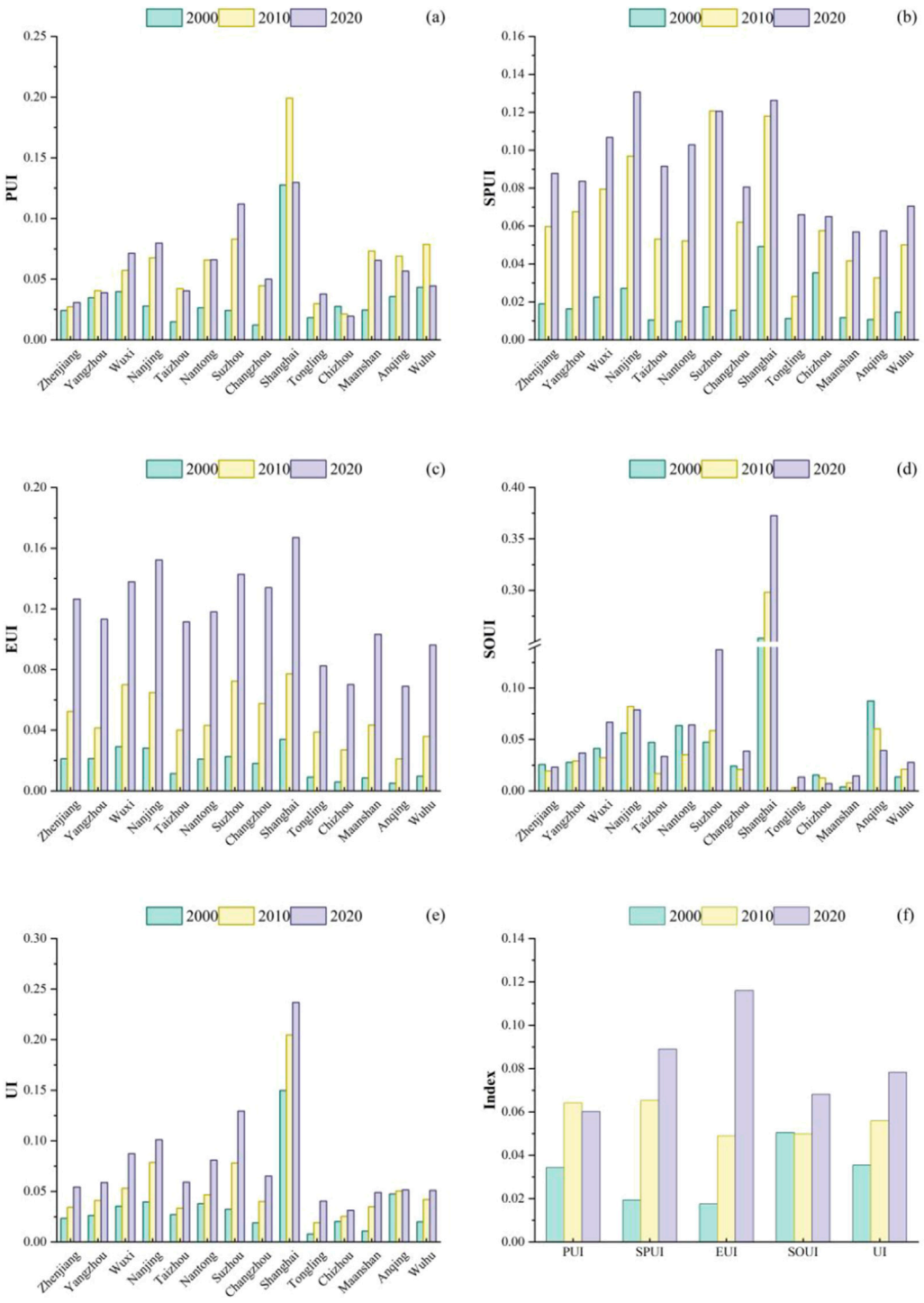


FIGURE 10
Urbanization level of various cities in CLRYR region from 2000 to 2020. **(a)** PUI; **(b)** SPUI; **(c)** EUI; **(d)** SOUI; **(e)** UI; **(f)** Index.

from lower to higher grades across most cities, notably with a notable rise in the number of cities in the higher-grade categories. Referring to Figures 11m-o, it is evident that as of 2020, only Chizhou, Anhui Province remains classified in the lowest urbanization grade, whereas all other cities have moved into middle and upper grades.

4.3.2 Distribution characteristics of urbanization level direction in the CLRYR region

This study depicts the evolution of CLRYR urbanization from 2000 to 2020 through the visualization of SDEs and the trajectory of the center of gravity migration. Figure 12 provides a spatial representation of this evolution, while Table 5, 6 analyze the

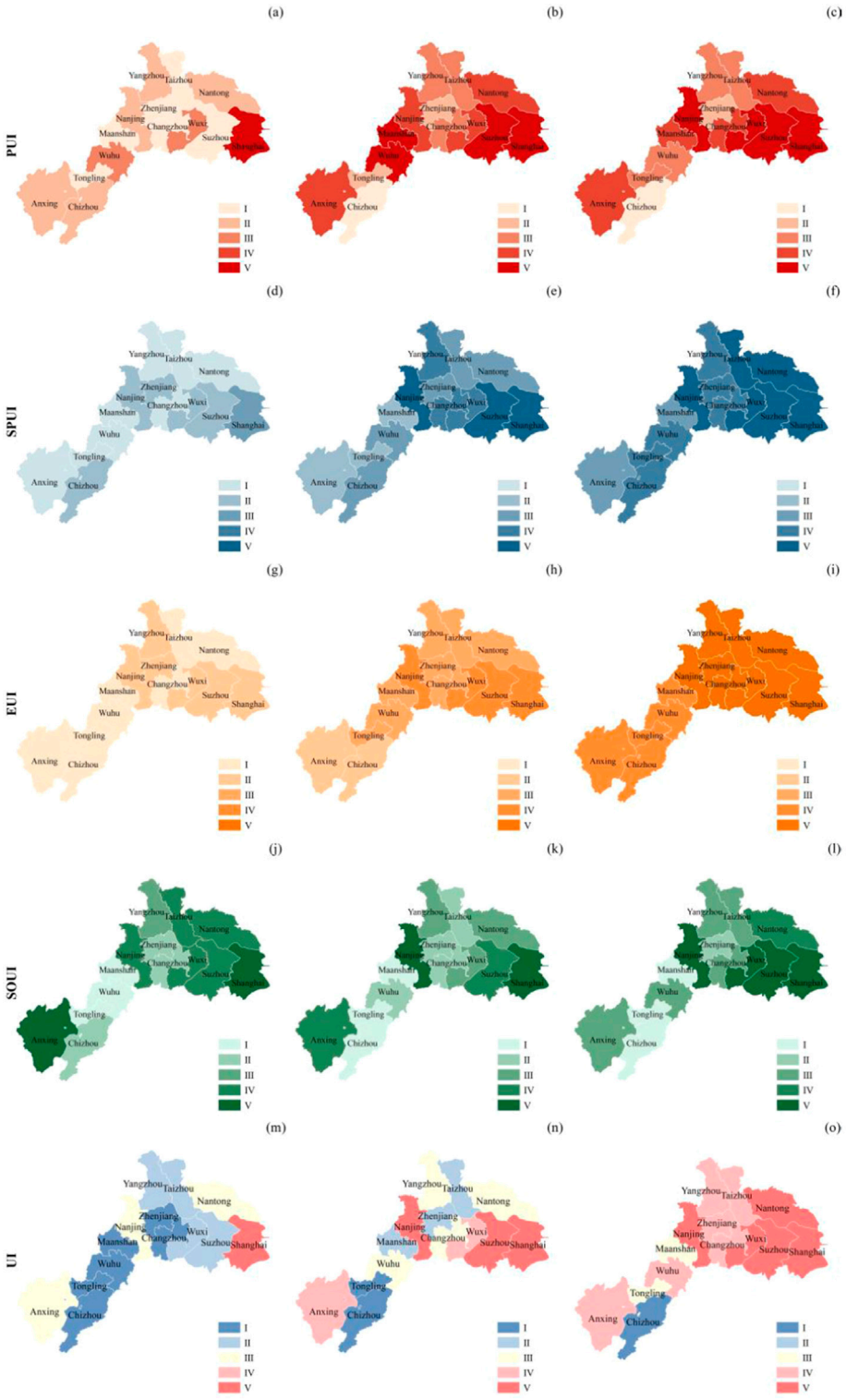


FIGURE 11
Spatial evolution of urbanization levels in various cities in CLRYR region from 2000 to 2020. **(a)** PUI in 2000; **(b)** PUI in 2010; **(c)** PUI in 2020; **(d)** SPUI in 2000; **(e)** SPUI in 2010; **(f)** SPUI in 2020; **(g)** EUI in 2000; **(h)** EUI in 2010; **(i)** EUI in 2020; **(j)** SOUI in 2000; **(k)** SOUI in 2010; **(l)** SOUI in 2020; **(m)** UI in 2000; **(n)** UI in 2010; **(o)** UI in 2020.

spatial distribution and dynamic characteristics of urbanization in CLRYR using the center of gravity and SDE parameters. The center of gravity of urbanization in CLRYR shifted from 2000 to 2020 between 119.78°E~119.82°E and 31.51°N~31.58°E. Specifically, the center of gravity migration went through two stages: in the first stage (2000–2010), it moved northwestward by

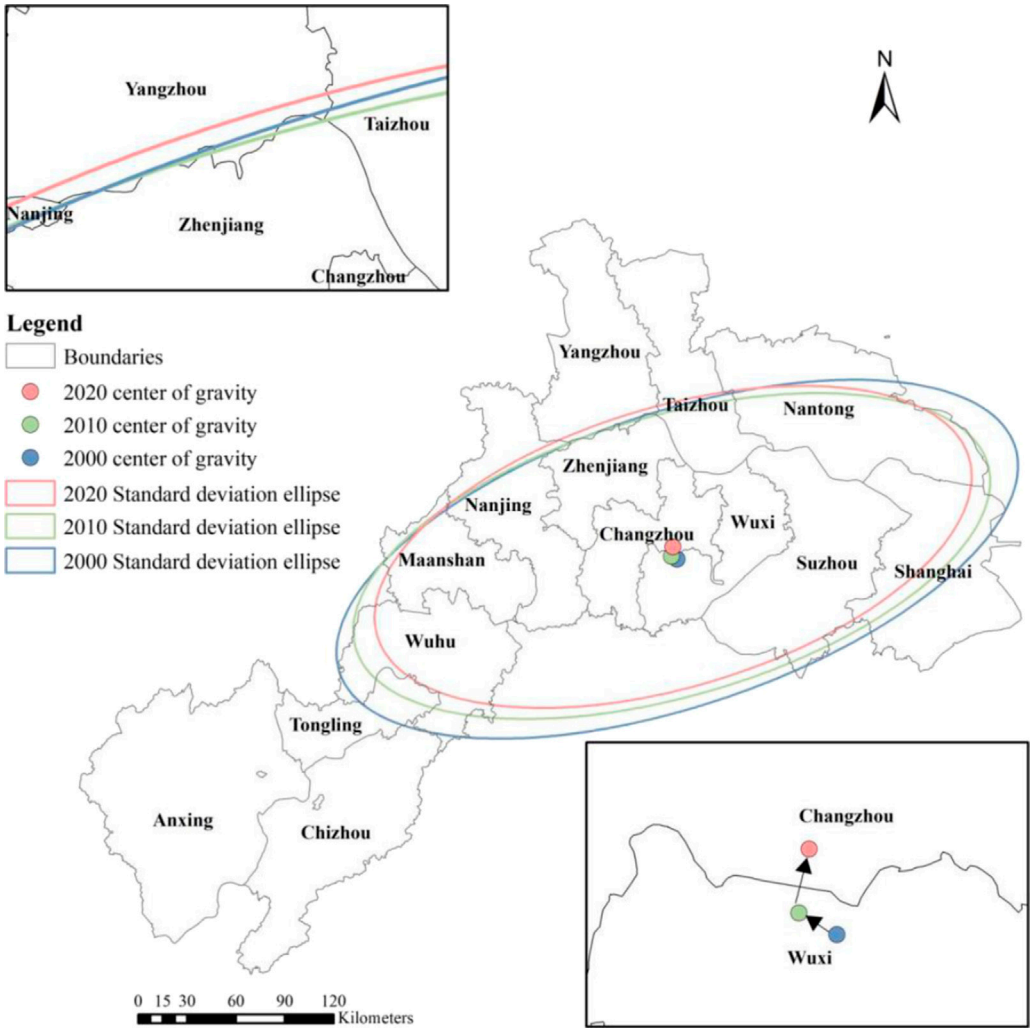


FIGURE 12
Directional distribution of urbanization index.

TABLE 5 Shift of urbanization index center of gravity in the CLRYR region during 2000–2020.

Year	The center of gravity coordinate	Displacement (km)	Movement direction
2000	(119°48′58″, 31°30′26″)	—	—
2010	(119°47′01″, 31°31′43″)	3.880	northwestern
2020	(119°48′08″, 31°34′37″)	5.649	northeastern

3.880 km, consistently situated in Wuxi; in the second stage (2010–2020), the migration accelerated northeastward from Wuxi to Changzhou. Overall, the center of gravity of urbanization in the CLRYR region demonstrated a predominant northward movement, reflecting the pronounced development of cities in the northern part of CLRYR as urbanization progressed.

From a spatial distribution perspective, the SDEs of urbanization in the CLRYR region from 2000 to 2020 are primarily concentrated in the eastern part of the area. These ellipses show a clear directionality, and their total area shows a trend of shrinking from 61,916.413 km^2 in 2000 to 51,242.005 km^2 in 2020, which reflects the phenomenon of increasing urbanization with more aggregated regional urban space. In terms of spatial distribution direction, the dominant azimuth of the SDE of urbanization in the CLRYR region has a maximum range of 2.358°, with urbanization predominantly following a “northeast-southwest” orientation. This spatial pattern underscores the increasingly concentrated urban growth in specific areas of the CLRYR region over the studied period.

TABLE 6 SDE parameters of urbanization index in CLRYR region.

Year	Long semi-axis (km)	Short semi-axis (km)	Area (km^2)	Azimuth (°)
2000	218.676	90.138	61916.413	71.396
2010	202.103	86.102	54661.979	73.754
2020	189.745	85.971	51242.005	73.147

4.3.3 Evolution of the decoupling relationship between urbanization and LER in the CLRYR region

The existence of developmental diversity in urbanization levels and spatial heterogeneity in LER among cities in the CLRYR region led to different performances in the state of decoupling among cities (as shown in Table 7). Generally, the decoupling relationship between LER and urbanization development in the CLRYR region manifests predominantly in two primary patterns: weak decoupling and strong decoupling, with strong decoupling representing the optimal state. In the first stage, the rate of change of both the ecological risk index and the urbanization index is greater than 0. However, the decoupling index of the municipalities from 2000 to 2010 is less than 0.8, indicating a state of weak decoupling. This suggests that during this period, urbanization levels in these cities increased while ecological risks persisted, albeit with a lower rate of change in LER compared to urbanization development. In the second stage, a majority of cities continue to exhibit weak decoupling. Differently, while the urbanization trend in Wuxi, Suzhou, and Changzhou continues, LERI showed negative growth from 2010 to 2020, with decoupling indexes of −0.0600, −0.0615, and −0.0323, respectively, indicating a transition from weak decoupling to a strong decoupling state. Among various decoupling relationships, strong decoupling is considered an ideal state. Based on the discussion of the relationship between LER and urbanization in this study, strong decoupling means a separation trend of positive and negative growth between the urbanization process and LER, that is, the increase of urbanization is accompanied by the decrease of LER. This achievement can be attributed to the continuous strengthening of rational land use planning in these cities, which has achieved significant results through promoting agricultural land consolidation and measures centered on efficient and intensive land use, strictly controlling the scale of construction land. These cities represent a minority achieving the ideal state, highlighting that in most others, urbanization progress likely continues at the expense of ecological concerns. Consequently, concerted efforts are essential in the CLRYR region to enhance LER management and foster sustainable, harmonious development between urban areas and ecosystems.

5 Discussion

5.1 Inspiration for urban planning

Drawing upon the established framework laid out in previous research (Hui et al., 2024; Vadén et al., 2020; Xin et al., 2023), studying the correlation between LER and urbanization from the perspective of PLES can provide a deeper understanding of the degree of disconnect between economic expansion, resource consumption, and environmental burden in the process of urbanization. The decoupling results show that only Wuxi, Suzhou, and Changzhou have shifted from weak decoupling to the ideal state of strong decoupling, highlighting the common challenges faced by most cities in ecological risk management during urbanization. Drawing upon these findings, several recommendations can be proposed.

5.1.1 Strengthening the integration of spatial planning and ecological protection

In response to the abundant wetland resources in the lower reaches of the Yangtze River, measures such as ecological red line delineation and wetland restoration should be taken to protect the key ecological functions of wetland ecosystems, such as water purification and carbon storage. In the planning, ecological protection zones and wetland protection belts can be established to prevent large-scale urban development from encroaching on and damaging wetlands. Based on the natural conditions of the lower reaches of the Yangtze River and the existing ecological network, plan an integrated green infrastructure system. For example, by restoring and connecting ecological environments such as forests, wetlands, and water bodies around cities, ecological corridors at the watershed scale can be formed to promote biodiversity conservation and enhance the adaptive capacity of urban ecosystems.

5.1.2 Promote the construction of ecological compensation mechanisms

Given that the lower reaches of the Yangtze River involve multiple administrative regions, it is possible to promote ecological compensation agreements between provinces or cities. By establishing unified compensation standards and funding allocation mechanisms, we can promote ecological cooperation between different cities and regions, and reduce the imbalance of ecological protection. Enterprises in the Yangtze River region, especially those involved in high ecological risks such as water resources and land development, can be incentivized to fulfill their ecological protection responsibilities through tax incentives, financial subsidies, and other means. It is suggested to introduce targeted incentive policies to encourage enterprises to carry out ecological restoration and green technology innovation and enhance their environmental awareness and social responsibility.

5.1.3 Strengthen environmental monitoring and assessment

In response to the ecological risks faced by cities along the lower reaches of the Yangtze River, such as water pollution and floods, it is recommended to establish an intelligent ecological risk warning system that utilizes technologies such as big data and the Internet of

TABLE 7 Decoupling index of urbanization and LER in CLRYR regional from 2000 to 2020.

City	2000–2010				2010–2020			
	r_{LERI}	r_{UI}	Decoupling elasticity	Decoupling states	r_{LERI}	r_{UI}	Decoupling elasticity	Decoupling states
Zhenjiang	0.0247	0.4705	0.0525	weak decoupling	0.0163	0.5821	0.0279	weak decoupling
Yangzhou	0.0148	0.5689	0.0261	weak decoupling	0.0356	0.4380	0.0814	weak decoupling
Wuxi	**0.0186**	**0.5032**	**0.0370**	**weak decoupling**	**−0.0386**	**0.6427**	**−0.0600**	**strong decoupling**
Nanjing	0.0266	0.9840	0.0270	weak decoupling	0.0086	0.2847	0.0303	weak decoupling
Taizhou	0.0149	0.2335	0.0636	weak decoupling	0.0122	0.7735	0.0158	weak decoupling
Nantong	0.0061	0.2322	0.0262	weak decoupling	0.0220	0.7323	0.0300	weak decoupling
Suzhou	**0.0293**	**1.4145**	**0.0207**	**weak decoupling**	**−0.0403**	**0.6556**	**−0.0615**	**strong decoupling**
Changzhou	**0.0223**	**1.1346**	**0.0197**	**weak decoupling**	**−0.0202**	**0.6238**	**−0.0323**	**strong decoupling**
Shanghai	0.0437	0.3679	0.1188	weak decoupling	0.0494	0.1565	0.3160	weak decoupling
Tongling	0.0049	1.4429	0.0034	weak decoupling	0.0162	1.1275	0.0144	weak decoupling
Chizhou	0.0039	0.2496	0.0155	weak decoupling	0.0266	0.2378	0.1117	weak decoupling
Ma'anshan	0.0084	2.2320	0.0037	weak decoupling	0.0418	0.3995	0.1045	weak decoupling
Anqing	0.0042	0.0648	0.0647	weak decoupling	0.0019	0.0202	0.0955	weak decoupling
Wuhu	0.0056	1.1189	0.0050	weak decoupling	0.0200	0.2110	0.0949	weak decoupling

Note: Bold font indicates cities that have transitioned to a strong decoupling state.

Things to monitor environmental changes in real-time, predict and respond to potential ecological risks in advance, and enhance the city's emergency response capabilities. Based on environmental monitoring, regular evaluations of urban ecological carrying capacity should be conducted to clarify the maximum carrying capacity of ecosystems in various regions, and plans for land use, urban expansion, resource development, and other aspects should be adjusted based on the evaluation results. This mechanism ensures that the urbanization process does not exceed the limit of ecological carrying capacity, thereby promoting the harmonious unity of the ecological environment and urban development.

5.2 Limitations and future research directions

In this study, we first proposed a land use classification system from the perspective of PLES and analyzed the spatiotemporal evolution of the PLES employing the transfer matrix model. The results of the study reveal that industrial production space and living space have shown a continuous growth trend in the past few years, reflecting the expansion of industrialization and urbanization scale in the urbanization process. In contrast, the area of agricultural production space has markedly diminished, potentially attributable to urban encroachment or conversion to alternative uses. The fluctuating pattern observed in ecological spaces underscores their susceptibility to the combined pressures of urbanization, industrialization, and environmental conservation policies. Secondly, building upon this foundation, the LER evaluation model was developed using a 5 km × 5 km grid as the assessment unit, employing landscape pattern indexes. It is found that the overall LER of the CLRYR area is rising and the highest-risk area is expanding, which means that the ecological ability of the area to resist external disturbances is poor and the ecological environment is more fragile. Finally, through the application of the Tapio decoupling model to dynamically analyze the interplay between urbanization and LER.

There is still some room for improvement. While previous scholars have explored various aspects of PLES classification, a standardized system remains elusive. With the help of related studies, this study reclassified the CNLUCC based on performance functions classified at the secondary level. However, whether this classification optimally serves LER evaluation in the CLRYR area warrants further investigation. In addition, the LER assessment model of this study relies too much on the status of land use functions. Yet, LER assessment is inherently intricate, involving uncertainties such as precipitation, soil quality, and socio-economic factors, which were not fully addressed. In addition, the LER assessment model is susceptible to the influence of landscape scale changes when combined with landscape ecology theory, and current research has not fully addressed the issue of scale selection. Therefore, future research should focus on exploring the optimal scale setting to improve the accuracy and reliability of evaluation results. Finally, the urbanization indicator system proposed in this study (including population, space, economy, and social subsystems) can provide a macro evaluation framework for the level of urbanization. However, it fails to fully reflect the complex informal urbanization patterns in China's urbanization process, especially in areas such as suburbanization and land speculation. These informal urbanization models have had a significant impact

on the spatial layout, social structure, and economic development of cities, and are worthy of attention in future research. Overall, to achieve sustainable development and ecological security of cities in the Yangtze River Basin, it is necessary to further deepen the research on the balance mechanism between urban development and ecological protection, to more accurately guide the formulation and implementation of regional ecological compensation policies.

6 Conclusion

To explore the spatiotemporal evolution of LER in the context of urbanization, this study focuses on the economically dynamic CLRYR region. We examined the evolving relationship between LER and urbanization, as well as emphasizing decoupling dynamics. Firstly, the spatiotemporal process of land function change in CLRYR is summarized using PLES as the study perspective. Secondly, the spatial distribution characteristics and patterns of ecological risk in CLRYR from 2000 to 2020 are revealed by constructing a LER assessment model. Lastly, the decoupling status between urbanization and LER is explored based on measurements of urbanization levels. The conclusion of this study is as follows:

(1) In the CLRYR region, production space and ecological space are the predominant types of PLES, with living space following closely. From 2000 to 2020, the area of industrial production space and living space steadily increased. On the contrary, the agricultural production space shows a downward trend, while the ecological space presents a fluctuating pattern.
(2) From 2000 to 2020, the LER in the CLRYR region showed an upward trend of 0.2508, 0.2524, 0.2547, 0.2576, and 0.2573, respectively, characterized by an increasing proportion of high-risk areas with wide spatial distribution. Results of Moran's I indicated a significant positive spatial autocorrelation of LER across the CLRYR region.
(3) Assessing the decoupling dynamics, only three cities—Wuxi, Suzhou, and Changzhou—transitioned from a period of unsustainable development between 2000 and 2010 to a mutually beneficial scenario for urbanization and the environment from 2010 to 2020. Conversely, other cities in the region have largely maintained a less favorable developmental trajectory during this period.

The study findings indicate that cities experiencing rapid social development also encounter elevated ecological risks, underscoring the critical need for monitoring and managing land use changes. These results offer a scientific foundation for regional policymakers to refine policies aimed at mitigating ecological risks and overcoming various challenges on the path to sustainable development in CLRYR. In addition, the construction of an LER assessment model based on the PLES analysis framework provides a scalable methodological tool for analyzing the ecological effects of urbanization, especially for exploring the balance between economic growth and ecological protection in ecologically sensitive urban agglomerations in developing countries.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YG: Writing – original draft. WW: Writing – original draft. XtZ: Writing – original draft. CL: Writing – review and editing. YW: Writing – review and editing. WC: Writing – review and editing. XW: Writing – review and editing. XnZ: Writing – original draft. YuL: Writing – original draft. XyZ: Writing – review and editing. YaL: Writing – original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Wei Liu,
Huaiyin Institute of Technology, China
Pan Mingming,
Anhui Polytechnic University, China
Wang Jiahao,
Liaoning University of International Business and Economics, China

*CORRESPONDENCE
Xiaoxin Liu,
lxx@hebnetu.edu.cn

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Research on the impact of urban-rural integration on rural land use efficiency in China

Hongxin Liu[1] and Xiaoxin Liu[2]*

[1]School of Economics and Management, The Open University of China, Beijing, China, [2]Finance Department, Hebei Open University, Hebei, China

As a core strategy in China's modernization process during the new era, urban-rural integration development is imperative for expanding the development space of Chinese-style modernization and advancing high-quality growth. This paper uses the panel data of provincial levels in China from 2012 to 2023 to construct a three-level indicator system to measure the level of urban-rural integration and rural land utilization efficiency in China's provinces, and explores the impact mechanism of China's urban-rural integration on rural land utilization efficiency. Findings include: (1) Urban-rural integration significantly enhances rural land use efficiency; (2) Mechanism analysis demonstrates that urban-rural integration boosts land transfer rates and labor mobility between urban and rural areas, thereby improving land use efficiency; (3) Regional heterogeneity analysis reveals stronger promoting effects in eastern and western regions, with statistically insignificant impacts in central China. Policy recommendations are proposed, focusing on establishing market-driven resource allocation mechanisms, implementing region-specific policies, and improving collaborative governance of land transfer and labor mobility. This research provides empirical support for deepening the theory of urban-rural integration, optimizing the allocation of land resources, formulating differentiated policies, and resolving regional development imbalances.

KEYWORDS

urban-rural integration, rural land use efficiency, land transfer, labor mobility between urban and rural areas, mediating mechanism

1 Introduction

The 20th Third Plenary Session of the Communist Party of China adopted The CPC Central Committee Decision on Further Comprehensively Deepening Reforms and Advancing Chinese-Style Modernization (hereafter the Decision), which emphasizes the necessity to "coordinate new-type industrialization, new-type urbanization, and comprehensive rural revitalization, holistically improve integrated urban-rural planning, construction, and governance, promote equal exchange and bidirectional flow of urban-rural factors, narrow urban-rural disparities, and foster shared prosperity." Urban-rural integration constitutes a pivotal strategic initiative for constructing China's dual-circulation development paradigm and driving high-quality economic growth. On the one hand, it requires leveraging the radiating and catalytic effects of new-type urbanization on rural areas to propel county-level economic development throughout its entire process. On the other hand, it necessitates promoting industrial convergence between urban and rural sectors, equalizing public services, and accelerating agricultural and rural modernization. As the core strategy of China's modernization in the new era, urban-rural integration

represents both an urgent demand for advancing high-quality economic development and an inherent requirement of Chinese-style modernization. Since the concept was first introduced in the 2014 National New-Type Urbanization Plan, urban-rural integration has evolved from institutional design to practical dimensions encompassing factor allocation optimization and spatial governance restructuring, emerging as a critical pathway to resolve the "agriculture, rural areas, and farmers issues and achieve common prosperity. This process is fundamentally reshaping the spatial configurations and economic logic of the traditional urban-rural dual structure. Within this historic transformation, land—as the key medium bridging urban and rural systems—plays a decisive role. The evolution of its allocation efficiency not only determines the implementation efficacy of rural revitalization but also profoundly influences the synergistic advancement of new-type urbanization and agricultural/rural modernization.

China's 2024 National Economic Performance Report, released by the National Bureau of Statistics, reveals that the urban permanent population reached 943.5 million by year-end, an increase of 10.83 million from 2023, while the rural permanent population declined by 12.22 million to 464.78 million. The report indicates that the urbanization rate rose to 67.00%, marking a 0.84 percentage-point increase year-on-year. These figures underscore the persistent urbanization trend alongside accelerating rural population shrinkage. Concurrently, the State Council Report on Farmland Protection indicates a structural shift in China's arable land dynamics: the longstanding pattern of "decrease in the south, increase in the north" has transitioned to "dual increases across both regions." The national arable land area now totals 1.929 billion mu (128.6 million hectares), with a net increase of 11.204 million mu (0.58%) compared to the Third National Land Survey.

This statistical evidence highlights a paradoxical phenomenon: rural residential land continues to expand despite population decline, exposing deep-seated contradictions in urban-rural land resource allocation. Such contradictions necessitate critical inquiries: How do factor flows within urban-rural integration reshape the efficiency characteristics of rural land use? Do their mechanisms exhibit significant regional heterogeneity? Addressing these questions holds theoretical value for enriching spatial governance frameworks and practical urgency for optimizing land resource allocation and achieving equitable urban-rural factor exchange.

China is currently undergoing a critical phase of deep adjustments in urban-rural relations. The Fifth Plenary Session of the 19th CPC Central Committee explicitly proposed "strengthening industry-agriculture linkages and urban-rural coordination to foster a New-Type Urban-Rural Relationship characterized by mutual reinforcement between industries and agriculture, functional complementarity, coordinated development, and shared prosperity." China's arable land resources are limited and unevenly distributed. Improving efficiency can alleviate the problems of fragmented land and inefficient utilization, and at the same time, it can address the land demand pressure brought about by urbanization, prevent the loss of arable land and ecological degradation, and is the core path for achieving agricultural modernization and rural revitalization. From the perspective of urban-rural integration development, we can explore how mechanisms such as land transfer and labor migration can reshape the rural land utilization model, provide systematic solutions for building a unified factor market and optimizing territorial space governance, and contribute to the common development of urban-rural integration theory and practice. Against this backdrop, systematically elucidating the mechanisms through which urban-rural integration affects rural land use efficiency is imperative. This endeavor not only advances market-oriented reforms in land resource allocation but also constitutes a pivotal agenda for establishing a new development paradigm and achieving high-quality growth. Through multidimensional and multiscale systematic analysis, this study aims to provide novel theoretical perspectives and policy insights for addressing urban-rural land allocation imbalances and enhancing sustainable rural land use efficiency. Empirical findings demonstrate that urban-rural integration significantly enhances rural land use efficiency at the 1% significance level, with land transfer and inter-regional labor mobility identified as critical mediating pathways. Regional heterogeneity analysis further reveals stronger promoting effects in eastern and western China, whereas the impact remains statistically insignificant in central regions.

2 Literature review

2.1 Research on urban-rural integration development

The concept of urban-rural integration traces its origins to Thomas More's Utopia (Thomas, 2006), which advocates holistic planning of urban and rural areas as a unified system. Western scholars have proposed micro-level frameworks such as "urban-rural spatial production" and "dynamic suburban development" (Gimpel et al., 2020), exploring integration through lenses of spatial layout, industrial convergence, social cohesion, and governance networks (Serra et al., 2014; Rastogi and Curtis, 2020; Van Sandt and Carpenter, 2022; Ovaska et al., 2021). In China, urban-rural integration has emerged as a critical research focus due to persistent disparities in income, consumption, and infrastructure between urban and rural populations (Liu et al., 2021). National strategies like new-type urbanization, rural revitalization, and common prosperity (Liu et al., 2020; Chen et al., 2021) have significantly advanced integration (Fang, 2022). Chinese scholars further propose a "three-phase strategy" for integration, emphasizing policy-driven frameworks combining new-type urbanization and rural revitalization (Cao et al., 2019; Long et al., 2022). Institutional reforms to narrow urban-rural gaps and enhance factor mobility remain pivotal (Sun and Zhang, 2022). Theoretical contributions include Li (2017) argument that balanced urban-rural coordination sustains urbanization by reconciling resident needs, and Zhou and He's (2022) Marxist analysis of China's evolving urban-rural relations.

Empirical studies employ composite indicator systems and coupling coordination models to quantify integration levels (Ma et al., 2018; Yang et al., 2020; Zhang et al., 2020). Spatially, Zhang et al. (2022) evaluate coordination in the Yellow River Basin through urban development, rural progress, and integration metrics. Cao

(2021) assesses China's "dual-wheel coordination" spatial patterns using coupling coordination models, while Lu et al. (2021) identify "factor-structure-function" coupling mechanisms via spatial Moran's index analyses. Regional case studies, such as Zhang et al. (2021) analysis of Jiangsu Province and Yao and Peng's (2021) examination of Nanjing, highlight localized challenges and policy solutions like equitable public service systems. Drivers of integration span macro-level factors (natural environments, socioeconomic conditions) and micro-level elements (demographics, infrastructure, technology) (Overbeek, 2009; Zhang, 2016; Chen et al., 2020; Gharaibeh et al., 2022).

2.2 Research on the rural land use efficiency

Research on Land Use Efficiency has progressively emerged as a central focus in China's agricultural studies and a critical pathway to address arable land scarcity. Scholars have identified a significant correlation between urban-rural functional complementarity and improvements in land use efficiency (Gutierrez-Velez et al., 2022; Bosworth and Venhorst, 2018). Methodologically, land use efficiency assessments exhibit dynamic evolution. Researchers have refined evaluation frameworks by incorporating undesirable outputs (Tone, 2001; Alemdar and Oren, 2006; Ke et al., 2021), advancing the measurement system for green land use efficiency. The paradigm has shifted from early static efficiency evaluations (Chen et al., 2016; Li et al., 2017) to integrated approaches combining super-efficiency SBM models with spatial econometric methods (Tan et al., 2024; Souza and Gomes, 2015). Spatial analysis tools like Moran's I index further reveal heterogeneous clustering patterns, characterized by "high-high" and "low-low" efficiency agglomerations. These methodological innovations not only validate interregional technology spillover effects but also expose environmental externalities such as pollution displacement. Currently, research scopes on rural land use efficiency have expanded systematically. Academic focus has extended from urban built-up areas (ULGUE) to cultivated land systems (CLGUE), forming a trinity evaluation framework encompassing economic, social, and ecological dimensions. Xie et al. (2018) broke through linear evaluation paradigms with their generalized directional distance function, while Zhou et al. (2023) demonstrated enhanced yet regionally divergent coordination between cultivated land green efficiency and high-quality agricultural development using composite indicators. Empirical studies based on SDG indicators (Lu et al., 2018; Guo C et al., 2024) suggest synergistic potential between land use efficiency and ecological benefits amid rapid urbanization. Furthermore, research on the determinants of rural land use efficiency exhibits multiscale interactive characteristics. At the micro level, household-specific attributes serve as foundational variables driving efficiency disparities. Human capital factors such as education levels (Khai and Yabe, 2011) and technical training (Naceur and Mongi, 2013) influence efficiency outcomes through production decision-making. At the meso level, the benefit distribution mechanisms embedded in land transfer systems (Fukuyama and Weber, 2010; Fukuyama et al., 2011) impose structural constraints. At the macro level, institutional innovations like innovative city pilot policies (Xu et al., 2025) enhance urban land green use efficiency (ULGUE), yet persistent regional development disparities (Qin et al., 2022; Hong and Mao, 2024) remain a major institutional barrier.

2.3 Literature review

Existing studies have extensively explored China's urban-rural integration and rural land use efficiency, identifying deepened urban-rural integration as a pivotal breakthrough for addressing rural land underutilization. This raises two critical questions: Does urban-rural integration effectively enhance rural land use efficiency? and Given regional disparities in resource endowments and labor mobility, does its impact exhibit significant spatial heterogeneity? To address these questions, this study employs provincial-level panel data (2012–2023) from China (provinces, autonomous regions, and municipalities) to construct a three-tier indicator system measuring urban-rural integration and rural land use efficiency. By comprehensively assessing their spatiotemporal dynamics, we further investigate the mechanisms through which urban-rural integration influences rural land efficiency, aiming to provide evidence-based insights for optimizing provincial land governance.

The study's marginal contributions are twofold. Theoretically, it enriches existing frameworks on rural land use efficiency by systematically analyzing the causal linkages between urban-rural integration and efficiency outcomes. Methodologically, it advances empirical rigor by identifying mediating mechanisms (e.g., factor mobility) and rigorously testing regional heterogeneity, thereby addressing gaps in prior research.

3 Theoretical analysis and research hypotheses

3.1 The direct mechanism by which urban-rural integration promotes the rural land use efficiency

Agglomeration Externality Theory posits that urban-rural integration drives the restructuring of spatial land factors between cities and rural areas. For instance, the interconnectivity of urban-rural infrastructure directly alleviates geographical constraints on land elements, integrating rural land into urban economic spheres' spatial production systems. This structural transformation of rural land productivity generates agglomeration economies, thereby enhancing rural land use efficiency. First, advancements in digital technologies—such as big data, 5G, and blockchain—have redefined the factor attributes of rural and urban land. This shift enables rural land management to transition from experience-driven to data-driven practices. Applications like precision fertilization and smart irrigation bypass the need for labor mobility as intermediaries, directly boosting marginal output per unit of land and improving efficiency. Second, industrial planning elevates urban-rural integration levels, establishing direct capitalization channels for rural land. Collectively-owned commercial construction land can now enter markets without expropriation, reflecting true market value. This incentivizes land users to optimize factor combinations, eliminates mismatches caused by spatial fragmentation, and expands land

productivity's Pareto Frontier through spatial reorganization and technological embedding. Additionally, mixed-use land development policies grant rural land multifunctional usage rights, breaking traditional monocultural agricultural constraints and fostering spatial factor flexibility, which further elevates efficiency.

Hypothesis 1: Urban-rural integration significantly enhances rural land use efficiency through agglomeration externalities, technological innovation, and institutional restructuring.

3.2 Indirect mechanism by which urban-rural integration promotes the rural land use efficiency

3.2.1 The integrated development of urban and rural areas promotes land transfer, thereby enhancing the rural land use efficiency

New Institutional Economics posits that urban-rural integration constitutes a systemic transformation driven by the co-evolution of institutional innovation and factor allocation. Through mechanisms such as land property rights refinement and transaction cost reduction, efficient property rights arrangements optimize resource allocation by lowering transaction costs, reshaping incentive structures for factor mobility, and dismantling institutional barriers embedded in the urban-rural dual system. This facilitates the transition of land resources from inefficient lock-ins to market-driven configurations. China's "Three Rights Separation" reform exemplifies this logic: by decoupling land contractual rights and management rights, it establishes an institutional foundation for land transfer, enabling fragmented plots to consolidate into scaled operational units and significantly improving land's marginal output elasticity (Sun and Zhou, 2019). Concurrently, the deepening market mechanisms in urban-rural integration have catalyzed new agricultural entities like family farms and cooperatives. Contract-based land transfers foster intensive land utilization, generating transaction cost advantages over fragmented household operations. Large-scale production through these entities reduces transaction costs in technology adoption, capital investment, and market access (Li et al., 2023). Thus, urban-rural integration enhances rural land use efficiency by promoting land transfer through property rights refinement and transaction cost reduction.

Hypothesis 2: Urban-rural integration promotes land transfer, thereby improving rural land use efficiency.

3.2.2 The integrated development of urban and rural areas promotes the mobility of the labor force between urban and rural areas, thereby enhancing the rural land use efficiency

From the Coupled Perspective of New Institutional Economics and Structural Transformation Theory, urban-rural integration dismantles institutional barriers such as the household registration (hukou) and land systems, reshaping incentive structures for labor migration and intensifying cross-regional labor mobility. First, the equalization of public services and reforms to the household registration system reduce urbanization costs for rural migrants, incentivizing labor shifts from low-productivity agricultural sectors to urban non-agricultural sectors (Wang et al., 2020). Second, the separation of land contractual rights and management rights creates an "exit-transfer-appreciation" closed loop through property rights refinement. This enables (left-behind farmers) to achieve scaled operations via land transfers, triggering intensive land reorganization and enhancing efficiency (Liao et al., 2020). Additionally, urban-rural human capital interactions accelerate technology diffusion. The "knowledge spillback" effect-driven by returning entrepreneurs and urban technological spillovers-upgrades traditional agriculture into high-value-added sectors. This reinforces path dependency in land efficiency improvements, spurring industrial restructuring where capital and technology substitute labor inputs, reducing per-unit management costs, and boosting total factor productivity (Hayami and Ruttan, 1985).

Hypothesis 3: Urban-rural integration promotes labor mobility between urban and rural areas, thereby enhancing rural land use efficiency.

4 Empirical design

4.1 Data selection and source explanation

4.1.1 Dependent variable: rural land use efficiency (*Rlue*)

To address input-output slack issues inherent in traditional Data Envelopment Analysis (DEA) with multiple inputs and outputs, this study employs an input-oriented Super-SBM-Undesirable model under constant returns to scale (CRS) to measure rural land use efficiency. This approach effectively resolves slack variable problems compared to conventional DEA frameworks.

Suppose there are n production decision-making units (DMU, $n = 1, 2, 3, \ldots, N$), and each DMU contains input and output variables with expected and undesirable outputs, with quantities of m, l and h respectively. The formula for calculating agricultural land use efficiency is as follows:

$$min\,\theta = \frac{1 + \frac{1}{m}\sum_{m=1}^{M}\left(\frac{S_m^x}{x_{jm}^t}\right)}{1 - \frac{1}{l+h}\left(\sum_{l=1}^{L}\left(\frac{S_l^y}{y_{jl}^t}\right) + \sum_{h=1}^{H}\frac{S_h^b}{b_{jh}^t}\right)} \tag{1}$$

$$\text{s.t. } x_{jm}^t \geq \sum_{j=1, j\neq 0}^{n} \lambda_j^t x_{jm}^t + S_m^x \tag{2}$$

$$y_{jl}^t \geq \sum_{j=1, j\neq k}^{n} \lambda_j^t y_{jl}^t - S_l^y \tag{3}$$

$$b_{jh}^t \geq \sum_{j=1, j\neq k}^{n} \lambda_j^t b_{jh}^t + S_h^b \tag{4}$$

Herein, $\lambda_j^t \geq 0$, $S_m^x \geq 0$, $S_l^y \geq 0$, $j = 1, \ldots\ldots, n; \theta$ represents of rural land use efficiency; x_j^t, y_j^t and b_j^t respectively represent the input, expected output and non-expected output values; S_m^x, S_l^y and S_h^b respectively denote the slack variables of input, expected output and non-expected output; λ represents the weight variable. Table 1 presents the three-level indicator system of input-output for rural land use efficiency.

TABLE 1 Inputs and outputs of rural land use efficiency.

Primary indicator	Secondary indicator	Tertiary indicator	Indicator meaning unit	Primary indicator
Rural land use efficiency	Investment indicators	Land input	Rural cultivated land area	1,000 hm^2
		Labor input	Number of people employed in the primary industry	10,000 people
		Capital input	Regional capital stock	10 billion yuan
	Expected output	Economic increment	Growth rate of the primary industry	10 billion yuan
		Social welfare	Grain output	10,000 tons
	Unanticipated output	Water pollution Air pollution	Agricultural wastewater discharge volume	10,000 tons
		Land input	Agricultural ammonia nitrogen discharge volume	10,000 tons

TABLE 2 Measurement and evaluation system for the level of urban-rural integration development in China.

Primary indicator	Secondary indicator	Third-level indicator	Calculation formula	Indicator nature
Urban-rural integrated development	Economic integration	Economic development level	Per capita GDP	+
		Income gap between urban and rural residents	Per capita disposable income of urban residents/Pe r capita disposable income of rural residents	−
		Expenditure gap between urban and rural residents	Per capita consumption expenditure of urban residents/Per capita consumption expenditure of rural residents	−
		Binary comparison coefficient	(Gross output value of the primary industry/Number of employed in the primary industry)/(Gross output value of the second and third industries/Number of employed)	+
	Social integration	Coverage rate of urban-rural old-age insurance	Number of insured for urban-rural old-age insurance/ Population of permanent residence	+
		Coverage rate of unemployment insurance	Number of participants in unemployment insurance/ Population of permanent residence	+
		Urban-rural *per capita* healthcare comparison coefficient	Per capita healthcare expenditure of urban residents/ Healthcare expenditure of rural residents	−
		Urban registered unemployment rate	Direct data	−
		Urban-rural education investment	Education expenditure/Fiscal expenditure	+
	Spatial integration	Number of private cars owned	Direct data Urbanization rate Number of urban population/Total population直接数据	+
		Urbanization rate	Number of urban population/Total population	+
		Urban-rural *per capita* transportation and communication comparison coefficient	Per capita transportation and communication expenditure of urban residents/Transportation and communication expenditure of rural residents	−
	Ecological integration	Harmless treatment of domestic waste	Direct data	+
		Forest coverage rate	Direct data	+
		Public toilet availability	Number of public toilets per 10,000 people	+

Note: The data is sourced from "China Statistical Yearbook," "China Rural Statistical Yearbook," "China Population and Employment Statistical Yearbook," "China Environmental Statistical Yearbook," "China Health Statistics Yearbook," "China Education Statistical Yearbook," "China Urban Construction Statistical Yearbook," and the statistical yearbooks of each province (municipality, district). Among them, the spherical distance between provincial capital cities was calculated using ArcGIS 10.8; the PM2.5 concentration data was obtained from the Atmospheric Composition Analysis Group of Dalhousie University.

4.1.2 Core explanatory variable: urban-rural integration level (*Cud*)

This study constructs an evaluation index system for urban-rural integration across four dimensions—economic, social, spatial, and ecological integration—as outlined in Table 2. (1) Economic Integration. Emphasizes free factor flows between urban and rural areas, reflecting regional living standards, developmental potential, and resource allocation efficiency. (2) Social Integration. Focuses on equitable access to social services and welfare, measuring the coordinated development of education, healthcare, and social security systems across urban and rural regions. (3) Spatial Integration. Serves as the spatial vehicle for integrated

development, evaluating population distribution, land use patterns, and the capacity for factor circulation and spillover effects. (4) Ecological Integration. Places urban and rural areas within a unified environmental system, assessing air/water quality, green infrastructure, and sustainability of development practices.

4.1.3 Panel entropy method + TOPSISI

The evaluation model for digital economy and rural land use efficiency is constructed using the panel information entropy. The specific calculation steps are as follows: Firstly, select the indicators: Let there be m cities and n indicators. Then, q_{ij} represents the j, the indicator of city i ($i = 1, 2, \ldots, n$). To address the dimensional issues caused by different units, the indicators are standardized. The absolute values of the indicators are transformed into relative values, and $q_{ij} = | q_{ij} |$ is adopted. The meanings represented by the numerical values of positive and negative indicators are different (the higher the value of positive indicators, the better; the smaller the value of negative indicators, the better). The following steps are adopted to standardize the indicators:

$$\text{Positive standardization: } q'ij = \frac{q_{ij} - min\{q_{1i}, \ldots, q_{mj}\}}{max\{q_{1i}, \ldots, q_{mj}\} - min\{q_{1i}, \ldots, q_{mj}\}} + 1 \quad (5)$$

$$\text{Negative standardization: } q'ij = \frac{max\{q_{1i}, \ldots, q_{mj}\} - q_{ij}}{max\{q_{1i}, \ldots, q_{mj}\} - min\{q_{1i}, \ldots, q_{mj}\}} + 1 \quad (6)$$

Determine the weight of the ith city in the jth indicator: Let $p_{ij} = \frac{q'ij}{\sum_{i=1}^{m} q'ij}$; calculate the entropy value of the jth indicator, $e_j = -k\sum_{i=1}^{m} q_{ij}\, ln(p_{ij})$, ($i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$), where $k > 0$, $k = \ln(m)$, represents the adjustment coefficient, ensuring that $0<e_j < 1$; calculate the information utility value of the jth item indicator: $d_j = 1\text{-}e_j$ ($j = 1, 2, \ldots, n$). The larger information utility value d_j is, the more important the indicator is; calculate the weight of the jth indicator: $wj = \frac{d_j}{\sum_{j=1}^{n} d_j}$ ($j = 1, 2, \ldots, n$); calculate the comprehensive score of the ith city: $S_j = \sum_j^n w_j p_{ij}$ ($i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$).

Secondly, to mitigate the potential bias in indicator weights caused by high numerical dispersion—where certain indicators dominate the evaluation due to scale differences—this study incorporates the Euclidean distance to measure the relative proximity of each evaluation unit to the ideal (or worst) solution. This approach adjusts for distortions in ranking results that may arise from excessive sensitivity to data accuracy or indicator selection.

By integrating this distance-based correction, the method not only maximizes the utilization of available data and minimizes information loss, but also reduces the influence of sample size limitations and reference sequence dependencies. As a result, it provides a more accurate and stable representation of regional differences and development trends in the digital economy and rural land use efficiency.

The specific computational steps are as follows: Calculate the weighted standardized matrix of each index. $R = (r_{ij})m \times n, r_{ij} = w_j x'_{ij} (1 \le i \le m, 1 \le j \le n)$; determine the optimal solution S_j^+ and the worst solution S_j^-. $S_j^+ = max(r_{ij}), S_j^- = min(r_{ij})$, where, $1 \le i \le m$, $1 \le j \le n$; calculate the Euclidean distance between each scheme and the optimal solution; $sep_i^+ = \sqrt{\sum_{j=1}^{n} (S_j^+ - r_{ij})^2}$, $sep_i^- = \sqrt{\sum_{j=1}^{n} (S_j^- - r_{ij})^2}$; calculate the comprehensive evaluation index of each scheme, $C_i = \frac{sep_i^-}{sep_i^- + sep_i^+}$, $C_i \in [0,1]$.

4.1.4 Mediating variables

(1) Land mobility (*Land-flow*), mainly reflected in the transfer of agricultural land to non-agricultural land. Therefore, the proxy variable for land mobility is the proportion of industrial and storage land area to the total urban construction land area. (2) Labor mobility (*Lab-flow*), measured using a two-way constrained semi-logarithmic gravity model. The specific calculation method is as shown in Equation 7:

$$Lab - flow_{ij} = ln\, Labq_i \times \ln\left(Wage_j - Wage_i\right) \times \ln\left(Priceh_i - Priceh_j\right) \times Dis_{ij}^{-2} \quad (7)$$

Among them, $Lab\text{-}flow_{ij}$ represents the number of labor force flowing from region i to region j, $Labq_i$ represents the total number of labor force in region i, $Wage_j$ and $Wage_i$ respectively represent the average wage level of on-the-job workers in region j and i, $Priceh_i$ and $Priceh_j$ respectively represent the average housing prices in region i and j, and Dis_{ij} represents the geographical distance between region i and region j.

4.1.5 Other control variables

To reduce the endogeneity problem that may be caused by omitted variables and to accurately reflect other factors influencing the rural land use efficiency, this paper sets the following control variables: (1) Economic development level (ln*GDP*). The economic development situation of each province is represented by the GDP of that province. (2) Human capital level (ln*Edu*), which is indicated by the number of college students per hundred people. (3) Social employment security (ln*Sis*), which is represented by the ratio of local fiscal social security and employment expenditures to local fiscal total expenditures. (4) Financial development level (ln*Find*), which is indicated by the proportion of financial loan balance at the end of the year to GDP. (5) Social consumption level (ln*Con*), which is indicated by the proportion of social consumption to GDP, the calculation formula is: total retail sales of consumer goods/GDP. (6) Labor cost (ln*Wage*). It is represented by the logarithm of the average annual salary of urban workers in each province (city). Descriptive statistics of the variables are shown in Table 3.

4.2 Empirical design

4.2.1 Model construction

4.2.1.1 Basic regression model

Based on the analysis in the previous text, a two-way fixed effects model was adopted to investigate the impact of urban-rural

TABLE 3 Descriptive statistics of variables.

Variable	Symbol	Variable description	Sample size	Mean value	Standard deviation	Minimum value	Maximum value
Dependent variable	*Rlue*	Rural land use efficiency, calculated based on the indicator system in Table 1	360	0.615	0.285	0.094	1.425
Independent variable	*Cud*	Urban-rural integration development level, calculated based on the indicator system in Table 2	360	0.354	0.092	0.145	0.634
Mediating variable	*Land-flow*	Land mobility, represented by the proportion of industrial and storage land area to the total urban construction land area	360	0.210	0.087	0.005	0.740
	Lab-flow	Labor mobility, measured by the two-way constrained semi-logarithmic gravity model for labor mobility volume	360	10.140	0.706	6.687	11.964
Control variables	ln*GDP*	Economic development level of each province, represented by the logarithm of the provincial GDP	360	9.684	1.003	6.416	11.587
	ln*Edu*	Human capital level, represented by the number of college students per hundred people	360	1.795	2.001	0.007	12.764
	ln*Sis*	Social employment security, represented by the ratio of local fiscal social security and employment expenditures to local fiscal total expenditures	360	0.131	0.046	0.001	0.443
	ln*Find*	Financial development level, represented by the proportion of end-of-year financial loan balance to GDP	360	1.060	0.663	0.118	9.622
	ln*Con*	Social consumption level, represented by the proportion of social consumption to GDP	360	0.385	0.116	0.001	2.227
	ln*Wage*	Labor cost. Represented by the logarithm of the annual average wage of urban employees in each province (city)	360	1.778	0.320	1.143	2.814

integration on the rural land use efficiency of Chinese provinces. The following settings were made:

$$Rlue_{it} = \alpha_0 + \alpha_1 Cud + \alpha_2 \ln GDP_{it} + \alpha_3 \ln Edu_{it} + \alpha_4 \ln Sis_{it} + \alpha_5 \ln Find_{it} + \alpha_6 \ln Con_{it} + \alpha_7 \ln Wage_{it} + \mu_{it} + \sigma_{it} + \varepsilon_{it} \quad (8)$$

Here, i represents the provinces (municipalities, autonomous regions) of China, and t represents the year; $Rlue_{it}$ represents rural land use efficiency of each province in China in year t and year t-1; Cud_{it} represents the level of urban-rural integration development in each province of China in year t; $lnGDP_{it}$ represents the economic development level of each province in year t; lnEdu_{it} represents the human development level of each province in year t; lnSis_{it} represents the social employment security level of each province; ln$Find_{it}$ represents the financial development level of each province in year t; lnCon_{it} represents the social consumption level of each province in year t; ln$Wage_{it}$ represents the labor cost of each province in year t; μ_{it} and σ_{it} respectively represent the fixed effects of provinces and time, and ε_{ijt} is the random error term.

4.2.1.2 Mediation effect model

To further explore the mediating effect of the mechanism variables in the impact of urban-rural integration on the rural land use efficiency of Chinese provinces, based on the analysis in the previous text, this paper, on the basis of Equation 8, combined with the analysis of the influencing mechanism in the previous text, establishes the following mediation effect model:

$$M_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_{it} + \varnothing_{it} + \varepsilon it \quad (9)$$

$$Y_{it} = \gamma_0 + \gamma_1 X_{it} + \gamma_2 M_{it} + \gamma_3 Z_{it} + \varnothing_{it} + \xi_{it} \quad (10)$$

Here, M_{it} represents the mechanism variable, indicating the land and labor mobility within each province of China; X_{it} are a series of control variables in Equation 8 that affect the rural land use efficiency of each province in China; φ_{it} represents the time and province fixed effects; ξ_{it} and ε_{it} are random error terms.

4.3 Analysis of the basic regression results

In the basic regression, a two-way fixed effects model is used for estimation. To alleviate the estimation bias caused by omitted variables and other factors, in the basic regression, both the year and province fixed effects are controlled separately. At the same time, robust standard errors are adopted to ensure the reliability of the regression results. The regression results are shown in Table 4.

TABLE 4 Basic regression (dependent variable: Rural land use efficiency).

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Cud	0.497*** (0.114)	0.317*** (0.105)	0.379*** (0.128)	0.281*** (0.166)	0.227*** (0.009)	0.201*** (0.029)
ln*GDP*		0.101** (0.0482)	0.208** (0.106)	0.128** (0.0513)	0.0333** (0.0160)	0.0556* (0.0337)
ln*Edu*			−0.0337*** (0.00968)	−0.179*** (0.0640)	−0.104*** (0.0373)	−0.123** (0.0715)
ln*Sis*			−0.0186* (0.00987)	−0.0119** (0.00829)	−0.0301*** (0.0113)	−0.0157** (0.0111)
ln*Find*				−0.0625 (0.0366)	−0.0594 (0.0410)	−0.0267 (0.0300)
ln*Con*					0.0658** (0.0287)	0.0628** (0.0274)
ln*Wage*						−0.109*** (0.0293)
Constant term	−1.794** (0.765)	−0.477* (0.247)	0.421* (0.232)	0.247 (0.209)	0.280*** (0.0483)	−0.024 (0.037)
Observation	360	360	360	360	360	360
Provincial fixed effect	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES
R-squared	0.249	0.269	0.429	0.944	0.586	0.810

Note: The symbols "***", "**", and "*" indicate significance levels of 1%, 5%, and 10% respectively. The values in parentheses represent the robust standard errors. The table below is the same.

Table 4 reports regression results for the full sample with province and year fixed effects. Column (1) presents baseline estimates with only the urban-rural integration level (*Cud*), while columns (2)–(6) sequentially incorporate control variables. The coefficients and significance of *Cud* remain stable across specifications, confirming result robustness. We focus on column (6), which includes all controls.

The coefficient for *Cud* is positive and statistically significant at the 1% level, indicating that urban-rural integration significantly enhances rural land use efficiency (Hypothesis 1 is validated). New Institutional Economics posits this efficiency gain as a Pareto improvement process driven by synergistic factor reallocation and institutional reforms. Dismantling the urban-rural dual system removes institutional barriers, enabling bidirectional flows of land, capital, and technology—termed the "counterflow effect"—which optimizes rural land productivity. Quantitatively, a 1% increase in *Cud* correlates with a 0.379% improvement in rural land use efficiency.

Key findings on control variables: Economic development (ln*GDP*): Significantly positive (1% level). Capital spillovers from developed regions to rural areas under diminishing marginal returns drive scaled operations and efficiency gains. Human capital (ln*Edu*) and social employment security (ln*Sis*): Significantly negative (5% level). Urbanization attracts skilled labor away from rural areas, lowering agricultural labor quality and suppressing efficiency. Financial development (ln*Find*): Statistically insignificant. Financial deepening exhibits no measurable impact on rural land efficiency. Social consumption (ln*Con*): Significantly positive (1% level). Rising demand for high-quality agricultural products incentivizes supply-side reforms, shifting land use from low-yield crops to high-value agriculture. Labor costs (ln*Wage*): Significantly negative (5% level). Higher urban wages exacerbate rural brain drain, reducing labor availability and efficiency despite potential skill upgrades.

4.4 Robustness test

In order to ensure the reliability of the regression results, this paper has conducted robustness tests from the following four aspects, as follows:

4.4.1 Alternative measurement for core explanatory variable

To address dimensional heterogeneity in indicators, the original index system was normalized. The traditional entropy method was improved using factor analysis: factor loadings and component scores derived from primary indicators were integrated with entropy-based difference coefficients to recalculate the dependent variable. As shown in Column (1) of Table 5, the coefficient signs and significance levels align with baseline results, confirming robustness.

4.4.2 Alternative measurement for dependent variable

The dependent variable was recalculated using the standard SBM-Undesirable model instead of the super-efficiency variant. Re-estimation results (Table 5, Column 2) show *Cud* remains significantly positive at the 1% level, further validating robustness.

4.4.3 Adjusted observation period

To mitigate temporal bias, the sample period was narrowed to 2014–2021. Regression results (Table 5, Column 3) demonstrate that *Cud* retains its positive significance, consistent with baseline findings.

4.4.4 Instrumental variable (IV) approach

To address potential endogeneity from temporal lag effects, one-period lagged *Cud* was employed as an IV in a two-stage least squares (2SLS) framework. The lagged variable correlates with current *Cud* but lacks direct contemporaneous influence on land use efficiency, satisfying IV relevance and exogeneity

TABLE 5 Robustness test.

Variable	(1)	(2)	(3)	(4)
Cud	0.012** (0.005)	0.137*** (1.026)	0.573*** (0.899)	1.430*** (0.257)
Control variables	YES	YES	YES	YES
Constant	−0.810*** (0.027)	−0.985* (0.457)	−1.899*** (0.056)	0.764*** (0.134)
Fixed effect	YES	YES	YES	YES
Anderson canon. corr. LM statistic	—	—	—	46.000*** (0.000)
C-D Wald F statistic	—	—	—	66.000 (16.38)
Observation	360	360	360	330
R-squared	0.899	0.889	0.895	0.732

TABLE 6 Mechanism verification.

Variable	(1)	(2)	(3)	(4)
	Land-flow	*Rlue*	*Lab-flow*	*Rlue*
Cud	0.538*** (0.316)	0.468*** (0.225)	0.130*** (0.157)	0.157*** (0.237)
Land-flow		0.225*** (0.014)		
Lab-flow				0.056*** (0.020)
Control variables	YES	YES	YES	YES
Constant	29.129*** (0.117)	9.100*** (0.131)	−1.066** (0.426)	−2.123*** (0.077)
Fixed effect	YES	YES	YES	YES
Observation	360	360	360	360
R-squared	0.910	0.943	0.104	0.100

requirements. Results (Table 5, Column 4) pass weak IV and validity tests, with coefficient signs and significance mirroring baseline estimates.

After conducting robustness and endogeneity tests using the above four methods, the coefficient sign and significance of the core explanatory variable (*Cud*) is consistent with the results of the basic regression. Therefore, the research conclusions of this paper are basically reliable.

4.5 Mechanism verification

Building on the theoretical mechanisms discussed earlier, urban-rural integration exerts an indirect impact on rural land use efficiency. To further investigate the mediating roles of land transfer and labor mobility between urban and rural areas, this study employs a mediation effect model. Regression results, presented in Table 6, confirm that these factors significantly channel the influence of urban-rural integration on efficiency improvements.

Columns (1)–(2) of Table 6 present regression results testing the mediating role of land transfer (*Land-flow*). Column (1) demonstrates that urban-rural integration significantly enhances land transfer rates at the 1% significance level. Column (2) confirms that urban-rural integration improves rural land use efficiency by promoting land transfer, thereby validating Hypothesis 2. The empirical results align with theoretical predictions. Urban-rural integration drives land property rights refinement and transaction cost reduction, which collectively optimize resource allocation and incentivize efficient land use. This institutional restructuring enables fragmented rural plots to consolidate into scaled operational units, directly boosting marginal productivity and reducing idle land resources.

Columns (3)–(4) of Table 6 present regression results testing the mediating role of labor mobility (*Lab-flow*) between urban and rural areas. Column (3) shows that urban-rural integration significantly enhances labor mobility at the 1% significance level. Column (4) confirms that integration improves rural land use efficiency by facilitating labor mobility, thereby validating Hypothesis 3. The empirical evidence aligns with theoretical mechanisms. Urban-rural integration dismantles institutional barriers, reshaping migration incentives and intensifying bidirectional labor flows. This dynamic accelerates the skill upgrading of rural labor through knowledge spillovers from urban sectors, while reducing labor redundancy in agriculture. Consequently, rural land management transitions toward capital- and technology-intensive practices, optimizing input-output ratios and elevating land productivity.

TABLE 7 Results of heterogeneity tests in different regions.

Variables	(1)	(2)	(3)
	Eastern region	Central region	Western region
Cud	0.726** (2.344)	0.166 (0.702)	1.563** (2.036)
Control variables	YES	YES	YES
Fixed effect	YES	YES	YES
Constant	1.531*** (6.600)	0.528* (1.898)	0.791*** (3.447)
Observations	132	96	132
R-squared	0.643	0.733	0.717

4.6 Heterogeneity test

4.6.1 Analysis of heterogeneity in different regions

As a vast agricultural country with diverse regional conditions, China has significant regional differences in terms of resource endowment, economic development, and population density. Therefore, there are considerable regional disparities in the degree of urban-rural integration in China. It is thus necessary to conduct research on the different impacts of urban-rural integration on the efficiency of rural land use in the eastern, central, and western regions, in order to better understand whether there are heterogeneities in the impact of urban-rural integration on rural land use efficiency under the background of regional heterogeneity. Empirical results, presented in Table 7, reveal distinct spatial patterns: Column (1) shows that urban-rural integration significantly enhances rural land use efficiency in the eastern region at the 5% significance level. Column (3) demonstrates a stronger positive effect in the western region, significant at the 1% level. Column (2) indicates an insignificant impact in the central region, despite a positive coefficient. From the perspective of the eastern region, benefits from robust economic foundations, advanced digital literacy among farmers, and a concentration of universities and research institutions, which elevate labor quality and technological adoption. These factors synergistically amplify integration's efficiency-enhancing effects. From the perspective of the western region, leverages abundant land resources and ecological advantages, enabling sustainable land use practices that offset economic constraints. From the perspective of the central region, faces challenges from the "siphoning effect" of eastern economies, where labor outflows reduce rural workforce quality and hinder efficiency. According to the statistics released by the National Bureau of Statistics of China, in 2023, among the migrant workers from the eastern region, those who moved across provinces accounted for 13.8%, those from the central region accounted for 51.7%, those from the western region accounted for 44.5%, and those from the northeastern region accounted for 30.9%. The high wage attraction effect in the eastern region led to the migration of labor force from the central region, resulting in the hollowing out of industries in the central region and insufficient factor concentration, making it difficult to enhance land utilization efficiency through urban-rural integration. Therefore, the central region should leverage the spillover effects of digital technology and the favorable policy environment to gain "latecomer advantages," thereby better promoting the level of urban-rural integration and enhancing the rural land use efficiency.

4.6.2 Heterogeneity across grain functional zones

The major grain-producing areas focus on ensuring food security as their core objective. The flow of urban and rural resources is mainly based on large-scale farming, but the land use is strictly restricted. The major grain-consuming areas, due to the pressure of self-sufficiency, are compelled to innovate the market mechanism and need to enhance marginal returns. The balanced areas need to balance production and market flexibility. These functional positioning differences result in the non-uniform impact of urban-rural integration on land use efficiency. Therefore, it is necessary to investigate whether there are any differences in the impact of urban-rural integration on the rural land use efficiency in different grain production zones. Following the classification standards of China's Ministry of Agriculture and Rural Affairs, the sample is divided into major grain production areas, major consumption areas, and balanced areas. Regression results were presented in Table 8, reveal significant efficiency improvements in production and consumption zones but no statistically significant impact in balanced zones, reflecting "uneven urban-rural development" across functional regions. In the major production areas, as core hubs of national grain supply, these regions benefit from policy tilting, technology intensification, and scale-oriented farming during integration, directly enhancing land use efficiency. In the major consumption areas, facing food self-sufficiency pressures, these areas reconfigure land use patterns through urban-rural factor counterflows, driving functional diversification and marginal benefit gains. In the balanced areas, constrained by weak self-sufficiency targets and limited factor interactions, land use remains dominated by traditional smallholder farming. This might be because in the main sales area, due to its policies emphasizing marketization, technological empowerment and functional integration, has been compelled to achieve efficient land utilization. However, the main production area is constrained by yield-oriented policies and institutional restrictions, and its efficiency improvement relies more on scale rather than innovation-driven approaches. This disparity reflects that the urban-rural integration policies need to be combined with regional functional positioning, and balance the dual goals of "ensuring security" and "improving efficiency."

TABLE 8 Results of heterogeneity test for food function areas.

Variables	(1)	(2)	(3)
	Major production areas	Major consumption areas	Balanced areas
Cud	0.241** (1.218)	0.825** (2.423)	0.527 (0.622)
Control variables	YES	YES	YES
Fixed effect	YES	YES	YES
Constant	0.522*** (4.042)	1.274*** (3.378)	−1.204*** (−5.991)
Observations	156	84	120
R-squared	0.674	0.775	0.622

Therefore, the level of urban-rural integration has an impact on the heterogeneity of the grain functional areas, which also reflects the unbalanced effects of institutional guarantees, market driving forces, and regional functional compatibility in spatial governance.

5 Conclusion

Enhancing urban-rural integration is of paramount significance for China's high-quality rural economic development, with rural land use efficiency serving as a critical determinant. Utilizing provincial-level panel data (2012–2023) from China (provinces, autonomous regions, and municipalities), this study constructs a three-tier indicator system to measure urban-rural integration and rural land use efficiency, on the one hand, the impact of the level of urban-rural integration on the efficiency of rural land use was examined, on the other hand, the differences in the influence of China's urban-rural integration level on rural land use efficiency under the background of different regional resource endowments and differences in the function of grain production were explored. Findings as follows:

First, the level of urban-rural integration has a significant effect (at the 1% level) on enhancing the rural land use efficiency. The urban-rural integration process essentially represents a Pareto improvement process resulting from the synergy of factor reallocation and institutional change. The dismantling of the urban-rural dual structure has eliminated the institutional barriers to factor mobility, thereby promoting the improvement of rural land use efficiency. From the coefficient perspective, for every 1% increase in the level of urban-rural integration in China, the rural land use efficiency will increase by 0.379%.

Second, the mechanism analysis reveals that land transfer and the urban-rural mobility of labor force are both channels through which the level of urban-rural integration promotes the improvement of rural land use efficiency. On one hand, urban-rural integration has facilitated the subdivision of land ownership, reduced transaction costs and other factors, lowering transaction costs and promoting the optimization of resource allocation, thereby enhancing the rural land use efficiency. On the other hand, urban-rural integration has eliminated institutional barriers such as household registration and land ownership, reshaped the incentive structure for labor migration, enabling more frequent migration of rural labor force, accelerating the improvement of rural laborers' skills, and thereby enhancing the rural land use efficiency.

Thirdly, the heterogeneity analysis shows that the level of urban-rural integration has a stronger promoting effect on the rural land use efficiency in the eastern and western regions of China, while the impact is not significant in the central region. Comparatively speaking, the eastern region has a clear advantage in economic foundation, the western region has a clear advantage in land resource environment, and the agricultural operating households in the eastern region have higher digital literacy, more universities and research institutions are concentrated in the eastern region, and the labor force quality is also higher. These conditions are all conducive to the improvement of the level of urban-rural integration. The labor force in the central region is affected by the suction effect of the eastern region, and the labor outflow is relatively obvious, which will reduce the quality of rural labor force and thereby affect the land use efficiency. Furthermore, the level of urban-rural integration has a significant promoting effect on the rural land utilization efficiency in major grain-producing areas and major grain-consuming areas, but has no significant impact on the rural land efficiency in grain balance areas. The heterogeneity effect of urban-rural integration on grain functional areas also reflects the non-equilibrium effect of institutional guarantees, market driving forces, and regional functional compatibility in spatial governance.

Based on the research conclusions of this article, the following suggestions are proposed: First, establish a market-oriented mechanism for the allocation of urban and rural factors and deepen institutional reforms. Continuously promote the reform of land property rights, establish a unified urban-rural construction land market, allow rural collective non-agricultural construction land to enter the market for transactions, and break the dual division system of urban and rural land. Promote the experience of "separation of three rights" reform, clarify the rights and functions of land contracting rights, operation rights, and income rights, and reduce the transaction costs of land transfer. At the same time, relax the restrictions on household registration in small and medium-sized cities, improve the rights protection mechanism for migrant workers' urbanization (such as housing, medical care, education), and reduce the institutional friction of labor mobility. Second, strengthen differentiated policy supply at the regional level to solve the "central depression" problem. The central region implements the "talent return" project. For example, establish a regional talent cooperation mechanism, promote the exchange of talents and skills between the eastern and western regions, and optimize the allocation of labor resources. By establishing a special fund for rural revitalization, for returnees who start businesses in their

hometowns, a 50% reduction in corporate income tax will be implemented for the first 3 years, and they will also be provided with a maximum 500,000 yuan interest-free loan. The focus will be on supporting key industries such as modern agriculture and ecommerce. Third, improve the collaborative governance framework for land transfer and labor mobility. Through the promotion of "land transfer performance insurance," introduce third-party assessment institutions to rate the credit of transfer entities, and reduce the risk of contract breach. Improve the rural social security network, incorporate landless farmers into the urban employee pension insurance system, and reduce the worries of land transfer. In particular, develop labor-intensive industries in county economies to promote "employment away from the land but staying in the village," achieve a positive interaction between land transfer and local employment of labor, and reduce institutional friction.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

HL: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review and editing. XL: Data curation, Formal Analysis, Investigation, Software, Writing – original draft.

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EDITED BY
Lingli Qing,
Guangzhou College of Commerce, China

REVIEWED BY
Yixiong He,
Zhejiang Ocean University, China
Guangnian Xiao,
Shanghai Maritime University, China

*CORRESPONDENCE
Jining Zhang,
zhangjn123@tongji.edu.cn

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Regional differences and convergence of land use efficiency towards carbon neutrality in China's Yangtze river economic belt

Kang Wang[1,2], Yifei Wang[3] and Jining Zhang[4]*

[1]Zhejiang University-Shanghai Tunnel Engineering Co., Ltd. (ZJU-STEC), Urban Development and Planning Innovation Joint Research Center, Zhejiang University, Hangzhou, China, [2]China Eco-city Academy Co., Ltd., Tianjin, China, [3]College of Architecture and Urban Planning, Tongji University, Shanghai, China, [4]College of Transportation, Tongji University, Shanghai, China

Beyond traditional carbon reduction approaches, vegetation carbon sinks play a critical role in advancing carbon-neutral urban development. This study refines the evaluation framework for land use efficiency (LUE) by incorporating regional carbon balance, and applies a global super-efficiency epsilon-based measure (EBM) model to assess LUE in 69 cities across the urban agglomerations of the Yangtze River Economic Belt (YREB) from 2005 to 2020. To examine regional disparities, the Dagum Gini coefficient and kernel density estimation are utilized, while spatial convergence models are employed to explore the dynamic evolution of LUE. The results reveal a U-shaped temporal trend in LUE across the YREB, alongside significant spatial heterogeneity among agglomerations. Inter-regional disparities and transvariation intensity are the main contributors to spatial differences, whereas intra-regional disparities have narrowed over time, particularly in the middle reaches of the Yangtze River—with the exception of the Chengdu-Chongqing region. Spatial convergence analysis further indicates significant absolute and conditional convergence within each agglomeration. These findings suggest that policy efforts to enhance LUE in the YREB should be tailored to the specific regional contexts of economic development, industrial structure, fiscal capacity, and business environment.

KEYWORDS

land use efficiency, carbon neutrality, carbon sinks, regional differences, spatial convergence

1 Introduction

The World Cities Report 2022 by the United Nations Human Settlements Programme highlights that the global urban population has surged from 25% in 1950 to nearly 50% in 2020. Historically, land use by humans has significantly altered and fragmented ecosystems (Hong et al., 2021). Urban expansion into low-density agricultural and forested areas has notably reduced ecological reserves, diminished carbon sequestration capacity, and increased both energy consumption and carbon emissions (Burchfield et al., 2006; Zhang and Xu, 2017; DeFries et al., 2022). Native vegetation and soils store substantial carbon, and their loss—driven by agricultural expansion and emissions from agricultural

practices—accounts for approximately 20%–25% of total global greenhouse gas (GHG) emissions (Searchinger et al., 2018).

Urban densification has been proposed to counteract the negative environmental impacts of sprawl by promoting more efficient land use and reducing ecological degradation (Haaland and van den Bosch, 2015). Intensive land use plays a crucial role in reducing GHG emissions and supporting low-carbon economic transitions (Xie et al., 2018; Ling et al., 2023). However, increased efficiency can paradoxically lead to further development and resource use—an outcome known as the Jevons paradox—which may exacerbate ecological degradation and carbon emissions (Alcott, 2005; Heiskanen, 2021; Ceddia and Zepharovich, 2017).

Urbanization and rural abandonment also disrupt the supply and demand of ecosystem services (Hasan et al., 2020) and contribute to increased biodiversity loss (Marques et al., 2019). Take China, for example, In recent decades, the Yangtze River Delta Urban Agglomeration has experienced concentrated expansion of construction land, leading to significant scale effects and the accelerated loss of previously undisturbed farmland and forest ecosystems (Zhai et al., 2024). To achieve carbon neutrality, regional carbon balance objectives must be integrated into land-use planning—especially at regional scales—given that ecosystem service flows often transcend municipal boundaries (González-García et al., 2020). Moreover, climate strategies in the land sector must be region-specific. Uniform approaches can exacerbate inequality and inflict economic harm, particularly in developing regions such as China, India, and African countries (Yu et al., 2023). Thus, measuring land use efficiency (LUE) under regional carbon balance constraints—while accounting for spatial disparities and convergence trends—is critical for sustainable land governance and equitable carbon neutrality.

Optimizing land management is a promising strategy for mitigating climate change (Sha et al., 2022). As the world's largest carbon emitter, China plays a pivotal role in global carbon neutrality efforts. The Yangtze River Economic Belt (YREB), one of China's most important economic zones, contributed 46.7% of national GDP in 2023. However, rapid urbanization in the YREB has intensified tensions between environmental sustainability and economic development. Excessive land expansion and inefficient industrial structures have led to declining LUE and increased ecological vulnerability, posing serious challenges to sustainable development. These challenges are further complicated by significant regional disparities (Yang et al., 2022).

In response, this study refines the LUE evaluation framework by explicitly incorporating regional carbon balance constraints. Using data from 69 cities across the three major urban agglomerations in the YREB from 2005 to 2020, a global super-efficiency epsilon-based measure (EBM) model is employed to assess LUE. To analyze regional disparities, we apply the Dagum Gini coefficient and kernel density estimation. Furthermore, spatial convergence models are introduced to investigate convergence patterns and identify the driving forces of LUE dynamics—offering empirical insights for land-use policymaking aligned with regional and carbon goals.

Extensive research has examined the interrelationship between land use and carbon emissions. Key topics include the measurement of carbon emissions and sinks from land use (Zhou et al., 2021; Luo et al., 2022), the drivers of land-based carbon emissions (Barati et al., 2023; Hong et al., 2021; Yang et al., 2023), low-carbon land-use strategies (Wartenberg et al., 2021; Chuai et al., 2015; Huang et al., 2021), and LUE accounting for carbon emissions (Prisley and Hall, 2024; Kuang et al., 2020; Wu et al., 2022). These studies highlight the dual role of land use in both carbon mitigation and carbon sequestration. Influencing factors include economic development, population growth, energy use, technological advancement, institutional frameworks, land policies, and openness.

At multiple spatial scales—provincial (Luo et al., 2020) and municipal (Liu et al., 2024; Chen et al., 2022)—LUE has been evaluated using diverse methodologies, including stochastic frontier analysis (Liu et al., 2020), slack-based measures (Tan et al., 2021; Xiao et al., 2022), and predictive modeling based on InVEST (Zafar et al., 2024).

Building upon this evaluative foundation, researchers have explored the spatiotemporal evolution and influencing mechanisms of LUE under carbon constraints (Zhou and Lu, 2023; Yang and Liu, 2023). Due to variations in geography, resource endowment, and socioeconomic factors, spatial imbalances in LUE persist (Liu et al., 2019). Several methods—such as the Gini coefficient (Zheng et al., 2013), Theil index (Xue et al., 2022), concentration index (Song et al., 2013; Wang et al., 2022), Hirschman–Herfindahl index (Song et al., 2013), and Moran's I (Wu et al., 2022)—have been used to characterize these disparities. Even without accounting for carbon sinks, substantial LUE imbalances have been identified within the YREB (Liu et al., 2021; Luo et al., 2020).

Despite the breadth of existing studies, several research gaps remain. First, the integration of carbon balance into LUE assessment remains insufficient. Second, current studies pay limited attention to urban agglomerations as focal units. Third, the spatial convergence of LUE has not been adequately explored using spatial econometric models.

This study aims to address these gaps with three main contributions:

(1) It refines the LUE assessment by integrating carbon emissions and sequestration to construct a more comprehensive carbon balance framework—responding to the global call for carbon-neutral land-use strategies.
(2) It focuses on urban agglomerations within the YREB rather than national or provincial levels, offering insights into the core engines of China's urban and economic transformation.
(3) It employs spatial convergence models to uncover dynamic patterns in regional LUE and enhance understanding of spatial inequalities over time.

The remainder of this paper is organized as follows: Section 2 presents the materials and methodology. Section 3 reports empirical results. Section 4 provides discussion and policy implications. Section 4.2 concludes the study and discusses limitations.

2 Materials and methods

2.1 Study area

We focus on the YREB's three main urban agglomerations: the Yangtze River Delta (YRD) with *Shanghai* at its heart, incorporating

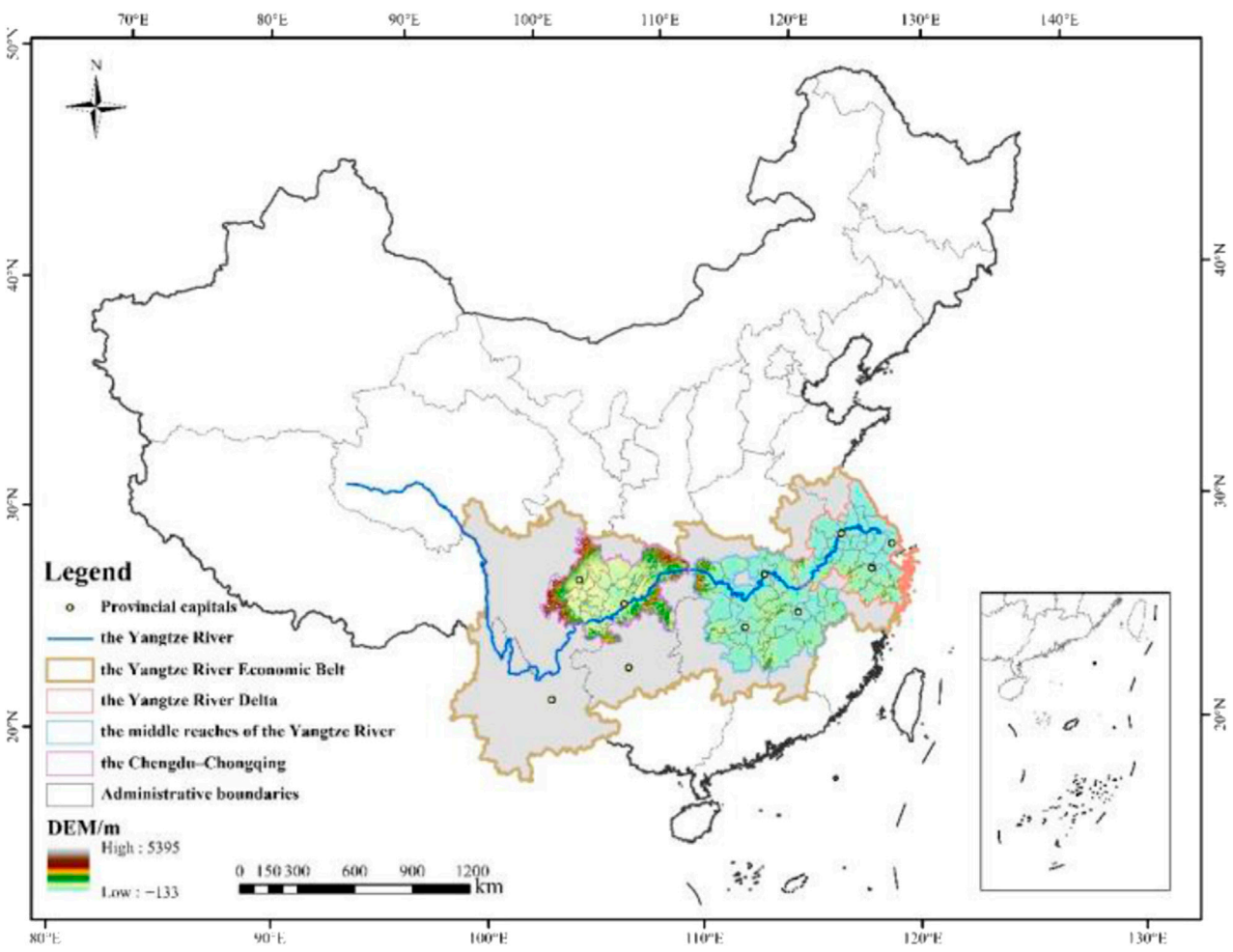


FIGURE 1
Study area.

26 cities across *Jiangsu*, *Zhejiang*, and *Anhui* provinces; the middle reaches of the Yangtze River (MRYR) with *Wuhan* at its heart, which encompasses 31 cities in *Hubei*, *Hunan*, and *Jiangxi* provinces; and Chengdu–Chongqing, including 16 cities such as *Deyang* and *Mianyang*, as the economic and cultural center in western China. Notably, *Xiantao*, *Qianjiang*, *Tianmen*, and *Xiangyang* were excluded from this analysis due to the absence of relevant statistics. In the end, we obtained 69 prefecture-level and above cities in the YREB and used them as the research objects of this study. A visualization of the study area is shown in Figure 1. The scope of this study excludes rural areas for two main reasons. First, the primary objective is to examine LUE dynamics within urban agglomerations of the YREB, which serve as the core drivers of regional economic transformation and carbon reduction strategies. Second, rural areas typically exhibit relatively homogeneous land use patterns, such as agricultural and ecological land, with limited variation in intensity and structure. As a result, changes in LUE within these areas are comparatively marginal and less relevant to the analytical framework adopted in this study.

2.2 Variable selection and data description

2.2.1 Index system of LUE towards carbon neutrality

Aligning urban LUE with carbon neutrality goals requires balancing economic growth with sustainable resource use and regional carbon balance. In a carbon-neutral city, urban carbon emissions are offset by equivalent carbon removals. Therefore, net carbon emissions serve as a critical indicator of urban carbon neutrality. When considering land use as a dynamic process of "input and output," the concept of land use toward carbon neutrality can be defined as a systematic approach that aims to steadily increase desired outputs, such as GDP, while managing production inputs efficiently and minimizing undesired outputs, particularly net carbon emissions (Figure 2). This framework focuses specifically on land use and its role in achieving carbon neutrality, without addressing other environmental pollutants. Table 1 shows the variable descriptions of inputs and outputs.

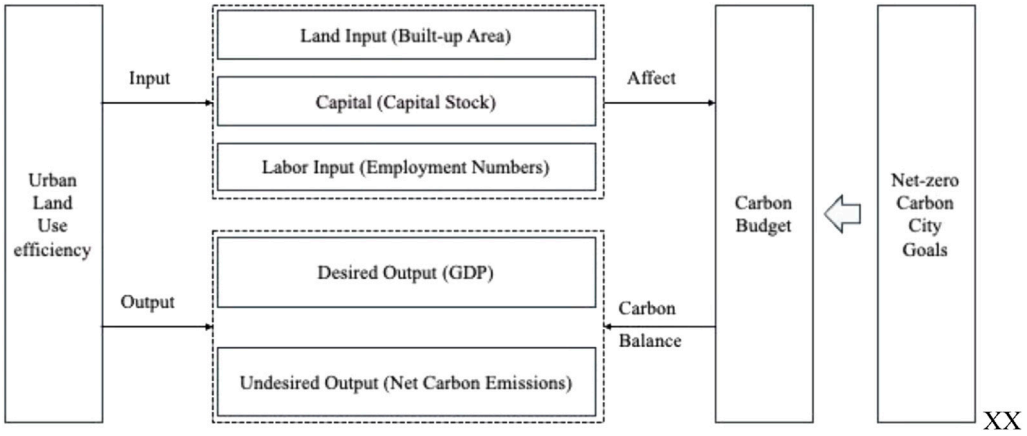


FIGURE 2
Theoretical framework for LUE under net-zero carbon city goals.

TABLE 1 Evaluation index system of urban LUE towards carbon neutrality.

Layer of criteria	Layer of factors	Layer of indicators	Unit
Inputs	Labor	Number of employees	10^4 persons
	Land	Area of built districts	km^2
	Capital	Capital stock	CNY 10^8
Outputs	Desired outputs	GDP	CNY 10^8
	Undesired outputs	Net carbon emissions	million tones (mt)

TABLE 2 Description of influencing factors.

Variable	Definition	Code	Unit
Financial deepening	Loan balances of financial institutions at the end of the year/regional GDP	*Loan*	%
Fiscal gap	(local fiscal expenditure—local fiscal revenue)/local fiscal revenue	*Gap*	%
Industrial structure	Secondary and tertiary industries' added value/regional GDP	*Indus*	%
Economic development	Natural logarithm of GDP *per capita*	*Pgdp*	-
Foreign direct investment	Actual amount of foreign capital used/regional GDP	*Fdi*	%

2.2.2 Influencing factors of LUE towards carbon neutrality

The influencing factors of LUE towards carbon neutrality include financial deepening (*Loan*), fiscal gap (*Gap*), industrial structure (*Indus*), economic development (*Pgdp*), and foreign direct investment (*Fdi*). Table 2 shows the specific definitions of control variables.

2.2.3 Data description

This study's period spans from 2005 to 2020. Due to the monopoly power of local governments in China over land (Gyourko et al., 2022), we had to carefully consider the possible discontinuities caused by planning and policy changes when clarifying the temporal border of the study. Based on the 11th Five-Year Plan (2006–2010) and incremental calculations in the spatial convergence analysis, we set the starting time point as 2005. To mitigate the discontinuous impact of the COVID-19 epidemic, we set the end-time point as 2020. Data on provincial carbon emissions were derived from the China Energy Statistical Yearbook. Nighttime light observations, including DMSP/OLS and NPP/VIIRS, were procured from the EOG. The original data of urban carbon sinks come from the MODIS NPP product (MOD17A3) released by NASA and the Landsat-derived annual land cover product of China (CLCD) data provided by Yang and Huang (2021). The urban built-up area data originated from the China Urban Construction Statistical Yearbook. Additional statistics were sourced from the China City Statistical Yearbook and the National Bureau of Statistics. To address the missing values,

linear interpolation was employed. Furthermore, all price variables were recalibrated to the 2005 metric to reflect actual changes. Table A1 in Supplementary Appendix SA1 shows the specific data description.

2.3 Methods

2.3.1 Carbon budget accounting

Carbon budget accounting requires accurate calculations of both carbon emissions and carbon sinks. We calculated carbon sinks using two key data sources: NASA's MOD17A3 net primary productivity (NPP) data and the CLCD data (Chen et al., 2020; Yang and Huang, 2021). First, we processed the MOD17A3 data by extracting relevant bands and merging the images using the HEGTool. Then, we applied coordinate transformation, mask extraction, and zonal statistics to both the MOD17A3 and CLCD datasets using ArcGIS 10.8. This enabled us to calculate the NPP for different land use types across various cities, providing annual estimates for each. For every Gram of dry biomass produced, approximately 1.62 g of CO_2 are sequestered, with this biomass constituting roughly 45% of the total NPP. Thus, carbon sinks are calculated using the formula: Carbon Sinks = (NPP/0.45) × 1.62.

Carbon emissions are calculated using the PSO-BP algorithm, which integrates DMSP/OLS and NPP/VIIRS nighttime light data with provincial carbon emission statistics (Chen et al., 2020). First, a relationship is established between provincial carbon emissions and nighttime light intensity, represented by the sum of DN values. Urban carbon emissions are then estimated by applying a weighted average to these DN values. Provincial carbon emissions follow the IPCC's inventory guidelines, using energy consumption data sourced from the energy balance sheets (Shan et al., 2020).

The net carbon emissions are calculated by subtracting carbon sinks from total carbon emissions, using the following formula: Net Carbon Emissions = Carbon Emissions - Carbon Sinks.

2.3.2 Global super-efficiency epsilon-based measure model

Following the research of Tone and Tsutsui (2010) and Wang et al. (2023), we consider k = (1, 2 … K) Decision-Making Units (DMUs) and construct a global technology production possibility set. For each DMU_k, J types of inputs, denoted as x_j (j = 1, 2 … J), generate M desired outputs, represented by y_m (m = 1, 2 … M), and N undesired outputs, denoted as b_n (n = 1, 2 … N). The resulting production possibility set is defined:

$$PPS\left\{(\bar{x},\bar{y},\bar{b})\middle|\begin{array}{ll}\sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}x_{kj}^{t}\lambda_k^t\le\overline{x^t}; & \sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}y_{km}^{t}\lambda_k^t\ge\overline{y^t}\\ \sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}b_{kn}^{t}\lambda_k^t\le\overline{b^t}; & \sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}\lambda_k^t=1;\boldsymbol{\lambda}\ge\mathbf{0}\end{array}\right\} \quad (2)$$

where $(\bar{x},\bar{y},\bar{b},)$ represents the optimal solution of the model. x_{kj}, y_{km}, b_{kn} represent the jth input factor, the mth desired output and the nth undesired output of the kth decision-making unit, and x_{kj}, y_{km}, b_{kn} is greater than 0; λ_k represents the weight. Adding the constraint of λ = 1 indicates variable returns to scale, and removing the constraint of λ = 1 indicates constant returns to scale (CRS).

The global super-efficiency epsilon-based measure model is:

$$\gamma^{*}=\min_{\theta,\varphi,\lambda,s^{-},s^{+}}\frac{\theta+\varepsilon_x\sum_{j=1}^{J}\frac{w_j^{-}s_j^{-}}{x_{jo}}}{\varphi-\varepsilon_y\sum_{m=1}^{M}\frac{w_m{}^{+}s_m{}^{+}}{y_{mo}}-\varepsilon_b\sum_{n=1}^{N}\frac{w_n{}^{b-}s_n{}^{b-}}{b_{no}}} \quad (3)$$

$$\begin{cases}\sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}x_{kj}^{t}\lambda_k^t-s_j^{-}\le\theta x_{jo},j=1,\ldots,J\\ \sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}y_{km}^{t}\lambda_k^t+s_m{}^{+}\ge\varphi y_{mo},m=1,\ldots,M\\ \sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}b_{kn}^{t}\lambda_k^t-s_n{}^{b-}\le b_{no},n=1,\ldots,N\\ \sum_{t=1}^{T}\sum_{k=1,k\neq 0}^{K}\lambda_k^t=1\\ \boldsymbol{\lambda}\ge\mathbf{0},s_j^{-}\ge 0,s_m{}^{+}\ge 0,s_n{}^{b-}\ge 0\end{cases} \quad (4)$$

where γ^{*} indicates the optimal efficiency under constant returns to scale. s_j^{-}, $s_m{}^{+}$, and s_n^{b-} correspond to non-negative slack variables of the jth input factor, the mth desired output and the nth undesired output, respectively. Similarly, w_j^{-}, $w_m{}^{+}$, and w_n^{-} to represent weights of the jth input factor, the mth desired output and the nth undesired output, respectively. θ is the radial part planning parameter; φ is the output expansion ratio; ε represents the importance of the non-radial part.

2.3.3 Dagum gini coefficient decomposition

According to Formulas 5–8, spatial differences (intra-regional and inter-regional Gini coefficients) are decomposed and analyzed. This method segments spatial differences into three components, intra-regional differences, inter-regional differences, and transvariation intensity (overlap between regions), thereby enabling a more precise identification of the sources of spatial differences (Dagum, 1997). A larger Gini coefficient indicates more pronounced spatial imbalances in LUE, whereas a smaller coefficient suggests narrower spatial gaps. The Dagum Gini coefficient is defined as follows:

$$G=\frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{hr}\right|}{2n^2\bar{y}} \quad (5)$$

where G represents the aggregate Gini coefficient, $\bar{y}$ denotes the mean LUE, and y_{ji} (y_{hr}) represent the LUE of i (r) city within j (h) urban agglomeration; k is the number of urban agglomerations (including the YRD, the MRYR, and Chengdu–Chongqing). The total count of cities within the YREB is given by n, with n_j (n_h) specifying the number of cities in j (h) urban agglomeration. The overall Gini coefficient encompasses the intra-regional difference contribution G_w, the inter-regional difference contribution G_{nb}, and the transvariation intensity contribution G_t:

$$G\equiv G_w+G_{nb}+G_t \quad (6)$$

where G_w is computed based on the intra-group Gini coefficient G_{jj}, while G_{nb} and G_t are calculated using the inter-group Gini coefficient G_{jh}.

The respective expressions for G_{jj} and G_{jh} are presented below:

$$G_{jj}=\frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|y_{ji}-y_{jr}\right|}{2n_j^2\bar{y}_j} \quad (7)$$

$$G_{jh}=\frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji}-y_{hr}\right|}{n_jn_h\left(\bar{y}_j+\bar{y}_h\right)} \quad (8)$$

where $\bar{y}_j$ ($\bar{y}_h$) is the average LUE of j (h) urban agglomeration. G_w, G_{nb}, and G_t can be calculated according to G_{jj} and G_{jh}.

2.3.4 Kernel density estimation

This study used kernel density estimation to describe the dynamic evolution of the distribution of urban LUE. As an important nonparametric method, kernel density estimation is now widely used in the study of imbalanced distributions (Tan et al., 2021; Zhao et al., 2023). It is mainly used to estimate the probability density of random variables and describe the distribution shape of random variables through a smooth and continuous density curve. Kernel density estimation expression is as follows:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{9}$$

$$K(x) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{x^2}{2}\right) \tag{10}$$

where $f(x)$ denotes the probability density function of the random variable x, $K(\bullet)$ represents the Gaussian kernel function, N is the total number of observations, and X refers to the observed value; h signifies the bandwidth parameter for the kernel function. Its value can affect the smoothness of the kernel function distribution curve. Since the kernel density function is sensitive to the choice of bandwidth, a smaller bandwidth is usually used to improve the estimation accuracy (Silverman, 1986). The bandwidth size h used in this study was 0.1.

2.3.5 Spatial convergence model

The neoclassical growth model uses technological progress to explain the gap in economic growth levels between countries. It believes that due to the diminishing marginal returns to capital, economic development will eventually reach a stable state. Economic growth theory calls this the convergence of economic growth (Quah, 1996). Widely recognized convergence models encompass σ-convergence and β-convergence models, which enable the statistical examination of the evolving trends in spatial differences. σ-Convergence was quantified using the coefficient of variation, indicative of a diminishing disparity in LUE over time. Disregarding the determinants of LUE, lower-efficiency cities within a region tend to grow at accelerated rates, ultimately achieving parity with higher-efficiency cities; this process is termed absolute β-convergence. Given that intensified interactions and mobility of elements between cities engender spatial effects, in this study, we constructed the spatial convergence model Durbin model (SDM), spatial autoregressive model (SAM), and spatial error model (SEM) for analyzing β-convergence, respectively. Conditional β-convergence was assessed by incorporating a set of control variables into the absolute β-convergence model to analyze the con-vergence tendency of LUE. Formulas 11–14 (Spatial α/β-convergence models) are applied to analyze LUE convergence, confirming absolute and conditional convergence with spatial spillover effects. The σ-convergence's formula is presented below:

$$\sigma = \frac{\sqrt{\sum_{i=1}^{n_j}\left(y_{ji} - \bar{y}_j\right)^2 / n_j}}{\bar{y}_j} \tag{11}$$

where y_{ij} signifies the LUE of city i within urban agglomeration j. Similarly, $\bar{y}_j$ is the average LUE for urban agglomeration j, while n_j is indicative of the total number of cities within urban agglomeration j.

The β-convergence's formula is presented below:

$$\ln\left(\frac{y_{i,t+1}}{y_{it}}\right) = \alpha + \rho W_{ij}\ln\left(\frac{y_{i,t+1}}{y_{it}}\right) + \beta\ln(y_{it}) + \theta W_{ij}\ln(y_{it}) + \mu_i + \eta_t + \varepsilon_{it} \tag{12}$$

$$\ln\left(\frac{y_{i,t+1}}{y_{it}}\right) = \alpha + \rho W_{ij}\ln\left(\frac{y_{i,t+1}}{y_{it}}\right) + \beta\ln(y_{it}) + \mu_i + \eta_t + \varepsilon_{it} \tag{13}$$

$$\ln\left(\frac{y_{i,t+1}}{y_{it}}\right) = \alpha + \beta\ln(y_{it}) + \mu_i + \eta_t + \varepsilon_{it}\ \varepsilon_{it} = \lambda W_{ij}\varepsilon_{kt} + \nu_{it} \tag{14}$$

where $y_{i,t+1}$ denotes the LUE of the city i in period $t + 1$, while y_{it} represents the same for period t. The coefficient β, indicative of convergence when negative, informs the rate of convergence, expressed as $\nu = -\ln(1- |\beta|)/T$. The parameters ρ, θ, μ_i, η_t, and ε_{it} correspond to the spatial autoregressive coefficient, spatial spillover effect, city-specific fixed effect, time-specific fixed effect, and the stochastic disturbance term, respectively.

3 Results

3.1 Measurement results of LUE towards carbon neutrality

According to Formulas 2–4, the global super-efficiency EBM model is applied to measure LUE across urban agglomerations, with robustness checks confirming the results. Figure 3 depicts the evolution of average net carbon emissions within the YREB. Between 2005 and 2020, the net carbon emissions within the YREB as a whole exhibited an increase trend until 2011 but then changed to a slight downward trend. Figure 4 depicts the evolution of the average LUE within the YREB. Between 2005 and 2020, the urban LUE within the YREB exhibited a decrease, followed by an increase since 2013. In a subregional comparison, the Chengdu–Chongqing demonstrated the highest LUE with a value of 0.793, followed by the MRYR and the YRD, with efficiencies of 0.715 and 0.676, respectively. The LUE of both the YRD and the MRYR increased rapidly after 2013, and the former was more significant, surpassing the overall level in 2019. By 2020, the YRD emerged as the most efficient agglomeration within the YREB. However, although Chengdu–Chongqing also rose rapidly after 2013, it experienced a decline after 2017.

The inaugural urbanization conference in Beijing emphasized the need to heighten urban LUE and optimize urbanization patterns and structures. In the subsequent year, the National New Urbanization Plan (2014–2020) was released. As these policies progressed, LUE showed year-on-year enhancement. Chengdu–Chongqing's leading efficiency is predominantly due to its extensive forest cover. Yet, recent urban sprawl, characterized by extensive land use and short-term technological stagnation, impeded improvements in efficiency since 2017. The more significant rise in the LUE after 2013 in the YRD is largely due to its success in industrial transformation and institutional innovation (Zhang and Chen, 2021).

To ensure the validity of the results, we verified them from the perspective of net carbon emissions and LUE respectively. Referring to the research of Chen et al. (2020) and Shan et al. (2020), from the

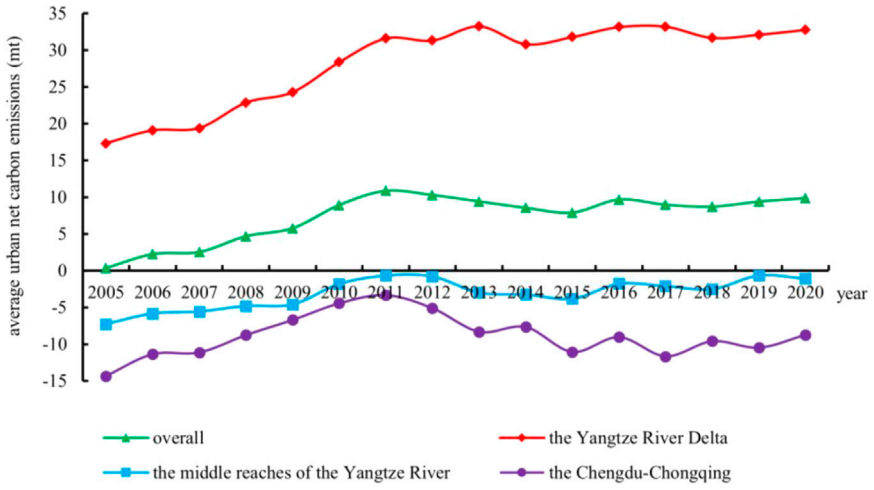


FIGURE 3
Trends of urban net carbon emissions in the YREB from 2005 to 2020.

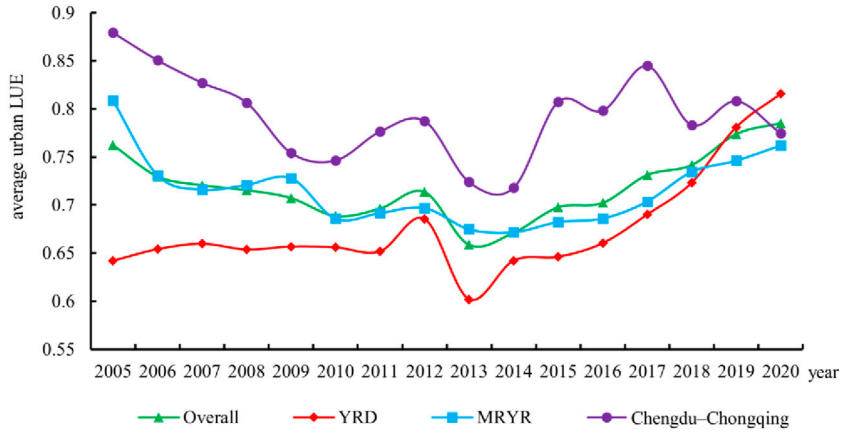


FIGURE 4
Trends of urban LUE in the YREB from 2005 to 2020.

perspective of carbon emissions and carbon sinks, we fit the data calculated in this study with the data calculated by them (Supplementary Appendix Figure A1). The fitting results show that our measurement results are relatively close to the existing literature, which illustrates the validity of our results to a certain extent. To ensure the validity of the global super-efficiency EBM model, we replaced the model settings of the distance function and returns to scale (RTS) for further tests (Supplementary Appendix Figure A2). The fitting results show that our results are still valid even if the model specification is changed. Supplementary Appendix Figures A2a,b, respectively, show the fitting results after the setting of the RTS is changed to CRS, and the setting of the distance function is changed to the SBM. It is worth noting that although the fitting effect of Supplementary Appendix Figure A2a is slightly worse than that of Supplementary Appendix Figure A2b, the R-squared value still reaches 0.991, and most of the observation points are on the diagonal line, which also illustrates the validity of the research results.

3.2 Spatial differences and source decomposition

3.2.1 Intra-regional differences

According to Model 7 analysis, Figure 5 depicts the intra-regional differences of the LUE across the YREB. During the sample period, the differences within the YREB demonstrated a general downward trend. When comparing urban agglomerations, the MRYR had the highest average Gini coefficient of 0.134, followed by the YRD at 0.130 and Chengdu–Chongqing at 0.118. Notably, the middle reaches experienced a significant reduction. Differences were pronounced before 2008, followed by an M-shaped pattern that mirrored the overall trend. In the YRD, two distinct phases were observed, namely, a stage of high variability around a Gini coefficient of 0.137 until 2013 and a subsequent decrease to 0.119 post-2014, likely influenced by the YRD Regional Plan, which facilitated a more uniform development pace. The Chengdu–Chongqing maintained lower intra-regional differences

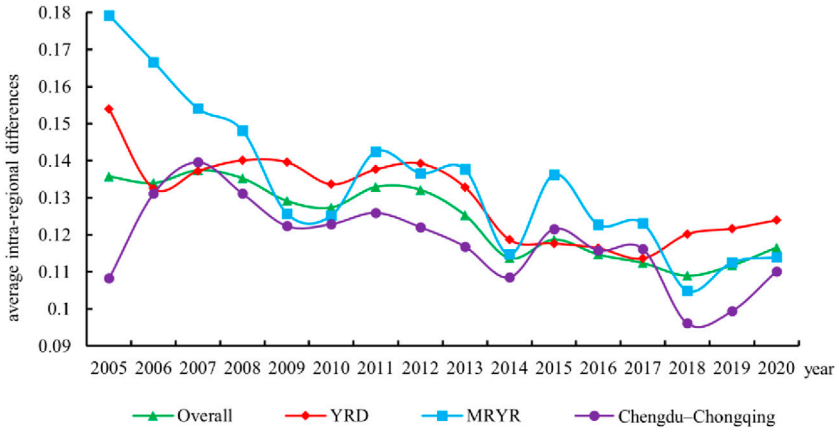


FIGURE 5
Intra-regional differences of urban LUE in the YREB from 2005 to 2020.

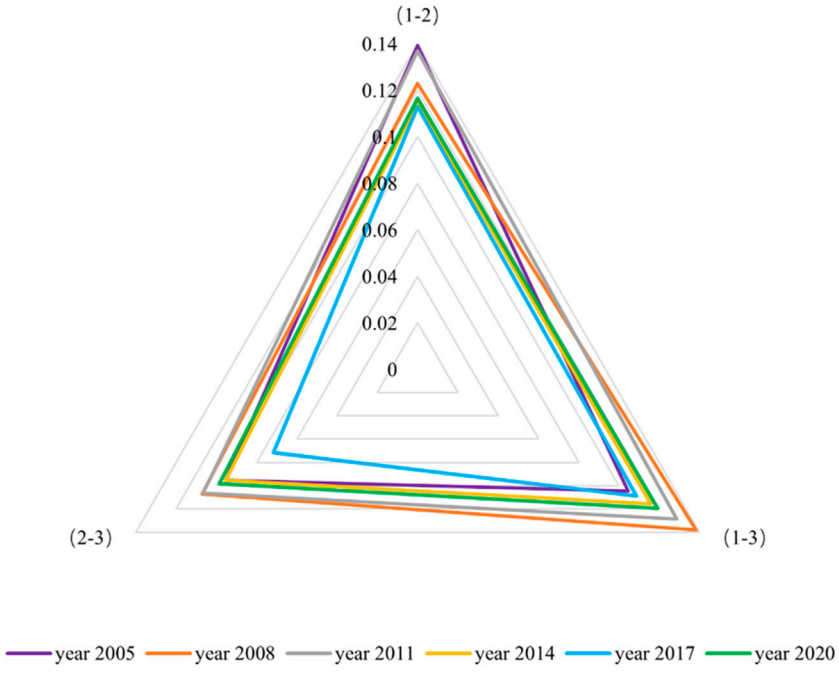


FIGURE 6
Inter-regional differences of urban LUE in the YREB from 2005 to 2020. Note: 1, 2, and three represent the YRD, the MRYR, and Chengdu–Chongqing, respectively.

than the overall area, with a brief rise before 2007 and a stabilization around 0.116 thereafter.

Waterway transportation has played an increasingly important role in the context of trade globalization due to its advantages of strong transportation capacity and low cost. As an important global Golden Inland Waterway, the Yangtze River's transportation demand and carrying capacity have increased significantly since China's accession to the WTO in 2001 (Wang et al., 2020). China's trade expansion has greatly promoted the development of the three urban agglomerations in the YREB. As urban agglomerations continue to develop, urban specialization will undergo a transformation from sectoral to functional specialization (Duranton and Puga, 2005). The spatial-functional urban specialization is reflected in the specialization and collaboration between cities and the spatial layout of different industries to achieve optimal efficiency, promoting coordinated development. Also, as conditions of transportation to central cities continue to improve and transportation costs continue to decrease (Sun et al., 2019), the attractiveness of peripheral cities will significantly increase for manufacturing companies that are more sensitive to cost increases. Therefore, the intra-regional differences are generally shrinking.

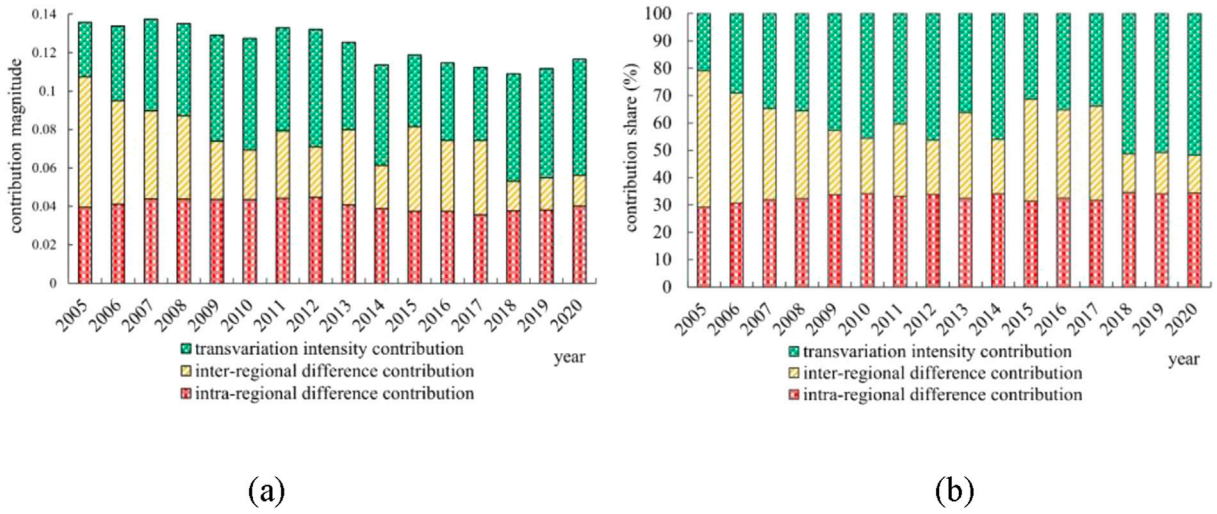


FIGURE 7
Source decomposition of regional LUE differences in the YREB from 2005 to 2020. Note: **(a,b)** depict the contribution magnitude and contribution share, respectively.

3.2.2 Inter-regional differences

According to Model 8 analysis, Figure 6 reveals a pattern of expansion–contraction–expansion, signifying a trend of deterioration–improvement–deterioration in the inter-regional differences among the three urban agglomerations. The most minimal differences were observed between the MRYR and Chengdu–Chongqing, with a modest mean index of 0.096. In contrast, the YRD exhibited a considerable variance from the other two agglomerations, with mean differences of 0.123 and 0.121 when compared to the MRYR and Chengdu–Chongqing, respectively. The YRD's unique status as a globally recognized urban agglomeration has been bolstered by its rapid advancements in urbanization, industrial upgrading, and successful adoption of green technologies to mitigate pollution and carbon emissions. This progressive path has led to pronounced differences with other agglomerations. Over the sample period, there was an annual decrease of 1.14% in the differences between the YRD and the MRYR, suggesting a gradual convergence in the LUE. The 2015 Development Planning of Urban Agglomeration in the MRYR aimed at fostering a new type of urbanization in central and western China and, together with the Special Plan for Reform and Innovation of Science and Technology Finance in Wuhan Metropolitan Areas, has significantly impacted technological innovation within the agglomeration. Conversely, the differences between the YRD and Chengdu–Chongqing saw a marginal annual rise of 0.9%, which is due to a downward trend in the latter's LUE in recent years. The relative stability in the differences between the MRYR and Chengdu–Chongqing, with a growth rate of just 0.21%, indicates a synchronous improvement.

3.2.3 Source decomposition

According to Models 5, 6 analysis, the temporal dynamics of the magnitude and shares of contributions to regional differences—decomposed into intra-regional difference contribution, inter-regional difference contribution and transvariation intensity contribution—are presented in Figure 7. Initially, the intra-regional difference within the YREB remained relatively stable throughout the observed period, commencing at 0.039 and concluding at 0.040. Its proportional share varied between 29.13% and 34.57%. Conversely, the inter-regional difference contribution demonstrated a general decline, initiating at 0.068, descending sharply to 0.026 by 2010, and thereafter exhibiting a fluctuating yet downward trend, ending at 0.016. Its share of the total contribution started at 50.1%, dropped significantly to 20.29% in 2010, and subsequently wavered, finishing at 13.79% in 2020, with an average rate of 27.77% across the sample period. Lastly, the magnitude of the transvariation intensity's contribution traced an N-shaped pattern over time, starting at 0.028, peaking at 0.061 in 2012, declining to 0.038 in 2017, and rising again to 0.060 by the end. Correspondingly, its share exhibited a fluctuation from 20.86% to 51.78%, averaging 39.46% throughout the time period of the study.

To conclude, the analysis reveals that inter-regional differences and transvariation intensity accounted for an average contribution rate of 67.23%. This underscores inter-regional differences and transvariation intensity as the primary contributor. While the inter-regional difference contribution decreased, the contribution from transvariation intensity demonstrated an increasing trend, with the latter being the most impactful at an average rate of 39.46%. These data suggest that the overlapping problem of LUE across agglomerations is chiefly responsible for the imbalanced development in the belt.

3.3 Distribution dynamics

Formulas 9, 10 (Kernel density estimation) are applied to analyze LUE distribution dynamics, revealing shifts, polarization trends, and extreme values. Table 3 summarizes the key features of the kernel density curves, and Figure 8 illustrates the specific curves.

Considering the distribution location, the overall and three urban agglomerations all showed a trend characterized by an

TABLE 3 Distribution dynamic characteristics of LUE in the YREB.

Region	Distribution location	Main peak distribution form	Distribution Ductility	Differentiation trend
Overall	Shifted left first and then right	The peak value first increases and then decreases, and the width first decreases and then increases	Left-trailing, broadening extension	Unipolar or bipolar differentiation
YRD	Shifted left first and then right	The peak value first increases and then decreases, and the width first decreases and then increases	Right-trailing, convergent extension	Unipolar or bipolar differentiation
MRYR	Shifted left first and then right	The peak value increases and the width decreases	Left-trailing, broadening extension	Unipolar or bipolar differentiation
Chengdu–Chongqing	Shifted left first and then right	The peak value increases, and the width first decreases and then in-creases	Left-trailing, broadening extension	Unipolar or bipolar differentiation

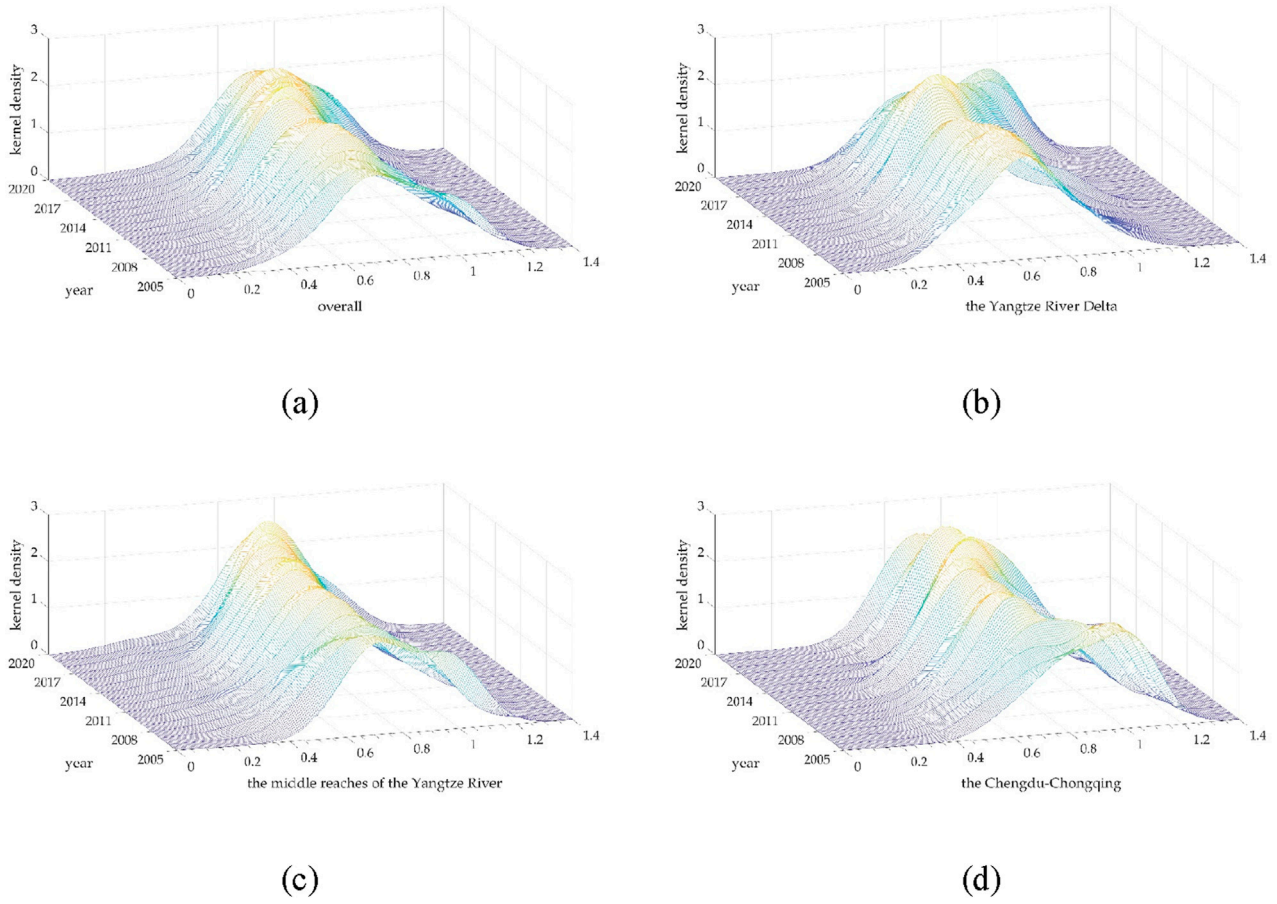


FIGURE 8
Distribution dynamics of LUE in the YREB from 2005 to 2020. Note: **(a–d)** depict the kernel density plot of the overall region, the YRD, the MRYR and Chengdu–Chongqing, respectively.

initial leftward shift until 2013 and a subsequent rightward shift from 2013 to 2020. This pattern suggests a decrease in the LUE from 2005 to 2013, with a subsequent increase from 2013 to 2020, corroborating the findings previously discussed in this paper. Prior to 2013, the YREB, a hub for industrial development, experienced a contraction in green space owing to intensive urbanization, industrialization, and an energy structure dependent on high consumption and emissions, leading to a surge in urban carbon emissions (Wang and Wang, 2022). Post-2013, in response to national policies on emission reduction and environmental protection, a new urbanization strategy emphasizing LUE and urban configuration began to yield positive results, as evidenced by the increasing efficiency in land use.

Upon considering the main peak distribution, it is evident that the overall peak value initially rises and then declines, while the bandwidth transitions from narrow to wide. This pattern demonstrates that the spatial differences first contract and subsequently expand. In the early sample period, economic

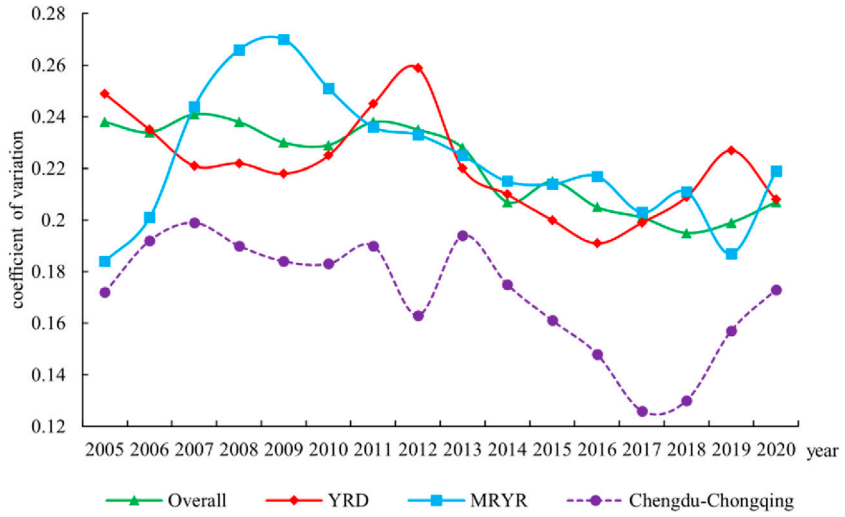


FIGURE 9
σ-Convergence results of LUE in the YREB from 2005 to 2020.

development among cities appeared to converge toward a state of stability. Subsequent to the development of national carbon emission reduction and new urbanization policies, differing industrial structures across cities have led to variable challenges in the green transition, resulting in the divergence of LUE. From a subregional perspective, the main peak distribution pattern in the YRD was similar to the overall trend, with LUE differences initially narrowing and later widening. Chengdu–Chongqing and the MRYR both exhibited an upward trend in peak value, yet their bandwidth evolution diverged. The MRYR's decreasing bandwidth indicates a reduction in spatial differences, whereas Chengdu–Chongqing's increasing bandwidth at the sample period's end suggests expanding differences.

When examining the distribution ductility, it can be observed that the overall region and the three urban agglomerations exhibited a left-trailing pattern. This suggests that some cities have LUEs significantly lower than others within urban agglomerations. The distribution curves broaden, indicating the presence of extremely low values, with certain cities such as *Ezhou* and *Huangshi* in the MRYR and *Suining* in Chengdu–Chongqing consistently at low-efficiency levels. Conversely, the YRD's distribution curve exhibits a right-trailing pattern, reflecting high-efficiency outliers in cities like *Shanghai*, *Jinhua*, and *Suzhou*, among others. *Shanghai*'s notable efficiency is attributed to its robust scientific infrastructure and comprehensive green industry. The converging pattern of the YRD's distribution curve suggests a reduction in extreme values, potentially due to a "trickle-down" or "radiation" effect (Qiu and Yu, 2024).

Upon examining the differentiation trend, it becomes apparent that the overall region and the three urban agglomerations exhibited bipolarity in urban LUE. These agglomerations initially displayed a dual-peak distribution but gradually converged to a single peak, suggesting a diminishing trend in polarization. Specifically, in the YRD, bipolarity emerged in 2018, with the left peak being less pronounced than the right peak. The separation between the peaks widened, indicating an increasing trend in bipolarity. These data indicate that while most cities in the YRD sustained high-efficiency levels, a few cities maintained moderate levels.

3.4 Spatial convergence analysis

3.4.1 σ-Convergence analysis

According to Model 11 analysis, Figure 9 demonstrates the σ-convergence results, revealing a contraction in the overall coefficient of variation from 0.238 to 0.207 during the study period. This change represents an average annual reduction of 0.93%, suggesting a steady harmonization of new urbanization and industrial upgrading among cities. Focusing on specific urban agglomerations, the YRD exhibited a decrease in LUE variation from 0.248 to 0.208, indicative of systematic convergence. Conversely, neither the MRYR nor Chengdu–Chongqing displayed significant σ-convergence, with final variation coefficients surpassing initial figures. However, in the medium term, the two showed obvious convergence trends. Particularly, Chengdu–Chongqing maintained a lower level of variation, presumably due to the uniformity in its industrial and energy profiles (Zhang et al., 2022).

3.4.2 β-Convergence analysis

According to Models 12-14 analysis, Table 4 presents the results of the absolute β-convergence. Firstly, the coefficient of β was significantly negative at the 1% level for both the overall region and the three urban agglomerations, suggesting the presence of absolute β-convergence. This implies that cities with initially lower LUE experience faster growth rates than their counterparts with initially higher efficiency, regardless of economic and social factors. Secondly, the speed of convergence varied among the agglomerations analyzed. The overall convergence rate was 0.022, with the MRYR exceeding the overall rate at 0.035, indicating that spatial interactions within this agglomeration fostered a more rapid convergence. Conversely, the YRD's convergence rate was below the overall rate at 0.018, and Chengdu–Chongqing exhibited the slowest rate at 0.011. Thirdly, spatial effects also differed across the overall sample and the three urban agglomerations. In the overall region and the YRD, both the dependent and independent variables showed spatial lags. This means that there were positive spatial spillover

TABLE 4 Absolute β-convergence results.

Region	Overall	YRD	MRYR	Chengdu–Chongqing
Model	SDM	SDM	SEM	SAR
β	−0.282 *** (0.021)	−0.234 *** (0.037)	−0.407 *** (0.030)	−0.157 *** (0.040)
θ	0.095 ** (0.037)	0.164 ** (0.073)	—	—
ρ or λ	0.274 *** (0.042)	0.092 * (0.055)<	0.044 * (0.026)	0.159 * (0.096)
v	0.022	0.018	0.035	0.011
City-specific fixed effect	Yes	Yes	Yes	Yes
Time-specific fixed effect	Yes	Yes	Yes	Yes
R^2	0.041	0.040	0.023	0.076

Note: *, **, and *** are significant at 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses. The econometric model was selected based on the results of the LM, test, Wald test, and LR, test.

TABLE 5 Conditional β-convergence results.

Region	Overall	YRD	MRYR	Chengdu–Chongqing
Model	SDM	SDM	SEM	SAR
B	−0.354 *** (0.023)	−0.315 *** (0.043)	−0.425 *** (0.029)	−0.198 *** (0.043)
θ	0.086 ** (0.042)	0.223 ** (0.108)	—	—
ρ or λ	0.238 *** (0.043)	0.105 ** (0.060)	0.018 * (0.011)	0.120 * (0.072)
Loan	0.070 *** (0.026)	0.044 (0.048)	0.114 *** (0.036)	0.073 (0.050)
Gap	−0.624 *** (0.113)	−0.525 *** (0.150)	−0.383 * (0.215)	−0.743 *** (0.185)
Indus	−0.007 *** (0.002)	−0.004 (0.005)	−0.007 *** (0.002)	−0.005 * (0.004)
Pgdp	0.061 ** (0.029)	0.004 (0.047)	0.192 *** (0.052)	−0.123 (0.076)
Fdi	5.313 *** (1.778)	5.119 ** (2.44)	12.560 *** (3.85)	−0.440 (4.53)
v	0.029	0.025	0.037	0.015
City-specific fixed effect	Yes	Yes	Yes	Yes
Time-specific fixed effect	Yes	Yes	Yes	Yes
R^2	0.053	0.051	0.062	0.001

effects that affected the rate of change in LUE. A spatial error correlation was present in the MRYR, while Chengdu–Chongqing exhibited a spatial lag in the dependent variable. Given that absolute β-convergence analysis omits several key determinants of LUE, a subsequent conditional β-convergence analysis is warranted.

Table 5 presents the findings of the conditional β-convergence analysis.

Firstly, the conditional β-convergence coefficient is significantly negative at the 1% level for the overall region and the three urban agglomerations, suggesting that LUE converges toward its steady-state level even when accounting for a range of economic and social factors. Specifically, convergence rates were highest in the MRYR, followed by the YRD, with the Chengdu–Chongqing region exhibiting the lowest rate. Second, the conditional β-convergence coefficients were higher than the absolute β-convergence coefficients

for the overall region and each urban agglomeration. They increased the speed of convergence by 0.007, 0.007, 0.002, and 0.004, in that order. This indicates a more rapid reduction in LUE differences when controlling for additional factors, affirming the appropriateness of the selected control variables. Lastly, spatial effects varied across the overall sample and each urban agglomeration, yet they aligned with the spatial patterns identified in the absolute β-convergence analysis.

Economic and social factors demonstrated considerable heterogeneity. Generally, an active financial sector, higher *per capita* GDP, and the adoption of new management methods and low-carbon technologies driven by foreign direct investment markedly promote the convergence of LUE toward superior values. In contrast, an increased fiscal gap and a higher proportion of secondary and tertiary industries are associated with convergence toward inferior efficiency levels. In analyzing specific urban agglomerations, the intensity of foreign direct investment in the YRD fostered the convergence of LUE toward higher values, while a widening fiscal gap led to convergence at lower values. Meanwhile, the effects of financial deepening, industrial structure, and economic development on this convergence were statistically insignificant. All factors under consideration influenced the rate of change in LUE in the MRYR, which was consistent with the overall trend. In Chengdu–Chongqing, a notable fiscal gap and industrial structure configuration had a significant detrimental effect on the rate of change in LUE, but other variables were found to be statistically insignificant.

4 Conclusion and discussion

4.1 Conclusion

Based on the proposed analytical framework and empirical findings, the main conclusions and implications of this study are summarized as follows:

(1) A comprehensive framework was developed to assess land use efficiency (LUE) under carbon neutrality goals. This framework integrates spatial analysis with convergence modeling, offering a practical approach to evaluate urban LUE in the Yangtze River Economic Belt (YREB) in the context of sustainable land management and dual carbon targets.

(2) LUE across the YREB exhibited a U-shaped temporal pattern with significant regional disparities. The Middle Reaches of the Yangtze River (MRYR) showed a steady narrowing of disparities, while Chengdu-Chongqing experienced increasing inequality in the later stages. In contrast, the Yangtze River Delta (YRD) revealed a clear trend of polarization.

(3) Inter-regional differences and transvariation intensity were key drivers of spatial inequality in LUE. The largest gaps existed between the YRD and MRYR, with the MRYR–Chengdu-Chongqing gap being the smallest. Internally, the MRYR showed the most severe imbalance, though it improved over time, while Chengdu-Chongqing remained relatively balanced throughout.

(4) Evidence of convergence was observed among the three urban agglomerations, albeit at different rates. The MRYR demonstrated the fastest convergence in LUE, followed by the YRD and then Chengdu-Chongqing. The heterogeneity in convergence dynamics reflects the influence of regional factors such as financial deepening, fiscal imbalance, industrial restructuring, and foreign direct investment.

(5) Future research should explore the causal mechanisms behind spatial LUE convergence. Investigating the role of specific policy instruments, institutional environments, and technological innovations could offer deeper insights. Moreover, extending the analysis to the county or municipal level could further support differentiated policy-making for carbon-neutral land governance.

4.2 Discussion

4.2.1 Key findings and contributions

This study presents a novel framework for evaluating urban land use efficiency (LUE) under carbon neutrality constraints by incorporating carbon sinks into the carbon accounting system. Unlike many previous studies that focused solely on carbon emissions and reported a "high in the east, low in the west" pattern (Zhang et al., 2022; Zhang et al., 2024), our results reveal a reversal of this trend. By integrating the carbon sequestration capacity of native vegetation into the LUE evaluation, we observed that from 2005 to 2020, the western regions of the Yangtze River Economic Belt (YREB) outperformed the eastern regions in average LUE. This finding highlights the critical role of vegetation carbon sinks in shaping low-carbon land use dynamics—an element often underrepresented in traditional LUE studies.

Our study further contributes to the literature by shifting the analytical scale from national and provincial levels to urban agglomerations, which serve as the primary engines of China's economic activity and carbon emissions. This focus allows for a more granular understanding of the spatial heterogeneity of LUE within the YREB. We identified that the Yangtze River Delta (YRD) has experienced the most substantial improvement in LUE over the study period, primarily due to intensified environmental governance initiatives such as the national "Action Plans" targeting pollution control between 2013 and 2016. Simultaneously, favorable land supply policies for the central and western regions (Lu et al., 2015; Lu and Wang, 2020) contributed to the LUE improvements observed in the Middle Reaches of the Yangtze River (MRYR) and Chengdu-Chongqing areas.

From a spatial perspective, our results indicate a general decline in regional disparities in LUE, with convergence occurring across the three urban agglomerations. However, by the end of the study period, the YRD exhibited the highest degree of internal polarization, characterized by multipolar differentiation. The persistent gap between the YRD and the other two regions suggests that inter-regional disparities and transvariation intensity remain dominant sources of inefficiency. These findings resonate with prior research indicating spatial imbalances in LUE caused by differences in location, resource endowment, and development stage (Liu et al., 2019; Ge et al., 2021).

More importantly, this study introduces the application of spatial convergence models into LUE analysis—an area that has been underexplored in the current literature. Our convergence analysis reveals that although all three urban agglomerations show signs of LUE convergence, the pace varies significantly. The MRYR exhibits the fastest rate of convergence, followed by the YRD, while Chengdu-Chongqing lags behind. The determinants of these convergence patterns include financial development, fiscal decentralization, industrial structure, economic growth, and foreign direct investment—factors widely acknowledged as critical in shaping land use and carbon emissions trajectories (Barati et al., 2023; Yang et al., 2023).

4.2.2 Research innovations and advancements

Compared to the existing literature, this study advances the field in three main aspects:

(1) Conceptual innovation: We establish a comprehensive carbon accounting-based LUE evaluation framework that balances emissions and sinks. This approach responds directly to recent academic calls for integrating carbon neutrality into sustainable land use metrics (Sha et al., 2022; Searchinger et al., 2018).
(2) Analytical scale refinement: By concentrating on urban agglomerations within the YREB, this research captures the micro-dynamics of spatial inequality that are obscured at broader geographic scales. The urban scale is particularly relevant for policymaking, considering cities are both the primary carbon emitters and the frontlines of low-carbon innovation.
(3) Methodological extension: The incorporation of the Dagum Gini coefficient, kernel density analysis, and spatial convergence models enables a multidimensional examination of spatiotemporal trends and policy implications. This expands the empirical tools available for regional land use-carbon efficiency studies.

4.2.3 Policy implications and future research directions

The empirical findings underscore the importance of regionalized strategies for improving LUE under carbon neutrality goals. To accelerate convergence and promote efficient, low-carbon land use, the MRYR should continue strengthening financial infrastructure and economic vitality. In contrast, the YRD and Chengdu-Chongqing should prioritize reforms in fiscal governance and industrial upgrading. Coordinated land-use planning across municipalities is also essential, as ecosystem service flows and carbon balances often transcend administrative boundaries (González-García et al., 2020).

Nonetheless, several limitations warrant attention. While our study incorporates carbon sinks into LUE assessments, further research should explore the integration of multidimensional objectives such as biodiversity conservation, socioeconomic equity, and green innovation. Future work should also employ dynamic simulation models and causal inference techniques to forecast LUE trajectories under various policy scenarios. Additionally, the impact of climate adaptation policies and international market dynamics on regional land use practices deserves further exploration.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

KW: Writing – original draft, Writing – review and editing, Conceptualization, Funding acquisition, Investigation, Project administration, Resources, Supervision, Validation. YW: Writing – review and editing, Conceptualization, Supervision. JZ: Data curation, Writing – review and editing, Formal Analysis, Methodology, Software, Visualization, Writing – original draft.

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Conflict of interest

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Supplementary material

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EDITED BY
Cunyi Yang,
Sun Yat-sen University, China

REVIEWED BY
Zeyu Wang,
Guangzhou University, China
Saige Wang,
University of Science and Technology Beijing, China

*CORRESPONDENCE
Jiawei Li,
lijiawei6869@163.com

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How can digital finance release the ecological value of land intensification: the insight of urban ecological resilience

Yarong Li[1], Chengxin Liu[2], Zijing Hu [2] and Jiawei Li[3,4]*

[1]Xi'an University of Architecture and Technology Huaqing College, Xi'an, China, [2]School of Economics, Minzu University of China, Beijing, China, [3]Yellow River Institute of Hydraulic Research, Yellow River Conservancy Commission, Zhengzhou, China, [4]Yellow River Laboratory, Zhengzhou, China

As a substantial developmental framework aimed at tackling environmental challenges, the development of intensive use of urban land (IUUL) has yet to actualize its ecological efficacy fully. Improving the spatial distribution of factor resources can play a pivotal role in unlocking the ecological potential of IUUL, with a special emphasis on the effective allocation of financial resources. The emergence of digital finance (DF), such as Alipay and Pocket Banking, has notably enhanced the efficiency of financial resource allocation. Nonetheless, empirical data concerning the ability of DF to enhance the ecological significance of IUUL are scarce, and the mechanisms driving these processes remain obscure. This research utilizes panel data from 282 prefecture-level cities spanning 2011–2020 to explore the potential of DF in enhancing the ecological value of IUUL through the lens of urban ecological resilience (UER). The results suggest that DF has the potential to significantly enhance the positive impacts of IUUL on UER significantly, thereby further unlocking the ecological value of IUUL. Mechanisms analysis reveals the potential of DF to unlock the ecological value of IUUL by fostering regional green innovation (GI), rationalizing industrial structure (RIS), and overall upgrading of industrial structure (OUIS). Moreover, the heterogeneity analysis suggests that the effect is more prominent in economically advanced eastern regions, regions with more comprehensive infrastructure, and regions with more favorable innovation environments. This paper highlights the potential of DF to enhance UER through IUUL, offering empirical evidence for the profound fusion of the digital economy and the real economy to drive green transformation. It also charts a course for the real economy's green transformation and the sustainable development of the economy.

KEYWORDS

digital finance, urban ecological resilience, intensive use of urban land, land intensification, ecological value, green transformation

1 Introduction

Urbanization is the predominant theme in contemporary global development; however, rapid urbanization and economic expansion have led to many ecological and environmental challenges. The continuous ramifications of human production activities, extensive infrastructure development, and ineffective resource management have led to the over-exploitation of energy resources, the degradation of urban ecology, and notable

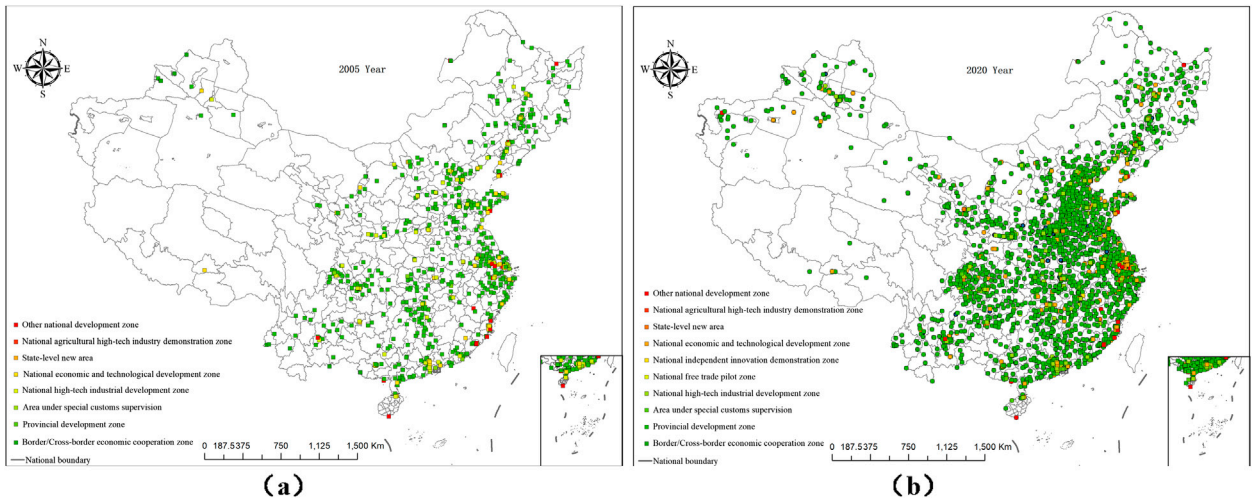


FIGURE 1
The number of IUUL development zones in China. **(a)** The number of IUUL development zones in China in 2005. **(b)** The number of IUUL development zones in China in 2020.

environmental issues. Despite the favorable outcomes stemming from China's recent economic advancement, the nation is grappling with substantial environmental challenges. To maintain economic growth, prioritize ecological advantages, and foster sustainable development, it is essential to investigate innovative approaches that can harmonize environmental considerations with economic progress.

Intensive use of urban land (IUUL), as a specific manifestation of land intensification, emerges as a crucial model for conserving land resources and striking a harmonious balance between ecological preservation and economic development. Viewed from an economic development standpoint, IUUL can trigger knowledge spillover effects and the scale effect within the regional economy, boost urban land use efficiency, and facilitate swift and efficient economic advancement, thereby forming a crucial element of high-quality economic growth. From an ecological standpoint, IUUL can yield several advantageous outcomes. Initially, it can help curb urban sprawl into neighboring natural terrains, thereby preserving biodiversity and ecological equilibrium. Additionally, it can foster the judicious management of hydropower resources. Thirdly, IUUL can curtail energy consumption and enhance urban ecological advantages. However, there are inherent constraints to the efficacy of IUUL in fostering eco-efficiency. In traditional economic models, the mobility of capital, information, and other production factors is relatively restricted. This limitation leads to insufficient incentives for innovation and suboptimal resource distribution, consequently limiting the ecological advantages derived from IUUL. The rise of the digital economy has heralded a paradigm shift in the allocation of production factor resources, hastening the optimization of methods that empower factor resource allocation. Digital finance (DF), a modern addition to the financial landscape, plays a critical role in refining resource allocation and facilitating the flow of information. It presents a promising route to enhance the mobility of production factors, improve resource allocation practices, and increase the eco-efficiency of urban areas. Currently, the existing knowledge base does not provide a conclusive determination regarding the capacity of DF to enable the ecological valorization of IUUL, and the precise mechanisms through which it operates remain incompletely understood. In this vein, conducting comprehensive research on how DF can enhance the optimization of IUUL is of paramount importance, both theoretically and practically. This exploration could show how DF might heighten urban eco-efficiency by refining IUUL.

The primary aim of IUUL is to optimize economic, social, and environmental advantages. The relentless pursuit of economic expansion and urban development has given rise to significant challenges, including the excessive depletion of natural resources and environmental degradation. With the advancement of national economic development, ecological conservation has emerged as a critical imperative. IUUL has been proven to foster economic advancement (Kong et al., 2014) and safeguard land reserves (Wang et al., 2023), offering a crucial solution. This trend stands as a key impetus behind the IUUL in urban growth. In China, land intensification has surged notably over the last twenty years, accompanied by a simultaneous expansion in the number of land intensification development zones (as depicted in Figure 1). Intensive development has emerged as a pivotal model of economic progress in China. Existing studies on the ecological efficiency of IUUL have predominantly concentrated on its contribution to alleviating air pollution challenges. Industrially speaking, IUUL hinges on businesses using fewer resources while upholding productive economic performance. This mechanism, consequently, works to curtail the influx of low-value-added and highly polluting industries. As a result, this process diminishes the volume of carbon emissions in the vicinity and mitigates the air pollution predicament (Wu et al., 2022). From a resource vantage point, IUUL can yield numerous advantages. These encompass the scale effect, improved resource utilization and recycling efficiency, and centralized handling of resource-induced pollution, ultimately

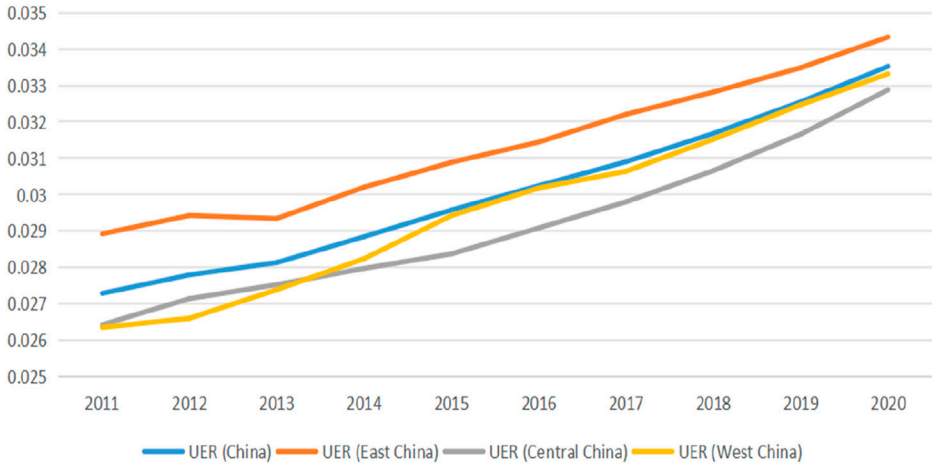


FIGURE 2
Changes in UER in eastern, central and western regions of China.

leading to decreased treatment expenses. As a result, this strategy can play a role in managing air pollution (Wang and Yin, 2017). This scale effect can stimulate the uptake of environmentally sustainable methods among local businesses, thus aiding in reducing pollutant emissions (Ling et al., 2023). Nevertheless, it is crucial to recognize that excessive industrial clustering and overly intense land development can potentially result in significant ecological issues. In terms of biodiversity, illogical land development has been demonstrated to adversely impact the functional diversity of land vertebrates (Etard et al., 2022), the intricacy of soil food chains (Tsiafouli et al., 2015), and the overall population of soil organisms (Yin et al., 2020). These consequences lead to a deterioration of the land's ecological functionality and a significant impact on soil resilience. With IUUL emerging as the prevailing theme in urban development and the ecological landscape demanding immediate consideration, there remains a dearth of research pinpointing how to refine the framework of IUUL to guarantee its role in enhancing urban ecological effectiveness. Building upon this premise, this paper pioneers an exploration of a novel trajectory for IUUL in the digital age approached through the lens of DF. Moreover, it advances strategic recommendations for IUUL, establishing a paradigm that reconciles economic development with ecological protection.

Urban ecological resilience (UER) definitions have a well-established historical background. The term "resilience" originally emerged in the field of materials science to signify a material's capability to absorb energy during plastic deformation and rupture. Over time, "resilience" was increasingly adopted within the ecological domain, defined as an ecosystem's ability to absorb state variables and driving forces while preserving its integrity (Holling, 1973). The concept is steadily gaining momentum, with one notable application being UER. UER is a key focus area in sustainable urban development, showcasing diverse significance. Economically, enhancing UER can enhance a city's ability to adapt to severe weather conditions and environmental pressures. The improvement of UER can effectively mitigate the impacts of disasters on infrastructure and the welfare of residents, thereby reducing social and economic costs (Lu and Luo, 2024). From a social well-being perspective, UER plays a crucial role in safeguarding urban ecosystem services. These services encompass, among others, air purification, water management, and temperature regulation. The profound influence of these services on improving residents' quality of life and health is extensively documented (Gómez-Baggethun et al., 2013). As the Chinese government attaches growing significance to ecological considerations, Chinese cities display a strengthened UER, as depicted in Figure 2. China's overall UER has experienced a steady improvement since 2011, with the eastern region showing a more significant enhancement. Human economic activities have been proven to have a dual effect on the resilience of urban ecological systems. Humans must conduct economic activities in a manner that ensures a harmonious balance between economic growth and ecological stability. IUUL is a developmental model that can harmonize economic growth and environmental conservation. Its central aim is to facilitate resource sharing by concentrating economic activities. This approach reduces unnecessary infrastructure development and resource depletion, fostering synergistic ecological advancement while enhancing production value. However, it is crucial to note that IUUL does not imply a random aggregation of economic activities. In areas characterized by a proliferation of polluting industries and overpopulation, the ecological advantages of IUUL diminish, resulting in exacerbated environmental deterioration and a decline in UER (Shi et al., 2022). Consequently, the question of how to implement green and value-driven IUUL has become a pivotal issue for enhancing UER and promoting the construction of environmentally sustainable cities.

IUUL can potentially harmonize economic progress and environmental conservation, thereby strengthening the UER of cities. Nonetheless, its efficacy is presently curtailed by several factors. Initially, the conventional factor-driven economic development model is characterized by non-green and high-intensity practices (Wang, 2024), which lead to issues such as land overexploitation and energy inefficiency. These challenges culminate in environmental pollution and ecological imbalances, ultimately compromising UER. Secondly, the lack of scientific planning and proficient management of industrial structure

throughout the process of IUUL has resulted in resource misalignment and excessive resource utilization (Fuhong and Yong, 2024), impeding the complete attainment of the ecological advantages associated with land intensification. Moreover, the process of IUUL continues to be marked by a level of disregard, with high-energy, high-pollution, and low-value-added industries prevailing (Li et al., 2023a). IUUL without concurrent industrial upgrading has been demonstrated to lead to the wastage of resources and ecological deterioration, subsequently weakening UER. Therefore, within the context of the current dual objectives of accelerating economic growth and preserving the environment, it is imperative to improve IUUL to maximize its ecological effectiveness. Finance, the crucial circulatory system of economic advancement, plays a pivotal role in providing essential capital for IUUL. Nevertheless, the traditional financial paradigm is characterized by notable information asymmetries, inefficient capital allocation, and limited service coverage (Jiang et al., 2019). These factors give rise to two primary limitations. Firstly, it hampers the ability of financial resources to back high-risk, innovative initiatives, thus obstructing the evolution of economic development. Secondly, it gives rise to a deficiency in industrial restructuring, restricted industrial upgrading, inefficient resource utilization, and excessive resource consumption. Digital finance (DF), as a quintessential product of the digital age, is distinguished by high informatization, liquidity, and universality (Tu et al., 2024). The integration of digital technology into the financial sector has the potential to empower IUUL. This fusion has brought about a transformative shift in financial products, heralding a new era of innovation. Simultaneously, technological progress has enhanced the ability to aggregate financial data, accelerating the flow of capital and lowering the barriers to capital financing. Under these conditions, the profit-seeking nature of capital will cause capital to flow more rapidly to high-productivity industries, stimulate the growth of these industries, transform the economy from a factor-driven to an innovation-driven model, and optimize the allocation of capital within the framework of land intensification. Consequently, this will increase regional resource use efficiency, reduce ecological overexploitation, and optimize UER. Therefore, this study focuses on DF to comprehensively explore its potential to increase IUUL. This approach aims to promote improved UER and establish a more equitable balance between economic development and ecological conservation.

This study employs a panel dataset encompassing 282 prefecture-level cities between 2011 and 2020 to examine the optimization of IUUL patterns through the lens of DF. The aim is to strike a balance between economic advancement and UER. The study's main conclusion is that IUUL has a positive influence on UER, with DF playing a vital role in this relationship. Furthermore, the paper thoroughly examines how DF enhances the IUUL model across three dimensions: industrial development dynamics, structure, and direction within the context of IUUL. Studies have shown that DF can enhance the degree of green innovation (GI) in urban regions, thereby supporting the green revolution of IUUL. DF also holds promise in rationalizing industrial structure (RIS). Consequently, this could trigger an internal restructuring of IUUL, ultimately showcasing characteristics synonymous with ecological harmony. DF can drive the overall upgrade of the industrial structure (OUIS), nudging it towards becoming knowledge-intensive, high-value-added, and highly processed. This shift could subsequently alleviate environmental strain and bolster UER. Heterogeneity analysis indicates that the empowering impact of DF on IUUL is particularly pronounced in eastern regions, areas with well-developed infrastructures, and areas characterized by substantial investment in science and education.

This paper offers notable contributions to research in the following ways: Firstly, it substantially advances existing literature concerning UER. The topic of UER is crucial for fostering sustainable economic growth and safeguarding the welfare of inhabitants. Existing research on human activities influencing UER primarily focuses on intensive development aspects, such as population agglomeration (Zhu et al., 2023) and urbanization (Wang et al., 2022). Nevertheless, there is a scarcity of studies that investigate unlocking the ecological potential of the intensive development model to bolster UER. This study draws on the theoretical foundations of DF to explore how it can activate the latent potential embedded in the development of IUUL, ultimately fostering the augmentation of UER. This pursuit carries substantial practical importance for advancing sustainable urban development initiatives.

Secondly, this paper also enriches the current research landscape on IUUL. IUUL stands out as a crucial urban development trend, offering a strategic approach to boost efficiency and optimize the urban landscape. Extensive research has explored the ameliorative impacts of IUUL on air pollution, encompassing aspects such as emission reductions (Zhao et al., 2017; Shang et al., 2022), facilitation of the low-carbon shift (Wei and Chen, 2021), and improvement of carbon emission efficiency (Liu et al., 2024a). However, there has been little research on the eco-efficiency of IUUL in the digital age. It directly examines the ecological merits of IUUL through the lens of UER, a comprehensive indicator of ecological benefits. Moreover, leveraging the perspective of DF, the paper investigates how DF promotes IUUL in the digital age, consequently enhancing its ecological effectiveness. This discovery holds profound theoretical and practical importance for merging the development of IUUL with digital technology.

Thirdly, this paper adds to the current research on the impact of DF services on the real economy. DF stands out as a notable innovation within the financial sector in the digital age. This technological progression has brought about a paradigmatic change in the economic development sphere, playing a crucial role in augmenting economic efficiency. Existing studies on DF have primarily focused on its direct effects on enterprise financing costs (Li et al., 2023b), financial performance (Wu and Huang, 2022), enterprise value (Tang et al., 2022), and total factor productivity (Li et al., 2024). On the contrary, investigations into the capacity of DF to enrich the conventional economic model and consequently delve deeper into the ecological worth embedded within the traditional economic framework have been relatively scarce. From the standpoint of UER, this study examines the moderating role of DF within the economic development model to unlock the potential of IUUL. It systematically examines how DF and IUUL mutually advance each other to expedite the development of the economic model, the optimization of industrial structure, and industrial improvement, thereby enhancing urban ecological efficacy. This study enhances the theoretical framework of DF by examining eco-efficiency and offers practical recommendations for

advancing DF, thereby highlighting its significant theoretical and practical implications.

The structure of the current study is outlined as follows: The second section comprises the theoretical analysis and research hypotheses. The third section introduces the research model design, variable selection, methods for constructing variables and descriptive statistics. The fourth section presents the empirical analysis, which incorporates basic regression, and robustness tests. The fifth section provides a more detailed analysis, focusing on mechanism testing and heterogeneity analysis. The sixth part comprises the study's conclusion and the development of policy recommendations.

2 Theoretical analysis and research hypotheses

2.1 Digital finance has the potential to facilitate the contribution of intensive use of urban land to urban ecological resilience

IUUL has been shown to optimize resource allocation, decrease land wastage, and capitalize on scale effects to lower resource consumption, ultimately bolstering UER. The level of UER significantly hinges on the diversity and intricacy of ecosystems (Shamsipour et al., 2024). Diversity refers to biofunctional diversity, which denotes the ecological functions of various species within an ecosystem. Complexity is characterized by the intricacy of an ecological network, representing the complexity of the pathways that enable the movement of energy and matter within it. An ecosystem exhibiting high levels of diversity and complexity can depend on diverse species with varied energy flow pathways to sustain its overall functionality in the presence of external disruptions, consequently enhancing ecosystem resilience (Downing et al., 2012). The advancement of IUUL has had a positive impact on the environment, as evidenced by its ability to lower pollution emissions and reduce resource exploitation. Consequently, this has been proven to mitigate the harm inflicted on the diversity and intricacy of ecosystems resulting from economic development. Initially, IUUL has been shown to enhance UER via multiple mechanisms. These encompass elevated land-use efficiency, safeguarding of land resources, direct deceleration of the pace of land development for urban expansion, and maintenance of the diversity and complexity inherent in undisturbed ecosystems (Zhao et al., 2021). Secondly, the theory of agglomeration economy asserts that IUUL promotes resource sharing for economic endeavors within the area (Weber, 1929), including the sharing of infrastructure, energy, and waste management. The utilization of shared resources has been proven to reduce duplication in infrastructure construction, enhance energy utilization efficiency, and lower the cost of managing pollutant emissions. Subsequently, these strategies effectively alleviate the ecological harm resulting from urban development, thereby bolstering UER.

The financial sector directs capital flows, stimulating economic growth and development. Effective capital flow can provide vital backing for developing IUUL and promote the advancement of high-productivity industries in the IUUL zones. Consequently, this can boost the efficiency of industrial resource usage and UER (Huang et al., 2025). Traditional finance presents drawbacks, including low efficiency, high costs, and restricted scope. These limitations contribute to constrained capital flow, resulting in issues such as regional resource mismatches and the clustering of inefficient industries during the development of IUUL. Consequently, this curtails the ecological benefits of IUUL development. DF, emerging as a disruptive innovation in the financial sector amidst rapid digital technology advancements, can bolster IUUL, thereby broadening its positive influence on urban ecological resilience. Firstly, DF has been proven to expedite the pace of capital flows (Tang et al., 2022), facilitating the effective distribution of capital to high-efficiency sectors. Consequently, this has been illustrated to enhance resource utilization efficiency, alleviate over-exploitation, and bolster UER. Secondly, the heightened liquidity features of DF will enable capital to respond swiftly to government environmental policies, stimulate urban GI, enable IUUL to maximize its eco-efficiency, and enhance UER (Wu et al., 2020). DF holds the potential to advance financial inclusion, alleviate consumer credit limitations, and spur diversification of consumer demand. Developments in DF will lead to the upgrading of the urban industrial structure and the encouragement of knowledge- and technology-driven services, as well as high-value-added manufacturing. The emergence of advanced industries often coincides with the integration of new technologies, thus facilitating the swift replacement or enhancement of industries marked by low value-added outputs and significant pollution levels. Urban industrial upgrading will significantly enhance the city's overall resource efficiency, reduce energy usage and pollution emissions, and amplify the beneficial effects of intensive land utilization on UER (Gu et al., 2024). Considering the above points, the current paper aims to:

Hypothesis 1: DF can potentially enhance the positive influence of IUUL on UER.

2.2 Mechanisms of digital finance in unlocking the urban ecological value of intensive use of urban land

IUUL represents a pivotal model for harmonizing economic progress with ecological preservation. A pressing concern lies in optimizing the ecological benefits of this model in the digital era. The degree to which IUUL can enhance UER is contingent on the characteristics of industries and the developmental pathways of industrial activities within IUUL frameworks. When an industry exhibits characteristics such as high value-added, low pollution, and high efficiency and progresses toward knowledge-intensive and technology-intensive operations, IUUL can further enhance UER beyond its original baseline. IUUL inherently fosters a clustering effect and serves as a possible catalyst for stimulating the growth of industries in the aforementioned direction. Nonetheless, within the traditional industrial framework, the mobility of capital factors is inadequate, thereby limiting the extent to which regional agglomeration effects can drive industrial upgrading. DF, characterized by its liquidity and widespread accessibility, stands out for its capacity to expedite intra-regional capital movements and

offer enhanced financial backing for industrial progress. This dynamic can magnify the agglomeration impact of IUUL, facilitate the reshaping of prevailing industrial development models, and further advance UER. In the forthcoming analysis, this paper will explore three key facets: industrial development dynamics, the structure of industrial advancement, and the trajectory of industrial progress within the context of IUUL. Subsequently, the discussion will elucidate how DF can catalyze the latent capabilities of IUUL, thereby amplifying the beneficial effects of these practices on UER.

2.2.1 Digital finance has been shown to effectively govern the intensive use of urban land, fostering a transition towards environmentally conscious industrial development dynamics

GI stands out as a crucial driver for reshaping the industrial development paradigm. It entails advancing resource conservation, environmental preservation, and sustainable growth through technological, managerial, and institutional breakthroughs in production and consumption. The overarching goal of GI is to boost environmental preservation and economic prosperity concurrently. This concept is intricately intertwined with the idea of UER. GI has proven to spur technological advancements and institutional transformations across diverse industries. Research has shown that GI can drive the eco-friendly evolution of industries, leading to reduced energy usage and lower pollution outputs. GI promises to boost the environmental standards of industries and urban areas, ultimately reinforcing UER (Khan et al., 2022; Zhou et al., 2025). According to agglomeration economy theory, IUUL can yield spillover effects and foster the advancement of GI (Chen et al., 2023). By focusing on regional enterprises, IUUL optimizes resource allocation, fosters the exchange of technology and knowledge, and accelerates the adoption of green practices and management strategies. Consequently, these factors bolster the efficiency and productivity of GI (Ke et al., 2022). Additionally, the effective execution of initiatives such as green buildings and environmentally friendly facilities in densely developed zones yields demonstrable results (Wang, 2021), showcasing the viability and advantages of green technologies to other businesses and regions. As a result, this contributes to the green transformation of other regions. GI often requires significant initial investment, with many green projects facing considerable financial constraints. Information asymmetry within the established economic framework's parameters commonly leads to a lack of comprehensive information regarding GI endeavors among investors. Consequently, this shortage contributes to a limited understanding among investors regarding green initiatives, thereby hindering the ability of such projects to garner adequate financial support. This situation inevitably hampers GI's progress. DF, a nascent product resulting from the fusion of digital technology and finance, promises to establish a clearer channel for information dissemination between investors and GI initiatives (Fu, 2024). DF can lower the cost of information acquisition for investors, boosting their confidence in investment decisions. This enables enterprises to possess adequate financial resources for GI and amplifies the knowledge spillover and demonstration effects of IUUL. Consequently, this advancement further propels the level of GI within the region. Considering the above points, the current paper aims to:

Hypothesis 2a: DF has been demonstrated to advance UER by amplifying the impact of IUUL on the progression of GI.

2.2.2 Digital finance has been illustrated as elevating the intensive use of urban land and encouraging the rationalization of industrial structure

The reconfiguration of industrial composition impacts UER. Following the principles of resource allocation, it is anticipated that resources will be directed toward industries showcasing heightened productivity levels. This trend is projected to trigger a modification in the industrial framework. Elevated productivity within these sectors signifies improved resource efficacy, increased value enhancement, and diminished energy consumption per product unit (Zhang and Dilanchiev, 2022). Assigning resources to these more efficient and environmentally conscious sectors promises to curb resource squandering and local pollution discharges, consequently boosting UER (Pan, 2019). IUUL has demonstrated attributes such as spatial streamlining and economic intensification, thereby fostering the rationalization of regional industrial frameworks. Primarily, IUUL constrains the spatial expansion of industrial growth, thereby directly limiting the advancement of industries that exhibit inefficient land resource utilization. Secondly, IUUL has proven to reduce the spatial gap between industries, streamlining their resource flow. This process enhances resource allocation efficiency and propels RIS (Zhang and Weng, 2022). Nonetheless, the impediments to information and capital transfer between the capital supply and demand sectors cannot be eliminated solely by diminishing geographical distances. This obstruction impedes RIS and the sustainable progress of urban areas. DF can efficiently enhance information and capital circulation, easing the breakdown of obstacles and expediting RIS. DF has emerged as a pivotal driver for disseminating financial information, fostering the creation of groundbreaking products that harness digital advancements to enhance investment decision-making processes. An exemplary instance is the deployment of intelligent investment advisors, which utilize cutting-edge technologies such as big data and artificial intelligence to assist investors in making informed investment decisions. These advisors methodically gather and scrutinize vast datasets to produce actionable suggestions, thereby enriching financial decision-making processes (Solanki et al., 2019). Simultaneously, the emergence of DF has decreased the expenses associated with gathering, analyzing, and divulging financial and operational data (e.g., XBRL). This advancement has not only markedly alleviated the restrictions on corporate finance (Li et al., 2023b) but has also facilitated improved corporate transparency (Jiang et al., 2022). The integration of technologies such as smart contracts and digital payments has proven to streamline the capital flow process, ultimately reducing associated costs and expediting capital flows (Бунич et al., 2024). Considering the above points, the current paper aims to:

Hypothesis 2b: DF has been demonstrated to enhance UER by amplifying the promotional effect of IUUL on RIS.

2.2.3 Digital finance has been shown to enhance the intensive use of urban land, thereby fostering advanced industrial development

The process of industrial upgrading in the region can yield several benefits, including the creation of added value, resource conservation, and the mitigation of environmental pressures under specific resource conditions. Consequently, this process can enhance UER. Industrial upgrading transforms industries from resource-intensive primary to secondary and tertiary industries. This transition aims to reduce the reliance of economic activities on natural resources, mitigate environmental impact, and enhance the ecological carrying capacity of cities (Shi et al., 2024). Moreover, industrial diversification has been shown to decrease the city's economic dependency on a single industry, thereby reducing systemic risks associated with the decline or collapse of a particular sector. This diversified economic framework can allocate more social resources to manage ecological crises and post-disaster recovery, thereby boosting UER (Tan et al., 2020). IUUL has been shown to facilitate the advancement of the secondary industry and drive the emergence of the tertiary industry, thereby achieving industrial upgrading. IUUL has been proven to offer more concentrated space and resources for the secondary industry, stimulate the establishment of industrial parks and science and technology parks, and foster the growth of advanced manufacturing and intelligent manufacturing. Consequently, this shift has resulted in an expedited transformation of the economic structure, transitioning from one that was predominantly reliant on the primary industry to one that is predominantly driven by the secondary industry (Cao et al., 2023). Simultaneously, IUUL can streamline the distribution of land resources and establish commercial hubs, financial service districts, scientific and technological innovation zones, and other clustered areas. It can attract capital and technology, foster the growth of cutting-edge industries and high-end service sectors, and subsequently steer the economic structure toward an upgrade in the direction of the service industry (Luo et al., 2022). In the digital era, DF has significantly hastened the process of industrial upgrading within the framework of IUUL. DF has been proven to boost land market transparency and enhance resource allocation efficiency by offering flexible and efficient financing avenues. As a result, DF has been illustrated to enhance IUUL and establish conducive circumstances for industrial upgrading (Xu, 2022). DF offers financial support for land development, infrastructure construction, and related projects by leveraging innovative financing tools. The integration of DF has been proven to enhance the effectiveness of land resource development and utilization. Moreover, the availability of these financial resources has been shown to offer spatial security for clustering high-value-added industries, such as industrial parks and innovation zones (Qiu et al., 2023). Simultaneously, DF has been demonstrated to improve transparency in the land market, reduce information asymmetries, enhance the efficiency of land transactions, and facilitate the optimal flow and redistribution of land (Zhang and Zhuang, 2022). This optimal allocation has been demonstrated to enhance the efficiency of IUUL and facilitate industrial upgrading. Considering the aforementioned points, the present paper aims to:

Hypothesis 2c: DF has been shown to enrich UER by amplifying the promotional impact of IUUL on the overall upgrade of industrial structure (OUIS).

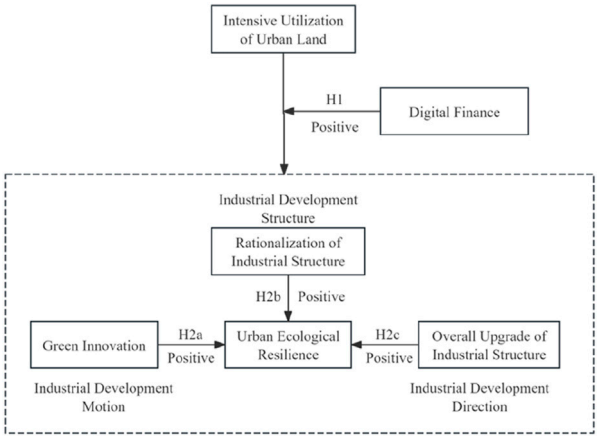


FIGURE 3
Theoretical mechanism.

The theoretical framework for this article is shown in Figure 3.

3 Research design

3.1 Data sources and data cleansing

The study encompasses the period from 2011 to 2020 and involves 282 cities at the prefecture level and above in mainland China. The data for this study were sourced from multiple outlets, including the Digital Finance Research Center of Peking University, the China Urban Statistical Yearbook, the China Urban Construction Statistical Yearbook, provincial and municipal statistical yearbooks, various public information sources, and other relevant materials. After removing missing values, 2778 valid sample data points were obtained. Continuous variables underwent trimming at the 1% and 99% levels to ensure the data's reasonableness and stability. This process aimed to mitigate the potential bias effects of outliers on the research outcomes, thereby establishing a robust data foundation for subsequent in-depth and precise analysis.

3.2 Model setup

3.2.1 Existence test model

The present study employs empirical analyses to investigate whether DF can positively influence the impact of IUUL on enhancing UER. The study explores the inherent connection between IUUL and UER. In this regard, correlation analysis and an Ordinary Least Squares (OLS) model are utilized to examine the findings. Subsequently, a two-way fixed effects model is constructed, guided by the outcomes of Hausman's test, which distinguishes between random and fixed effects (Equations 1, 2). A two-way fixed effects model is developed to explore the correlation between IUUL and UER and further evaluate DF's moderating role in this context.

$$UER_{c,t} = \alpha_0 + \alpha_1 IUUL_{c,t} + \gamma_1 \sum Controls_{cjt} + \mu_c + \delta_t + \varepsilon_{c,t} \quad (1)$$

TABLE 1 UER Index measure.

Variable	Measurement dimensions	Specific indicators	Unit	Orientations
Urban Ecological Resilience Index (*UER*)	Urban Ecological Resilience State Index (*UERSI*)	Water resources *per capita*	Cubic meters/person	Positively oriented
		Greening coverage in built-up areas	%	Positively oriented
		Green space *per capita* in parks (municipal districts)	Hectares/ten thousand people	Positively oriented
		Built-up area *per capita* (municipal districts)	Square kilometers/ten thousand people	Positively oriented
	Urban Ecological Resilience Pressure Index (*UERPI*)	Industrial wastewater discharge *per capita*	Tons/person	Negatively oriented
		Industrial sulfur oxide emissions *per capita*	Tons/person	Negatively oriented
		Industrial soot emissions *per capita*	Tons/person	Negatively oriented
		Industrial NOx *per capita*	Tons/person	Negatively oriented
		Annual average concentration of PM2.5	Ug/m^3	Negatively oriented
	Urban Ecological Resilience Response Index (*UERRI*)	Industrial sulfur dioxide removal	Tons	Positively oriented
		Industrial fume removal	Tons	Positively oriented
		Non-hazardous treatment rate of domestic waste	%	Positively oriented
		Centralized treatment rate of sewage treatment plants	%	Positively oriented
		Comprehensive utilization rate of industrial solid waste	%	Positively oriented

$$UER_{c,t} = \beta_0 + \beta_1 DFIU_{c,t} + \beta_2 IUUL_{c,t} + \beta_3 DF_{c,t} + \gamma_2 \sum Controls_{cjt} + \mu_c + \delta_t + \varepsilon_{c,t} \quad (2)$$

In this study, the region is represented by c, the year by t, and the type of control variable by j. The independent variable signifies UER, while the dependent variable indicates IUUL. The variables in the model are defined as follows:

The explanatory variable $UER_{c,t}$ denotes the urban ecological resilience.

The explanatory variable $IUUL_{c,t}$ denotes the intensive use of urban land.

The interaction term $DFIU_{c,t}$ denotes the interaction of DF and IUUL.

$Controls_{cjt}$ denotes the area-level control variables.

μ_c represents an individual city fixed effect.

δ_t represents a year-fixed effect.

As previously discussed, it is expected that α_1 in the model will show a substantial positive value if IUUL enhances UER. It is hypothesized that if DF exerts a positive moderating effect on IUUL, thereby enhancing UER, then the parameter β_1 will exhibit a significant positive value.

3.2.2 Mechanistic analytical modeling of the moderating effect

This paper employs a two-step approach to investigate the relationship between IUUL and UER from the perspective of DF (Equation 3) (Ting, 2022). The first step entails assessing the mediating effect through regulatory effect testing. The second step involves constructing the channel model. The specific model is defined as follows:

$$M_{c,t} = \theta_0 + \theta_1 DFIU_{c,t} + \theta_2 IUUL_{c,t} + \theta_3 DF_{c,t} + \gamma_3 \sum Controls_{cjt} + \mu_c + \delta_t + \varepsilon_{c,t} \quad (3)$$

It is imperative to note that $M_{c,t}$ is the mediating variable.

3.3 Variable definitions and descriptions

3.3.1 Explained variable: urban ecological resilience (UER)

The primary explanatory variable in this study is UER. This index assesses the comprehensive capacity of an urban ecosystem to regulate pollutant emissions, maintain ecological stability, and enhance governance in the face of stress or emergencies. The current study examines UER from three perspectives: state resilience, pressure resilience, and response resilience, utilizing 14 tertiary indicators. These perspectives and indicators are compared against established practices in mainstream literature (Chen et al., 2022; Zhang et al., 2023), as depicted in Table 1. In this study, the sub-indicators were dimensionless, and the entropy

TABLE 2 IUUL Index measure.

Variable	Measurement dimensions	Specific indicators	Unit	Orientations
Intensive use of urban land (*IUUL*)	Investment intensity	Investment in fixed assets per unit of land	Ten thousand yuan/km^2	Positively oriented
	Employment intensity	Unit land employment	Persons/km^2	Positively oriented
	Energy consumption intensity	Electricity consumption per unit of land	Ten thousand kWh/km^2	Positively oriented
	Economic output intensity	Output per unit of land GDP	Ten thousand yuan/km^2	Positively oriented

method was employed to assign weights for synthesizing the indicators of UER.

3.3.2 Explanatory variables: the intensive use of urban land (IUUL)

The explanatory variable in this research is IUUL, a crucial comprehensive indicator of urban land resource efficiency. As depicted in the Table 2, this study assesses the level of IUUL through four dimensions: investment intensity, employment intensity, energy consumption intensity, and economic output intensity. This assessment is informed by existing research in the field (Wu et al., 2022; Pan et al., 2024). The indicator is constructed from four foundational indicators: investment in fixed assets per unit of land, employment per unit of land, electricity consumption per unit of land, and GDP output per unit of land. These indicators are weighted utilizing the entropy value method, and the aggregated weighted sum is employed to evaluate the level of intensification of IUUL.

3.3.3 Moderating variable: digital finance (DF)

In its broadest sense, DF is characterized as a novel financial model that merges traditional financial methodologies with digital technology (Liu and Shen, 2021). This integration enables the efficient allocation of resources within a particular region, showcasing attributes such as universality and efficiency. This research selects the natural logarithm of Peking University's Digital Financial Inclusion Index as a proxy variable for DF (Yu et al., 2022; Li et al., 2020). The Digital Financial Inclusion Index is a comprehensive measure that assesses the coverage, depth of utilization, and digitization of digital financial services within a specific region. It offers a detailed insight into the developmental stage of a region. This index provides a comprehensive overview of the adoption and use of digital financial services across various geographical areas, thereby capturing the differences in accessibility and utilization of these services.

3.3.4 Mechanism variables

3.3.4.1 Green innovation (GI)

The utilization of GI indicators is crucial in evaluating the degree of GI within a specific region. This study aligns with established research methodologies by utilizing the logarithm of the count of green patents granted to the region in a particular year as a proxy variable for the level of GI in that region. The indicator of the number of GI licenses in a region evaluates a region's GI capacity from the perspective of innovation outcomes. It can visualize the specific green technologies, products, or processes generated within a region during a specified period. Regarding logical correlation, a higher count of green patents granted in a region indicates a stronger GI capacity. This suggests that regions with more green patents will likely exhibit a more robust ability to innovate in green technologies, products, or processes.

3.3.4.2 Rationalization of industrial structure (RIS)

The RIS index represents the outcomes of comprehensive coordination among industries and the effects of resource utilization. It measures the degree of coupling between the factor input and industrial structures. Currently, the academic community utilizes the degree of structural deviation to assess the RIS, employing the Equation 4:

$$E = \sum_{i=1}^{n}\left|\frac{Y_i/L_i}{Y/L}-1\right| = \sum_{i=1}^{n}\left|\frac{Y_i/Y}{L_i/L}-1\right| \tag{4}$$

In this model, E represents the degree of structural deviation, indicating the coupling of the output and employment structures. A smaller value of E suggests a more balanced economic situation and a more rational industrial structure. The value of output is denoted by Y, employment by L, the industry by i, and the number of industrial sectors by n. Productivity is represented by Y/L, where Y_i/L_i denotes the output structure, and L_i/L indicates the employment structure. According to classical economic assumptions, when the economy is in equilibrium, the level of productivity is uniform across industries. This means the economy is in equilibrium when $Y_i/L_i = Y/L$ and $E = 0$. However, the structural deviation index does not adequately consider variations in the importance of different industries within the economy. Moreover, the absolute value calculation method poses challenges during data processing. As a solution, this paper introduces a new Tel index to evaluate RIS, aiming to overcome these limitations.

The Theil Index (TL) is a widely used measure of income inequality. This paper refers to the mainstream literature on this subject (Equation 5) (Yang et al., 2023). The construction of the Theil Index is as follows:

$$TL = \sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right) ln\left(\frac{Y_i}{L_i}\Big/\frac{Y}{L}\right) \tag{5}$$

A novel Tyrell index has been created to address the challenge of computing absolute values, considering industry weighting, and maintaining the economic significance of structural deviations.

TABLE 3 Status of variables.

Variable type	Variable name	Variable symbol	Significance of variables
Explained variable	Urban ecological resilience	UER	Measuring UER, using the entropy method to construct
Explanatory variable	Intensive use of urban land	IUUL	Measuring IUUL, using the entropy method to construct
Mechanism variables	Digital finance	DF	The digital financial inclusion index takes logarithms
	Interactive items of digital finance and intensive land use	DFIU	Interactive items of DF and IUUL
	Rationalization of industrial structure	RIS	Tyrell's Index. The smaller the Tyrell's Index, the more rational the industry
	Overall upgrade of industrial structure	OUIS	Reflecting the tendency or process of transformation of industrial structure from lower to higher forms
	Green innovation	GI	The logarithm of the number of green patents granted in the year
Control variables	Level of financial development	LFD	The logarithm of GDP *per capita*
	Level of opening to the outside world	LOOW	Actual Utilized Foreign Capital/Gross Regional Product
	Degree of government intervention	DGI	General government expenditure/gross regional product
	Infrastructure development	ID	Number of books in public libraries per 100 people
	Environmental regulation	ER	Comprehensive utilization rate of general industrial solid waste

Within industrial structure analysis, the Tel index is a quantitative measure for assessing the relative importance of various industry sectors. A lower Tel index signifies a more equitable distribution of industry impact.

3.3.4.3 Overall upgrade of industrial structure (OUIS)

The term "OUIS" refers to the ongoing tendency or process of continuously upgrading the industrial structure from a lower to a higher level based on industrial advancements (Xiao et al., 2024). The present study utilizes the industrial structure hierarchy coefficient as a proxy variable for OUIS (Hu et al., 2017), as Equation 6:

$$OUIS = \sum_{i=1}^{q} q_i * i = q_1 * 1 + q_2 * 2 + q_3 * 3 \quad (6)$$

In industrial structure analysis, the overall upgrading of industrial structure is denoted by *OUIS*, representing the share of the output value of industry i as q_i and industry i as i.

3.3.5 Control variables (controls)

Concerning the selection of control variables, the following have been selected in alignment with relevant mainstream literature (Liu et al., 2024b; Liu et al., 2022): Level of financial development (LFD), Level of opening to the outside world (LOOW), Degree of government intervention (DGI), Infrastructure development (ID), Environmental regulation (ER). The variables discussed in this study are listed in Table 3 below:

3.4 Descriptive statistics

The descriptive statistical results of the samples are shown in Table 4. We can find that the mean value of the explanatory variable UER is 0.030, with a maximum value of 0.069. This suggests that the UER level of Chinese cities is relatively low amidst the rapid development of the digital economy. Regarding infrastructure development (ID), the mean value is 64.4, with a maximum value of 553 and a standard deviation of 85.2, indicating a substantial variation in infrastructure development across cities. Regarding environmental regulation (ER), the mean value is 79.420, with a maximum value of 100 and a standard deviation of 22.490, indicating notable disparities among cities in terms of environmental protection, corporate environmental disclosure, and achieving harmonized economic and environmental progress. These metrics highlight the diverse levels of infrastructure development and environmental regulatory practices across cities, emphasizing the importance of addressing these disparities to promote sustainable economic and environmental growth. The regional variances in the remaining control variables are minimal, with the degree of government intervention (DGI) showcasing the lowest standard deviation of 0.093. This observation is consistent with the established descriptive statistics reported in existing literature. The degree of government intervention across regions shows relatively slight variation, suggesting a level of consistency in this aspect across the studied cities or regions.

In addition to these findings, the study utilizes a spatial distribution to represent the shifts in urban land visual use efficiency across China from 2011 to 2020 (Figure 4).

In the map, darker colors indicate higher levels of efficiency. Figures 4a,b depict the alterations in the UER of Chinese cities over the decade. The analysis reveals that the UER of China's eastern coastal cities generally exhibits higher levels, with a discernible trend toward increasing UER over time. The mean value of the explanatory variable IUUL is 0.003, indicating that the current benefits derived by cities from their limited land area are relatively modest. The maximum value of IUUL is 0.009 with a

TABLE 4 Descriptive statistics.

Variable	N	Mean	Sd	Min	p25	Median	p75	Max
UER	2,778	0.030	0.007	0.019	0.026	0.029	0.032	0.069
IUUL	2,778	0.003	0.002	0.001	0.002	0.003	0.004	0.009
DF	2,778	5.061	0.505	3.563	4.828	5.222	5.439	5.690
RIS	2,778	0.284	0.201	0.004	0.118	0.245	0.416	0.851
OUIS	2,778	2.297	0.141	1.964	2.199	2.291	2.385	2.688
GI	2,778	4.398	1.655	0.693	3.258	4.304	5.460	8.463
LFD	2,778	2.460	1.128	1.013	1.675	2.151	2.890	6.752
LOOW	2,778	0.169	0.259	0.001	0.028	0.075	0.190	1.495
DGI	2,778	0.200	0.093	0.077	0.135	0.176	0.237	0.572
ID	2778	64.400	85.200	6	23	36	67	553
ER	2,778	79.420	22.490	11.620	70.030	88.95	96	100

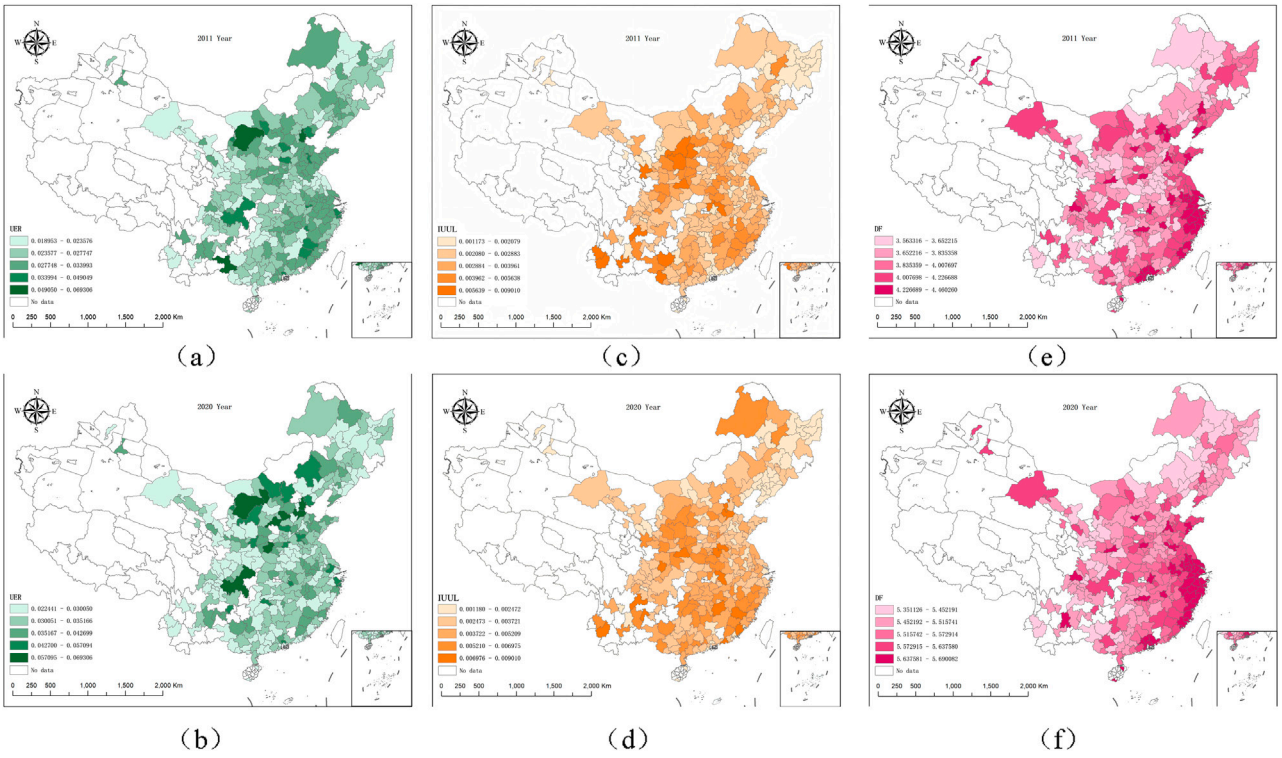


FIGURE 4
Spatial distribution of UER, IUUL, and DF in China. **(a)** Distribution and Index of UER in Chinese Cities in 2011. **(b)** Distribution and Index of UER in Chinese Cities in 2020. **(c)** Distribution and Index of IUUL in Chinese Cities in 2011. **(d)** Distribution and Index of IUUL in Chinese Cities in 2020. **(e)** Distribution and Index of DF in Chinese Cities in 2011. **(f)** Distribution and Index of DF in Chinese Cities in 2020.

standard deviation of 0.002, suggesting that there is no significant disparity in the level of IUUL across cities.

Figures 4c,d in the study illustrate the transformations in China's IUUL efficiency over the 10 years. These figures illustrate that cities characterized by higher levels of IUUL are predominantly clustered in the eastern coastal region. Moreover, the level of IUUL has shown an uptrend in the northeastern region over the years. The degree of DF exhibited minimal variation across regions, evidenced by a standard deviation of 0.505. The median and mean values were closely aligned, with a median of 5.222 and a mean of 5.061, indicating a relatively stable distribution of DF levels across regions.

Figures 4e,f visually represent the significant changes in China's DF development over the 10 years under study. Notably, the figures reveal more developed DF areas in the eastern region. Conversely, a

TABLE 5 Results of existence tests and moderating effects of digital finance.

Variable	(1)	(2)
	UER	UER
IUUL	0.2124**	−0.7096
	(0.1041)	(0.4619)
DFIU		0.1721**
		(0.0861)
LFD	0.0005***	0.0006***
	(0.0002)	(0.0002)
LOOW	0.0007	−0.0003
	(0.0009)	(0.0009)
DGI	0.0011	0.0001
	(0.0021)	(0.0021)
ID	0.0000	0.0000
	(0.0000)	(0.0000)
ER	0.0000***	0.0000***
	(0.0000)	(0.0000)
DF		0.0038***
		(0.0011)
Year FE	YES	YES
City FE	YES	YES
Constant	0.0256***	0.0070
	(0.0007)	(0.0055)
Observations	2,778	2,778
R^2	0.842	0.844

Note: ***, **, and * represent confidence levels of 1%, 5%, and 10% respectively. The figures in parentheses are robust standard errors.

decline in the level of DF development has been observed in the Northeast region over the same period. These findings highlight the spatial disparities in digital financial development across various regions of China, with contrasting trends observed in the eastern and northeastern regions. The observed decline in DF development in the Northeast region can be attributed to the region's less sophisticated model of DF advancement, leading to a reduction in the efficiency of DF development, as discussed in reference (Wantong, 2024).

4 Empirical results

4.1 Existence tests and moderating effects tests for digital finance

Based on the provided information, the sample has been subjected to regression analysis using Equations 1, 2, with the year and region fixed in both directions to examine the relationship between IUUL, DF, and UER. The regression results are then presented in column (1) of Table 5 to illustrate the analysis outcomes. The regression coefficient for IUUL is 0.2124, which is positive and statistically significant at the 5% level. This indicates that for every unit increase in IUUL, the UER of the corresponding city increases by 0.2124. The second column of Table 5 presents the findings from incorporating the moderating effect of DF. Specifically, the interaction term (DFIU) coefficient between DF and IUUL is 0.1721, indicating a positive association at the 5% significance level. From an economic perspective, this suggests that for each unit of improvement in IUUL facilitated by DF, the UER of the corresponding city is expected to increase by 0.1721.

The findings illustrated in column (1) of Table 5 establish a favorable correlation between IUUL and the extent of UER within the research locale, thus affirming Hypothesis 1. Similarly, the results depicted in column (2) of Table 5 indicate that DF has the potential to significantly enhance the influence of IUUL on UER significantly, thereby confirming Hypothesis 1.

4.2 Robustness testing

4.2.1 Lagged period tes

Considering that DF-driven IUUL may have a time delay effect on UER, this study adopts a method similar to existing studies to address this issue (Wang and Ma, 2022). Specifically, the explanatory variables are lagged by one period, and the empirical analysis is reiterated using L.DFIU, L.DF, and L.IUUL. The outcomes of this regression analysis are delineated in column (1) of Table 6. As in column (1) of Table 6, the coefficient associated with the interaction term (L.DFIU) of DF and IUUL demonstrates a positive significance at the 1% level. This discovery aligns with the initial regression outcomes, thereby enhancing the robustness of the findings to a certain degree.

4.2.2 Reduction of sample period

The developmental trajectory of DF in China exhibited volatility, particularly during economic crises, with its driving impact arguably less pronounced. The year 2013 marks the inception of China's Internet finance (Shen and Huang, 2016), a period during which the evolution of DF stabilized. Consequently, this study shortens the sample period of the baseline regression and adjusts the starting year to 2013. The regression outcomes are detailed in column (2) of Table 6. The interaction term (DFIU) coefficient of DF and IUUL is also positive at the 5% significance level, consistent with the results of the benchmark regression.

4.2.3 Excluding the Xinjiang sample

As a resource-based economy, Xinjiang's digital economy penetration rate is lower than the national average, potentially creating a structural deviation. Due to its climatic peculiarities, the UER in this area needs to be measured differently. To ensure the reliability of the experimental results, this study excludes the sample of cities from the Xinjiang Uygur Autonomous Region and reruns the regression analysis. The outcomes are detailed in column

TABLE 6 Robustness testing.

Variable	(1)	(2)	(3)	(4)
	UER	UER	UER	UER
L. DFIU	0.2143**			
	(0.0843)			
L.DF	0.0004			
	(0.0008)			
L.IUUL	−1.0203**			
	(0.4500)			
DFIU		0.3837**	0.1725**	
		(0.1617)	(0.0865)	
DF		0.0004	0.0037***	0.0041***
		(0.0021)	(0.0011)	(0.0009)
IUUL		−1.7321**	−0.7132	
		(0.8776)	(0.4638)	
DFEA				0.0011***
				(0.0002)
EA				−0.0065***
				(0.0012)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Observations	2,778	2,227	2,758	2,778
R^2	0.842	0.888	0.845	0.843

Note: ***, **, and * represent confidence levels of 1%, 5%, and 10% respectively. The figures in parentheses are robust standard errors.

(3) of Table 6; the coefficient of the interaction term (DFIU) between DF and IUUL is statistically significant at the 5% level of confidence. This result concurs with the benchmark regression findings, thereby underlining the sustained robustness of the conclusions.

4.2.4 Replacement of explanatory variables

In the research design section, IUUL indicators were selected based on perspectives related to investment, employment, energy, and output. Regarding the economic emphasis of IUUL, this research conducts regression analyses from an economic output perspective (Miguelez and Moreno, 2017; Hu et al., 2024). It integrates insights from mainstream academic literature and substitutes the explanatory variables with indicators of economic agglomeration (EA). Subsequent regression tests are conducted, with the EA indicator quantified as non-farm economic output per unit of land. The outcomes are presented in column (4) of Table 6. The interaction term (DFEA) coefficient of DF and EA is positive at the 1% significance level, consistent with the benchmark regression results, and the study's results remain robust.

5 Further analysis

5.1 Mechanisms analysis

5.1.1 Improvement of GI

Preliminary analyses suggest that DF can mitigate information asymmetries between GI projects and external stakeholders. It can facilitate financial services for GI endeavors, thereby amplifying the influence of knowledge and technology spillovers in land intensification and utilization. Consequently, this can elevate the significance of GI and bolster the role of IUUL in advancing UER. The regression outcomes of the mechanism test are delineated in column (1) of Table 7. The results in this column illustrate that the regression outcome of the cross-multiplier term DFIU on GI is positive, indicating a favorable moderating impact of DF on innovation spillovers from IUUL. This validates Hypothesis 2a as posited in the study.

5.1.2 Promoting RIS

As evidenced in the preceding theoretical analysis, RIS has positively impacted the development of efficient, high-value-added industries in the region. The enhancement of industrial structure is a multifaceted and pivotal procedure, with the intervention of DF introducing a fresh impetus to this progression. DF has been shown to expedite the velocity of capital circulation and enhance RIS by streamlining the information disclosure practices of enterprises and simplifying investment and financing procedures (Shen and Ren, 2023). The results are displayed in column (2) of Table 7. The result of the cross-multiplier term DFIU on the RIS indicator is negative, suggesting that DF can advance the synergistic advancement of IUUL and RIS. This occurrence inhibits the irrationalization of industrial structure and strengthens the influence of IUUL utilization on UER. The current study scrutinized Hypothesis 2b in this context.

5.1.3 Promoting OUIS

Initial analyses suggest that DF can offer significant financial backing for land development and the establishment of expansive parks. Moreover, it can improve the transparency of the land market and stimulate the rational allocation of land resources, thereby fostering OUIS. As depicted in column (3) of Table 7, the cross-multiplier term DFIU displays a positive regression coefficient for OUIS. This suggests that DF could stimulate IUUL, thereby enhancing OUIS and strengthening the impact of IUUL on improving UER. The current study investigated Hypothesis 2c in this context.

5.2 Heterogeneity analysis

5.2.1 Heterogeneity in levels of economic development

The positive impact of IUUL, propelled by DF, on UER varies across regions with distinct levels of economic development. Regions with a higher echelon of economic development typically exhibit greater capital endowment. DF facilitates the circulation of capital, which allocates resources preferentially to high-productivity industries within economically advanced regions. This process

TABLE 7 Mechanistic regression.

Variable	(1)	(2)	(3)
	GI	RIS	OUIS
DFIU	48.5422***	−4.5030*	2.6466***
	(10.6154)	(2.4703)	(0.9648)
DF	0.2459*	−0.0439	0.0706***
	(0.1333)	(0.0310)	(0.0121)
IUUL	−2.4e+02***	18.7223	−10.3148**
	(56.9588)	(13.2548)	(5.1767)
Controls	YES	YES	YES
Year FE	YES	YES	YES
City FE	YES	YES	YES
Observations	2,778	2,778	2,778
R^2	0.958	0.846	0.953

Note: ***, **, and * represent confidence levels of 1%, 5%, and 10% respectively. The figures in parentheses are robust standard errors.

enhances the overall efficiency of resource allocation, mitigates excessive developmental pressures, and strengthens UER. Simultaneously, economically advanced regions possess more sophisticated market mechanisms, reduced transaction costs, and greater information transparency. These areas are better positioned to facilitate capital allocation through DF, a process that renders IUUL more instrumental in enhancing UER. On the other hand, less economically developed regions typically face challenges such as limited economic development, inadequate capital resources, and imperfect market structures. As a result, the positive influence of IUUL, underpinned by DF, on UER is not as pronounced in these regions due to these constraints. Uneven regional development is a common phenomenon in the modernization process of developing countries. In China, differences in natural geographical conditions, insufficient accumulation of historical foundations, and gaps in industrial structure and innovation capacity have led to more rapid economic development in the eastern region than in the central and western regions (Li et al., 2022). Reference to existing studies (Lei et al., 2024), which categorize the sample into eastern, central, and western regions based on the province of location and perform separate regression analyses for each category. The regression results are presented in columns (1)–(3) of Table 8. Notably, in column (1) of Table 8, the regression coefficient of the interaction term (DFIU) between DF and IUUL is positive and retains statistical significance at the 5% level. The regression coefficients about the interaction term (DFIU) between DF and IUUL in columns (2) and (3) do not exhibit statistical significance. This indicates that the advancement of UER through IUUL, facilitated by DF, holds greater significance within the eastern region.

5.2.2 Heterogeneity of urban infrastructure

The positive contribution of DF-driven IUUL to UER exhibits heterogeneity across cities of divergent scales. Urban infrastructure is a crucial component for industrial progress, with the comprehensiveness and caliber of prevailing infrastructure directly influencing the pace of industrial development. Major cities boast more comprehensive infrastructure, providing a robust groundwork for industrial advancement. In this context, the infusion of capital into a high-productivity sector and meeting its capital requisites is positioned to spur the industry's rapid growth. Consequently, this phenomenon is anticipated to lead to a notable improvement in resource utilization efficiency and UER. Conversely, areas defined by smaller cities exhibit a relatively weaker foundation for industrial growth. This is predominantly due to their recent entry into industrial development, the lack of well-established infrastructures, and environments that are less supportive of information exchange and innovation. It is apparent that, even though the financial needs of high-productivity industries are met, their capacity for growth remains limited. This occurrence contributes to a gradual improvement in UER, stemming from IUUL within the framework of DF. This study conducts group regressions, categorizing the large city size sample as the high infrastructure level group and the small city size sample as the low infrastructure level group. These regression analyses are predicated on the city size metric delineated by the World Bank (Alves et al., 2015). The outcomes of these regressions are delineated in columns (4) and (5) of Table 8. Within these results, the regression coefficient associated with the interaction term between DF and IUUL (DFIU) in column (4) retains statistical significance at the 1% level. In contrast, the regression coefficient for the same interaction term in column (5) lacks significance. This discovery suggests that the advancement of UER through DF-enabled IUUL holds greater importance in cities endowed with more comprehensive infrastructures.

5.2.3 Heterogeneity of innovation environments

The moderating impacts of DF exhibit diversity across various innovation environment regions. Advancements in scientific and educational infrastructure serve as foundational support for the innovation and advancement of digital finance. Primarily, regions characterized by exceptional innovation landscapes typically exhibit enhanced research capabilities, a more robust talent pool, and accelerated IT advancements. This framework provides technical support for the development of DF; simultaneously, a conducive innovation environment fosters environments favorable for GI, thereby amplifying the mutually beneficial impact of DF and IUUL on GI and consequently strengthening UER. Conversely, regions with less robust innovation ecosystems face challenges, including technological obsolescence and shortages of skilled personnel. This not only imposes substantial obstacles to the advancement and dissemination of DF-related products but also introduces limitations to GI, thereby making the positive contribution of DF to UER via its positive regulation of IUUL less pronounced or evident. Regions that allocate substantial resources to scientific endeavors and educational initiatives are better positioned to draw in talented individuals and stimulate innovation. The OECD approach was employed to quantify science and education expenditures (Organization For Economic Cooperation And Development, 2016), using Research and Development (R&D) expenditure as a percentage of GDP to gauge these expenditures. The dataset was subsequently divided into regions with elevated science and education expenditures

TABLE 8 Heterogeneity analysis.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Eastern	Central	Western	High level of infrastructure	Low level of infrastructure	High level of scientific education	Low level of scientific education
	UER	UER	UER	UER	UER	UER	UER
DFIU	0.5100**	−0.2236	0.1536	0.4112***	−0.103	0.7769***	0.0183
	(−0.2129)	(−0.1401)	(-0.1376)	(−0.152)	(-0.0983)	(−0.1947)	(−0.0993)
DF	0.0070***	0.0047**	0.0038**	0.0008	0.0058***	0.0005	0.0046***
	(-0.002)	(-0.0023)	(-0.0019)	(−0.0018)	(-0.0012)	(−0.0024)	(−0.0013)
IUUL	−2.0316*	0.657	−0.7408	−1.5185*	0.2981	−3.4119***	−0.2251
	(−1.1886)	(−0.7132)	(−0.7554)	(−0.8157)	(−0.5233)	(−1.0516)	(−0.5237)
Controls	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Observations	987	810	972	1,396	1,381	1,385	1,353
R^2	0.853	0.864	0.769	0.842	0.863	0.887	0.802

Note: ***, **, and * represent confidence levels of 1%, 5%, and 10% respectively. The figures in parentheses are robust standard errors.

compared to those with lower expenditures, based on the median annual expenditure for science and education. As evidenced in columns (6) and (7) of Table 8, the regression coefficients associated with the interaction term (DFIU) between DF and IUUL in column (6) exhibit statistical significance at the 1% level. On the contrary, the regression coefficients of the interaction term (DFIU) between DF and IUUL in column (7) do not demonstrate statistical significance. This implies that the moderating influence of DF is more conspicuous in regions characterized by elevated science and education expenditures.

6 Conclusion and policy recommendations

6.1 Conclusion

Urbanization, a core process of worldwide progress, has spurred a significant ecological dilemma alongside economic advancement. China's historic economic advancement strategy, labeled "leapfrogging," has traditionally leaned on a conventional and rudimentary model. Nevertheless, this strategy has encountered notable hurdles, encompassing environmental constraints and deficient governance. The current juncture is defined by a pressing necessity to surmount the existing dichotomy between "environment" and to forge a sustainable trajectory through technological advancements, institutional enhancements, and eco-friendly transitions. It is essential to strike a dynamic balance between economic progress and ecological sustainability. This research utilizes panel data from 282 prefecture-level cities spanning the period from 2011 to 2020 to investigate the influence of IUUL on strengthening UER. Additionally, it scrutinizes how DF propels IUUL, consequently amplifying UER. The study's outcomes suggest that DF can augment IUUL, thus positively impacting the mounting influence of IUUL on UER. The consistency of the results persists even after undergoing a battery of robustness tests. Additional research is crucial to delineate the precise pathway of digital financial empowerment of IUUL in industrial development dynamics, industrial development structure, and industrial development orientation. Mechanism analysis reveals the following: the current study showcases a favorable moderating impact of innovation spillovers from DF on IUUL; at the same time, DF holds the potential to enhance the synergy between IUUL and RIS, consequently curbing the irrationalization of the industrial structure. Furthermore, DF can enhance the efficacy of IUUL in driving holistic industrial structure upgrading, thus strengthening the effect of IUUL on UER. Heterogeneity analysis discloses that the influence of DF facilitates IUUL, thereby augmenting the impact of IUUL on UER. This effect is more pronounced in cities with higher levels of economic development, well-developed infrastructure, and robust innovation ecosystems.

6.2 Policy recommendations

Firstly, it is crucial for policies to prioritize macro-control and resource guidance to facilitate the seamless integration of IUUL and DF. The government should enhance land-use planning, intensify the management of urban land resources, and steer efficient land utilization through optimized policies. Simultaneously, robust

support for DF, particularly in infrastructure construction and inclusive finance, is essential. Additionally, the government should provide technical aid and financial resources to less developed regions. Moreover, proactive implementation of policies that promote green innovation is vital. Initiatives such as establishing special funds or offering tax incentives can incentivize enterprises and financial institutions to increase investments in green technology research and development. The government may consider establishing pilot industrial parks that focus on integrating green and digital transformation, accompanied by targeted financial subsidies and tax incentives. These initiatives aim to create a conducive environment for enterprises to engage in green innovation and adopt sustainable production practices. Furthermore, prioritizing regional synergistic development is key. By leveraging the demonstration effect of the eastern region and cities with notable scientific and educational contributions, the government can foster balanced regional progress by exchanging experiences and replicating successful policies.

Secondly, the synergistic relationship between IUUL and DF presents a significant opportunity for enterprises to undergo a green transformation. Aligned with government policies, enterprises should actively adopt digital tools and green technologies to enhance land use efficiency, thereby accelerating the optimization of their industrial structures. Digitalization is a tool for green development, and its rational use can promote and drive sustainable progress (Zeng et al., 2025). Within the framework of DF empowerment, enterprises are obliged to prioritize the enhancement of their GI capacities, explore novel business paradigms and technological implementations, and cultivate sustainable competitive advantages. Enterprises should establish dedicated green R&D departments or innovation teams to implement innovative practices in green product development, low-carbon process innovation, and circular economy models. Enterprises should also actively seek new financial products, such as green loans and digital green bonds with ESG rating functions, to provide long-term and stable financial support for their green transformation. Large enterprises are urged to shoulder greater social responsibility, serving as exemplars for environmentally sustainable development. They should lead by example in guiding small and medium-sized enterprises to collectively contribute to creating eco-friendly cities through the dissemination of technology and collaborative demonstrations. Conversely, small and medium-sized enterprises can leverage the inclusive nature of DF to lower financing barriers and enhance competitiveness in land resource utilization with financial support.

Thirdly, the pivotal role of DF in IUUL demands a strengthening through the innovation of financial products and service models. Financial institutions must prioritize the development of green financial products, such as green credit and bonds, focusing on supporting green projects and technological advancements within intensive land-use contexts. Simultaneously, leveraging fintech to boost service efficiency, reduce operational costs, and extend the reach of DF is essential. Digitization is the key to efficiency in today's age, and so is the financial industry (Wu et al., 2024). Financial institutions can use big data and artificial intelligence technology to conduct credit assessments on enterprises and projects, accurately identify projects with green development potential, and improve loan approval efficiency. At the same time, they can develop an online green project financing platform to digitize the entire process, from financing application and assessment to approval and loan issuance, thereby lowering the financing threshold for small and medium-sized green projects. Financial institutions should forge stronger partnerships with the government and enterprises, crafting financial support schemes aligned with market demands through coordination with policy frameworks and industry requirements. Moreover, financial institutions should enhance their risk management capabilities, particularly when supporting GI and OUIS projects. They ought to conduct scientific assessments of project feasibility to ensure the secure and effective allocation of financial resources and facilitate the enhancement of UER.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.stats.gov.cn/.

Author contributions

YL: Conceptualization, Data curation, Investigation, Project administration, Supervision, Writing – original draft, Writing – review and editing. CL: Conceptualization, Formal Analysis, Methodology, Software, Writing – original draft, Writing – review and editing. ZH: Methodology, Software, Supervision, Writing – original draft, Writing – review and editing. JL: Formal Analysis, Funding acquisition, Resources, Visualization, Writing – original draft, Writing – review and editing.

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EDITED BY
Lingli Qing,
Guangzhou College of Commerce, China

REVIEWED BY
Dongqing Li,
Beijing Forestry University, China
Zhuoya Ma,
Beijing Forestry University, China

*CORRESPONDENCE
Zhiyi Gai
✉ gaizhiyi@126.com
Bao Zhang
✉ zhangbao108@126.com

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The impact of grassland ecological compensation policy on overgrazing behavior of herdsmen with non-pastoral employment: evidence from Inner Mongolia, China

Wenjie Ouyang, Fang Ju, Jiali Han, Zhiyi Gai* and Bao Zhang*

College of Economics and Management, Inner Mongolia Agricultural University, Hohhot, China

Introduction: The Grassland Ecological Compensation Policy (GECP) not only improves the grassland ecosystem, but also encourages more and more full-time herdsmen to take up non-pastoral employment. This raises an important question: does non-pastoral employment have a differential impact on overgrazing among herdsmen, and how does it affect the effectiveness of policy implementation? Addressing this question will provide a scientific foundation for the sustainable development of grassland pastoral areas.

Methods: Utilizing data from 542 herdsmen in the pastoral areas of Inner Mongolia, this paper employs a double difference model to analyze the impact of the GECP on the overgrazing behavior of herdsmen with non-pastoral employment.

Results: The research findings indicate that: (1) The GECP exacerbates overgrazing behavior among full-time pastoral herdsmen (PH1 herdsmen) and those with non-pastoral employment at low levels (PH2 herdsmen), while it mitigates such behavior among herdsmen with non-pastoral employment at high levels (PH3 herdsmen); (2) Non-pastoral employment significantly enhances the inhibitory effects of the GECP on herdsmen's overgrazing behavior; (3) The influence of grassland rent-in and barn feeding on herdsmen's overgrazing behavior varies according to the levels of non-pastoral employment among herdsmen.

Discussion: Therefore, this paper suggests that the government should continue to optimize the policy, along with differentiated subsidy methods and content. It also advocates for guiding herdsmen towards non-pastoral employment to achieve sustainable development of both ecological and economic aspects in pastoral areas.

KEYWORDS

grassland ecological compensation policy (GECP), overgrazing, non-pastoral employment, difference-in-differences model (DID), farmer model

1 Introduction

Payments for Environmental Services (PES) is a widely utilized approach for restoring natural resource ecosystems (Wunder, 2015; Engel et al., 2008). This approach aims to incentivize behavior that promote ecosystem conservation and sustainable use by providing financial compensation to the providers of ecosystem services (McAfee and Shapiro, 2010; McElwee et al., 2014). Over the past two decades, global climate warming and human over-utilization of grasslands have led to

significant grassland degradation (Wu et al., 2021; Zhang et al., 2023). This degradation not only causes a decline in vegetation cover and disrupts the regional ecological balance, but also hinders the sustainable development of the pastoral economy (Tan, 2020; Yan et al., 2013). To mitigate this crisis, countries worldwide have adopted various policy measures. In Europe, the Common Agricultural Policy (CAP) encourages farmers to designate ecological compensation areas on their farms by providing subsidies, which in turn promotes biodiversity restoration (Sannou and Guenther, 2025). In Africa, the Great Green Wall (GGW) program addresses increasing land degradation through a community-participatory approach to sustainable grazing management, desertification, and climate change (Khafagy and Vigani, 2022). In the United States, the Conservation Reserve Program (CRP) allows environmentally sensitive agricultural land to remain fallow, thereby reducing soil erosion, improving water quality, and enhancing ecological security (Barnes et al., 2023). Similarly, China has implemented the Grassland Ecological Compensation Policy (GECP), recognized as the largest and most representative ecological compensation program globally, aimed at protecting grassland ecology and mitigating overgrazing (Liu et al., 2023b; Hou et al., 2021). Unlike the policies of other countries, the GECP operates as a top-down administrative mandate rather than a voluntary participation mechanism. Is aims to encourage herdsmen to provide a sufficient supply of ecological products by offering financial compensation, thereby incentivizing herdsmen to reduce livestock numbers and pursue livelihood transformations through financial subsidies, ultimately achieving the goal of protecting grassland ecology (Hou et al., 2021; Deng et al., 2022; Yin R. et al., 2018).

By 2025, the GECP has been implemented up to the third round, with its coverage gradually expanding from the initial 8 grassland pastoral provinces to 13 provinces, including Hebei, Liaoning, and Jilin. Additionally, since 2016, the annual grassland ecological protection compensation and reward fund has increased to 18.76 billion yuan (Approximately 2.58 billion dollar).[1] Over the past decade, the average overgrazing rate of livestock in key natural grasslands across the nation has decreased to 10.1%, representing a reduction of 17.9 percentage points compared to 2011,[2] this indicates that the efforts to reduce livestock in grasslands have yielded some phased results (Huang et al., 2018; Liu et al., 2018). However, the current situation of overgrazing has not been fundamentally changed (Hua and Squires, 2015; Byrne et al., 2020). This may be due to the fact that the policy of coercion ignores the subjective willingness of the herdsmen to change their livelihoods, thus leading to a delay in the active reduction of livestock by the herdsmen (Zhang et al., 2019). To this end, the government has further proposed to encourage herdsmen to reduce their inputs in the pastoral production sector by incentivizing the transfer of pastoral labor to the non-pastoral sector, thereby easing the grass-animal conflict.

Inner Mongolia owns the second largest grassland area in China and plays an vital role in the national supply of livestock products.[3] Meanwhile, the implementation of GECP has contributed to the sustainable development of the livestock economy in this region. However, the challenges encountered in implementing the GECP in Inner Mongolia are highly similar to those faced throughout China. Furthermore, Inner Mongolia's vast grassland area, encompassing diverse grassland types, makes it a representative case study for examining the implementation of the GECP in China. Thus, the conclusions of our study are also broadly generalizable. In recent years, the rise of non-pastoral employment opportunities in pastoral areas has led to a gradual differentiation of herdsmen from homogeneous groups primarily engaged in agriculture and pastoralism into heterogeneous groups with diverse livelihoods (Zhou S. et al., 2022; Zhou J. et al., 2022; Chang et al., 2022). This diversification of livelihoods renders the impact of the GECP on herdsmen's overgrazing behavior ambiguous (Hu et al., 2017; Ding et al., 2020). Therefore, it is essential to investigate the behavioral logic underlying the overgrazing practices of herdsmen engaged in non-pastoral employment within the context of the GECP's implementation.

Engaging in non-pastoral employment represents a rational choice made by herdsmen aimed at maximizing their earnings, taking into account their individual characteristics and the constraints imposed by external economic factors (Pascual and Barbier, 2007; Barbier, 2007). Theoretically, non-pastoral employment influences the production decision-making behavior of herdsmen through two mechanisms: the "part-time effect" and the "income effect" (Wang et al., 2005). On one hand, the rise of non-pastoral employment attracts a significant transfer of pastoral workforce, resulting in a decrease in the available pastoral workforce (Li and Wang, 2023; Wang et al., 2020). As a labor-intensive industry, pastoralism requires substantial labor and capital investment throughout its production processes (Wang et al., 2018). When family labor resources are constrained, herdsmen typically scale back their breeding operations, which directly alleviates grazing pressure on grassland. On the other hand, increased non-pastoral income reduces herdsmen's reliance on livestock production (Huang et al., 2024). A considerable and stable non-pastoral income can effectively offset the losses incurred by herdsmen due to reduced livestock numbers, providing them with a robust safety net against economic risks (Hu et al., 2019). However, some scholars argue that certain herdsmen choose to utilize non-pastoral income to expand their livestock production in pursuit of greater economic benefits (Wang et al., 2024), which exacerbates grazing pressure on grasslands.

Furthermore, some scholars have noted that varying levels of non-pastoral employment among herdsmen have resulted in significant disparities in resource utilization, policy responsiveness, and market adaptation strategies. These disparities, in turn, influence the effectiveness of the GECP (Qiu et al., 2020; Dong et al., 2023). On one hand, herdsmen with non-pastoral employment at low levels may continue to rely heavily on herding, making it challenging to alter overgrazing behavior (Zhou and Zhao, 2019; Ding et al., 2022). Conversely, herdsmen with non-pastoral employment at high levels may possess sufficient economic resources to comply with ecological conservation requirements, thereby mitigating overgrazing (Su et al., 2024). In light of this, this paper seeks to address the following questions: (1) Can the GECP effectively inhibit overgrazing behavior among herdsmen with non-pastoral employment? (2) What role does non-pastoral employment play in the mechanism through which the GECP influences herdsmen's overgrazing behavior? (3) What does the

1 National Forestry and Grassland. Available online at: https://www.forestry.gov.cn/c/www/zxft/574713.jhtml (Accessed June 28, 2025).

2 National Forestry and Grassland. Available online at: https://www.forestry.gov.cn/c/www/xxgcesdjs/29672.jhtml (Accessed June 28, 2025).

3 National Meteorological Information Center/China Meteorological Administration (NMIC/CMA). Available online at: http://data.Cma.cn/data/detail/dataCode/SURF_CLI_CHN_MUL_DAY_V3.0/keywords/ (Accessed May 18, 2025).

case of Inner Mongolia tell us about global policy optimization in grassland pastoralism? The answers to these questions will not only provide a scientific foundation for the development of precise and differentiated policy, but will also hold significant theoretical and practical implications for promoting sustainable development in pastoral regions.

Although existing research provides important theoretical support for this paper, several shortcomings remain: (1) Existing studies have not formed a consistent view on the impact of GECP on the overgrazing behavior of herdsmen. (2) Few studies have explored the mechanism of GECP on herdsmen's overgrazing behavior from the perspective of differences in the level of herdsmen's non-pastoral employment. (3) No research has elucidated the role of non-grazing income in the process by which GECP influences the overgrazing behavior of herding households. The main contributions of this paper are as follows: (1) From a research perspective, this paper is based on the perspective of differences in the level of non-pastoral employment, in-depth discussion of the overgrazing behavior of herdsmen; (2) In terms of research content, this paper focuses on the impact of GECP on the degree of overgrazing of herdsmen with non-pastoral employment, thus filling the gap in micro research in this area. (3) By analyzing the moderating role of non-herding employment in the overgrazing behavior of herdsmen affected by GECP, the research findings provide empirical evidence and decision-making references for enhancing the effectiveness of policy implementation.

This paper is structured as follows. Section 2 presents the theoretical framework and research hypotheses. Section 3 presents the data sources and methodology. Section 4 presents the empirical results. Section 5 presents the conclusions and policy recommendations.

2 Theoretical framework and research hypotheses

2.1 Model construction

According to neoclassical economic theory, herdsmen are regarded as rational economic agents. Their allocation of production factors, such as land and labor, exemplifies their pursuit of maximizing family income (Wuepper et al., 2023). When external conditions change, herdsmen reallocate production factors to optimize their interests. Therefore, this paper constructs a family production behavior model based on the Becker farmer model and existing research findings (Sun et al., 2022; Zhang and Zhang, 2015), reflecting the production characteristics of herdsmen. The aim is to investigate how to optimize the family production behavior of herdsmen following the implementation of the GECP, ultimately maximizing family income. We assume an income maximization function for a herdsman represented by the following equation.

$$\max Y = PQ\left(L_a, T_a, K\right) - P_K\ K + w\left(L - L_a\right) + R\left(T - T_a\right) \quad (1)$$

$$L = L_a + L_b \quad (2)$$

$$Q = AL_a^{\alpha} T_a^{\beta} K^{\gamma} \quad (3)$$

Equation 1 is the utility function of the herdsman, where Y is the total income of the herdsman; Equation 2 represents the labor time constraints. In Equation 1, P is the market price of various types of livestock products, $Q\left(L_a, T_a, K\right)$ represents the herdsmen's pastoral production function, L_a is the herdsmen's input into pastoral production of the labor time, T_a is the herdsmen's actual operation of the grassland area, K represents the amount of capital input in pastoral production of herdsmen, P_K represents the market price of capital in pastoral production, w represents the wage of herdsmen in non-pastoral employment market, L represents the total time that herdsmen put into production, L_a represents the time of pastoral production, L_b represents the time of non-pastoral labor, R represents the rent of the grass per acre, T represents the area of grass contracted by herdsmen, and $\left(T - T_a\right)$ represents the area of grass that is transferred to the herdsmen.

Equation 3 is the herdsmen's pastoral production function, in which A represents the inclusion of the factors of technological progress in pastoral production, external environmental factors, as well as other influences that cannot be explained by L_a , T_a , and K . á , β , and γ represent the herdsmen's time in pastoral production, the area of the actual operation of the grassland, and the output elasticity of the amount of capital in the production of pastoral production, respectively. Equation 4 can be obtained by substituting Equation 3 into Equation 2:

$$\max Y = PAL_a^{\alpha} T_a^{\beta} K^{\gamma} - P_K K + w\left(L - L_a\right) + R\left(T - T_a\right) \quad (4)$$

In the pursuit of maximizing revenue, the herdsmen allocate various production factors in the pastoral and non-pastoral husbandry industries. In order to obtain the optimal production decision of herdsmen, the Lagrange multiplier method is adopted to solve Equations (5–7). The partial derivatives of L_a , T_a and K are obtained by using Y :

$$\partial Y / L_a = \alpha PAL_a^{\alpha-1} T_a^{\beta} K^{\gamma} - w = 0 \quad (5)$$

$$\partial Y / T_a = \beta PAL_a^{\alpha} T_a^{\beta-1} K^{\gamma} - R = 0 \quad (6)$$

$$\partial Y / K = \gamma PAL_a^{\alpha} T_a^{\beta} K^{\gamma-1} - P_K = 0 \quad (7)$$

Combining the above equations can be solved: $L_a^* = \frac{\alpha PQ}{w}$, $T_a^* = \frac{\beta PQ}{R}$, $K^* = \frac{\gamma PQ}{P_K}$. By substituting each optimal production factor into the herdsmen's utility function, the optimal utility Y_0 and the optimal production scale Q^* can be obtained. The impact of the GECP on herdsmen includes limiting the use of grassland and giving herdsmen certain ecological compensation. In this case, the herdsmen's production conditions change, and the herdsmen's utility function will become the following function:

$$\max Y = PAL_a^{\alpha}\left(iT_a^{\beta}\right)K^{\gamma} - P_K K + w\left(L - L_a\right) + R\left(T - T_a\right) + SubT \quad (8)$$

In Equation 8, i is the maximum utilization rate of grassland stipulated by the policy (referring to the maximum utilization rate of

grassland set up to maintain the grass-animal balance, and the herdsmen need to graze their animals within a reasonable range of the utilization rate ($0<i<1$), the herdsman's pastoral production function becomes $Q=AL_a^{\alpha}\left(iT_a^{\beta}\right)K^{\gamma}$, Sub represents the amount of grassland compensation subsidies per acre, and the total amount of grassland ecological compensation subsidies obtained by the herdsmen is $SubT$, and the meaning of the rest of the variable explanations are unchanged. In the same way, it can be solved that the optimal production factors of the herdsmen at this time are L_a^{**} , T_a^{**} and K^{**} .the optimal utility Y_1 and the optimal production scale Q^{**} can also be obtained.

Before investigating the impact of GECP on the production behavior of herdsmen, it is necessary to assume that there are no significant changes in factors including herdsmen' husbandry skills, non-pastoral employment market wages and grassland rents. Therefore, Y_1-Y_0 can be used to obtain the effect of GECP on the change of herdsmen' utility. The specific formula is as follows:

$$Y_1-Y_0=P\left(Q^{**}-Q^{*}\right)-P_K\left(K^{**}-K^{*}\right)+w\left(L_a^{*}-L_a^{**}\right)+R\left(T_a^{*}-T_a^{**}\right)+SubT \tag{9}$$

In Equation 9, $P\left(Q^{**}-Q^{*}\right)$ represents the change in total income of herdsmen after the implementation of the GECP, $P_K\left(K^{**}-K^{*}\right)$ represents the change in pastoral production costs of herdsmen, $w\left(L_a^{*}-L_a^{**}\right)$ represents the change in the non-pastoral income of herdsmen, and $R\left(T_a^{*}-T_a^{**}\right)$ represents the change in income due to the change in the area of grassland actually operated by herdsmen, and as a result, the change in the utility of herdsmen after the implementation of the GECP includes the following four specific situations:

$$\text{Situation 1}: P\left(Q^{**}-Q^{*}\right)<0;\quad P_K\left(K^{**}-K^{*}\right)=0; w\left(L_a^{*}-L_a^{**}\right)=0; R\left(T_a^{*}-T_a^{**}\right)=0.$$

In this scenario, herdsmen opt to directly reduce their livestock numbers to decrease the utilization rate of grassland. However, this reduction in breeding scale inevitably leads to a decrease in their pastoral income. Simultaneously, most herdsmen are solely engaged in livestock production, resulting in no significant changes in non-livestock income. Consequently, the total amount of compensation subsidies received by herdsmen, combined with the loss of income from pastoralism, dictates changes in their utility, which in turn affects their overgrazing behavior.

$$\text{Situation 2}: P\left(Q^{**}-Q^{*}\right)=0;\quad P_K\left(K^{**}-K^{*}\right)>0; w\left(L_a^{*}-L_a^{**}\right)<0; R\left(T_a^{*}-T_a^{**}\right)=0$$

In this scenario, herdsmen will adopt the practice of barn feeding to maintain the original scale of livestock breeding, which will keep their pastoral income and grassland management area intact. However, barn feeding typically requires more significant labor and capital inputs. Consequently, following the implementation of the GECP, herdsmen's pastoral production costs will increase due to barn feeding, while their non-pastoral income will decrease due to reduced labor time allocated to non-pastoral activities. At this time, changes in herdsmen's overgrazing behavior and utility will depend on the interplay among the total amount of subsidies, the costs associated with barn feeding, and the fluctuations in non-pastoral income.

$$\text{Situation 3}: P\left(Q^{**}-Q^{*}\right)=0;\quad P_K\left(K^{**}-K^{*}\right)=0; w\left(L_a^{*}-L_a^{**}\right)=0; R\left(T_a^{*}-T_a^{**}\right)<0$$

In this scenario, herdsmen adapt by renting grassland to maintain their original scale of breeding. The pastoral income and production costs before and after the implementation of the policy remain unchanged; however, renting grassland incurs a corresponding rent expense. Simultaneously, herdsmen sustain their breeding scale through this rental arrangement, which minimally affects the duration of their non-pastoral employment, leaving their non-pastoral income unchanged. At this time, the total compensation and subsidies received by herdsmen, along with the grassland rent, dictate changes in their utility and overgrazing behavior.

$$\text{Situation 4}: P\left(Q^{**}-Q^{*}\right)\left\langle\begin{matrix}0; P_K\left(K^{**}-K^{*}\right)=0;\\ w\left(L_a^{*}-L_a^{**}\right)\end{matrix}\right\rangle 0; R\left(T_a^{*}-T_a^{**}\right)=0$$

In this scenario, similar to the situation 1, herdsmen may choose to directly reduce livestock numbers to decrease the utilization rate of grassland. This decision does not alter their grassland operating area or the production cost of each unit of animal husbandry products. However, a reduction in the scale of breeding will lead to a decline in pastoral income. In addition, because labor in livestock production and grassland is complementary, some herdsmen will divert surplus labor generated by the reduction of livestock to non-livestock industries. Consequently, the non-pastoral income of herdsmen is expected to rise following the implementation of the GECP. At this point, the total compensation received by herdsmen, along with their non-pastoral income and the losses incurred from livestock reduction, collectively determines the changes in herdsmen's utility and overgrazing behavior.

In summary, the change in the production behavior of herdsmen is influenced not only by policies but also by non-pastoral income. Therefore, this paper further analyzes the mechanism of the GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment.

2.2 Research hypotheses

2.2.1 The influence of GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment

According to the theory of The New Economics of Labor Migration, in the event of changes in the external environment, herdsmen will reallocate labor and other resource factors between agriculture and non-agricultural industries in order to maximize household returns (Zhou et al., 2019). Therefore, with the increase in non-pastoral employment opportunities in pastoral areas, the production model of herdsmen has gradually shifted from a singular

focus to a diversified approach (Mirzabaev et al., 2015; Ito et al., 2016). Traditional livestock husbandry herdsmen have transformed into new herdsmen, who engaged in various fields, including the semi-agricultural and semi-pastoral, pastoral and industrial, and non-pastoral types (Liu et al., 2020; Yang et al., 2024). While academia presents numerous standards for classifying herdsmen, non-pastoral income serves as the fundamental criterion. In this paper, we categorize herdsmen into three types: one is full-time pastoral herdsmen (PH1), tow is herdsmen with non-pastoral employment at low levels (PH2) and three is herdsmen with non-pastoral employment at high levels (PH3).[4] We will conduct a thorough analysis of the changes in overgrazing behavior among different types of herdsmen under the GECP.

For PH1 herdsmen, the choices they make are more in line with the situation 1. Following the implementation of the GECP, the actual grazing area available to PH1 herdsmen has been reduced. In order to protect the ecological environment, they are faced with two choices, one is to reduce the scale of farming, and the other is to choose to barn feeding or rent into grassland to reduce the pressure of grassland grazing (Zhang et al., 2021). However, many PH1 herdsmen are unable to afford the additional rental fees or high feeding costs due to their low-income levels and singular income structures (Wen and Jiang, 2024). As a result, direct livestock reduction has become the primary response policy. Unfortunately, the compensation provided by GECP is significantly lower than the income losses incurred from livestock reduction, placing many PH1 herdsmen under severe survival pressure (Tan et al., 2014; Zhang et al., 2018). To secure their family's livelihood, many PH1 herdsmen engage in practices such as "stealing grazing" and "night grazing" to maintain their original breeding scale (Xie X. et al., 2018). Therefore, it is difficult for the GECP to alleviate the overgrazing behavior of PH1 herdsmen.

For PH2 herdsmen, the choices they make are more in line with the situation 2 or 3. At this point, a portion of the family's non-pastoral income leads herdsmen to be more inclined to adopt barn feeding or rent grassland to achieve a sustainable livestock load. However, on one hand, the high rent of grassland reduces the profits of herdsmen (Liu et al., 2023a); on the other hand, barn feeding demands more labor and time, which results in decreased non-pastoral income (Dai and Tan, 2018). The interplay of these factors ultimately reduces the total income of the pastoral. As a result, some PH1 herdsmen will blindly expand their farming scale in order to maximize their income, while neglecting the sustainable limits of the feeding environment (Zhang and Tan, 2022). This ultimately leads to increased grazing pressure on the grasslands, and overgrazing cannot be effectively curbed.

For PH3 herdsmen, the choices they make are more in line with the situation 4. The significant proportion of income derived from non-pastoral employment leads PH3 herdsmen to exhibit a relatively low dependence on animal husbandry production (Yu et al., 2021). To a considerable extent, the subsidies offset the decline in opportunity costs and breeding income associated with the response policy (Jones and Marinescu, 2022). Consequently, in pursuit of maximizing family utility, PH2 herdsmen are inclined to reallocate the surplus labor extracted from livestock husbandry to the non-pastoral employment, thereby increasing their overall family income. When PH3 herdsmen are no longer dependent on pastoral production, their degree of overgrazing will decrease, which in turn will lead to the protection of the grassland ecosystem (Detailed transmission path is shown in Figure 1). Combined with the above analysis, the hypotheses are as following:

> *Hypothesis 1:* The mitigating effect of the GECP on the overgrazing behavior of full-time pastoral herdsmen (PH1) is not obvious.
>
> *Hypothesis 2:* The mitigating effect of the GECP on the overgrazing behavior of herdsmen with non-pastoral employment at low levels (PH2) is not obvious.
>
> *Hypothesis 3:* The GECP has effectively mitigated the overgrazing behavior of herdsmen with non-pastoral employment at high levels (PH3).

2.2.2 The effect of not-pastoral in the process of GECP affecting the overgrazing behavior of herdsmen

According to the theory of ecological compensation, ecological compensation is defined as a social and economic activity that generates positive externalities. The core principle of the GECP is to offset the positive externalities associated with grassland ecological protection. Essentially, the government provides financial compensation to the "protectors" of the ecological environment through various economic instruments, thereby incentivizing the provision of essential ecological products (Lundberg et al., 2018; Grima et al., 2016). However, the reliance on a singular reward method and the establishment of low subsidies often fail to adequately compensate for the income loss resulting from both direct livestock reductions and barn feeding. When economic interests conflict with ecological interests, herdsmen tend to prioritize immediate economic benefits over ecological considerations, demonstrating a reluctance to reduce livestock numbers (Xie X. et al., 2018). In some cases, herdsmen even choose to expand their breeding operations to offset the income loss caused by the GECP in the short term, which is further undermines the effectiveness of the GECP. Thus, the effective supply of ecological benefits can only be ensured if the economic interests of herdsmen are satisfied and their livelihood conversion capacity is improved (Yin Y. et al., 2018). Non-pastoral employment can reduce the pressure on herdsman's livelihoods due to the reduction of livestock through the "income effect" and "part-time effect" in terms of employment and income, thus alleviating in the short term the trend of expanding the scale of livestock breeding due to the inability of subsidies to make up for the loss of herdsman's livestock production. Specifically, the "income effect" from non-pastoral employment can provide additional income to herdsmen, and the stability of this non-pastoral income can help to alleviate the financial pressures faced by these herdsmen due to policy constraints. This ensures that the living standards and incomes of herdsmen do not experience significant declines as a result of government regulations on livestock breeding (Xie L. et al., 2018). Furthermore, the "part-time

4 Note: Referring to existing studies, the proportion of non-pastoral income in the total household income of herdsmen is used as a demarcation threshold, with less than 0.05 being a full-time pastoral herdsman (PH1), more than 0.05 and less than 0.5 being a herdsman with low degree non-pastoral employment (PH2), and more than 0.5 and less than 0.95 being a herdsman with high degree non-pastoral employment (PH3).

effect" generated by non-pastoral employment can effectively address the issue of labor surplus resulting from livestock reductions in herdsmen, facilitating the efficient transfer of excess family labor and thereby promoting a reduction in livestock numbers (Wu et al., 2019). In other words, enhancing non-pastoral employment can mitigate the income loss and labor transfer challenges faced by herdsmen during the implementation of the GECP, ultimately promoting better compliance with livestock reduction initiatives (Yin R. et al., 2018). Consequently, increasing non-pastoral employment may alleviate the income reduction and labor transfer issues encountered by herdsmen in the context of the GECP, thereby reducing overgrazing behavior and supporting the effective execution of the policy. Therefore, this paper proposes hypothesis 4 for testing.

> *Hypothesis 4:* Non-pastoral employment has a positive moderating role in the mechanism of the GECP's influence on herdsmen' overgrazing behavior.

3 Data sources and methodology

3.1 Data sources

The data utilized in this study were collected through field surveys conducted by the research team from January to May 2024 in Hulunbeier City, Xilingol League, and Ordos City, Inner Mongolia. In this study, we employed a combination of random sampling and stratified sampling methods, specifically consider factor such as per capita net income, herding situation, grassland type and non-pastoral employment to select sample units including flags (counties), Sumu (townships), and Gacha (villages). Initially, we selected 1 to 4 flags (counties) from each league (city), followed by selecting 1 to 3 Sumu (townships) from each sample flag (county). Subsequently, we chose 2 to 3 Gacha (villages) from each Sumu (township), and finally, we surveyed 12 to 17 herdsmen in each Gacha (village) as our sample population. The research covers livestock breeding situation, access to grassland ecological subsidies, and non-pastoral employment situation among the herdsmen interviewed in 2020 and 2023. A total of 600 questionnaires were distributed to herdsmen, excluding invalid samples, and finally 542 valid questionnaires were obtained from herdsmen, with a validity rate of 90.33%. (The sample distribution is shown in Table 1).

3.2 Variable selection

3.2.1 Dependent variable

Degree of overgrazing. In this paper, this paper refers to existing research to measure the degree of overgrazing by comparing the beginning of the year livestock stock of the

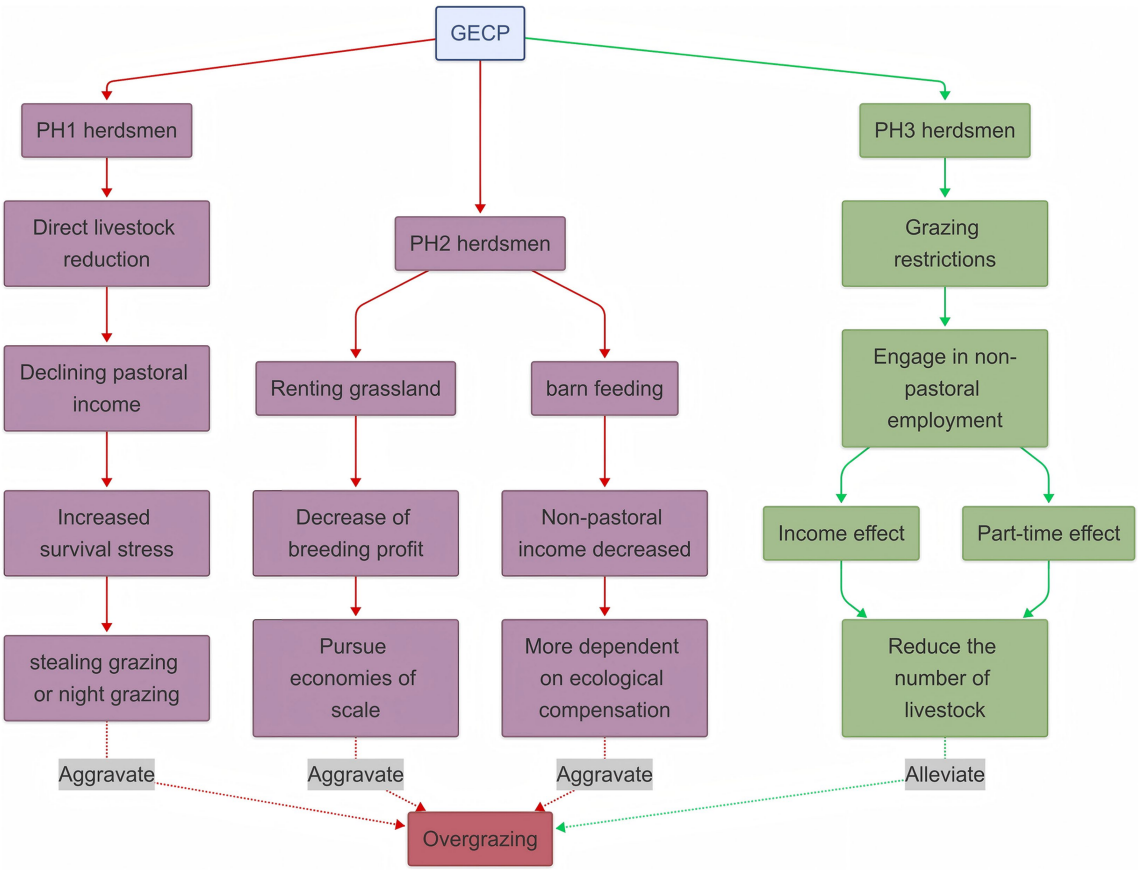


FIGURE 1
Mechanism diagram of the effect of GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment.

TABLE 1 Distribution of the survey sample.

Grassland types	League (city)	Banners (counties)	sums (townships)	Sample size (household)	Sample proportion (%)	PH1 herdsmen (%)	PH2 herdsmen (%)	PH3 herdsmen (%)
Meadow steppe	Hulunbeier	2	5	205	37.82	93.23	2.08	4.69
Typical steppe	Xilingol	3	7	177	32.66	35.56	61.11	3.33
Desert steppe	Ordos	3	6	160	29.52	21.76	22.00	58.24

TABLE 2 Descriptive statistical analysis of the degree of overgrazing of different types of herdsmen.

Type	Degree of overgrazing in 2020 (Sheep unit)	Degree of overgrazing in 2023 (Sheep unit)	Number of overgrazing herdsmen in 2020 (unit)	Proportion of overgrazing herdsmen in 2020 (%)	Number of overgrazing herdsmen in 2023 (unit)	Proportion of overgrazing herdsmen in 2023 (%)
Total sample	84.24	101.49	434	80.07	442	81.55
PH1 herdsmen	112.11	137.46	245	87.5	251	89.64
PH2 herdsmen	115.07	139.35	127	85.81	132	89.19
PH3 herdsmen	−24.22	−36.03	62	54.39	59	51.76

herdsmen to the reasonable livestock carrying capacity of grassland set by the government the data is calculated by the government based on the quality of the grassland) (Ma et al., 2024; Feng et al., 2019). The reasonable livestock carrying capacity is calculated by local governments in accordance with the agricultural industry standard of the People's Republic of China (NY/T635-2015),[5] titled "Calculation of Reasonable Livestock Carrying Capacity of Natural Grassland." This calculation typically considers various factors, including grassland productivity, ecological sustainability, and the demands of animal husbandry. Given the significant variability in grass production across different grassland types (e.g., typical steppe, desert steppe, meadow steppe) and the substantial impact of herding practices (e.g., rotational grazing, fallow grazing, and semi-barning feeding) on grassland utilization efficiency, local governments can dynamically adjust and manage these standards based on the specific circumstances encountered during implementation.[6,7] This approach ensures the sustainable utilization of grassland resources and the healthy development of the animal husbandry industry. Therefore, it is more accurate to calculate the degree of overgrazing using the reasonable livestock carrying capacity set by the Government. The first step involves calculating the actual livestock carrying capacity of each herdsman based on field survey data. Considering that the value of different livestock varies, during the calculation of the actual carrying capacity, various livestock are converted into sheep units according to the conversion rates of "1 cow = 5 sheep units, 1 horse = 6 sheep units 1 camel = 7 sheep units," ultimately obtaining the herdsmen's actual carrying capacity. The second step is to multiply the herdsmen's managed grassland area (comprising both contracted and transferred grassland areas) by the standard mu coefficient determined by the county-level government to establish the reasonable carrying capacity. Finally, the actual carrying capacity is subtracted from the reasonable carrying capacity to assess the herdsmen's degree of overgrazing, a positive value indicates overgrazing, with higher values reflecting a greater degree of overgrazing; conversely, a negative or zero value signifies that the herdsman is not overgrazing.

Table 2 shows the degree of overgrazing of herdsmen with varying levels of non-pastoral employment in 2020 and 2023. Statistics show that in 2023, the degree of overgrazing of all sample herdsmen reached 101.49 sheep units, an increase of 17.25 sheep units compared with 2020. Among all sample herdsmen, the proportion of herdsmen with overgrazing behavior in 2020 was 80.07 and 81.55% in 2023, respectively. Among all PH1 herdsmen, the proportion of herdsmen with overgrazing behavior in 2020 and 2023 was 87.5 and 89.64%, respectively, the degree of overgrazing of PH1 herdsmen in 2023 was 137.46 sheep units, 25.35 sheep units deeper than in 2020. Among all PH2 herdsmen, the proportion of herdsmen with overgrazing behavior in 2020 and 2023 was 85.81 and 89.19%, respectively, the degree of overgrazing in 2023 was 139.35 in 2023, which deepened 24.28 sheep units compared with 2020. Among all PH3 herdsmen, the proportion of herdsmen with overgrazing behavior in 2020 and 2023 was 54.39 and 51.76%, respectively, the degree of overgrazing in 2023 was −36.03, reducing 11.81 sheep units compared with 2020. It can be seen that under the background of the implementation of the GECP, herdsmen still have serious overgrazing, and there are obvious differences in the degree of overgrazing among different types of herdsmen. PH1 herdsmen and PH2 herdsmen are the main body of overgrazing, and PH3 herdsmen respond more positively to the livestock reduction policy.

5 Department of Agriculture and Animal Husbandry of the Inner Mongolia Autonomous Region. Available online at: https://www.nmg.gov.cn/zwgk/zfgb/2000n_5210/200008/200008/t20000801_308826.html (Accessed May 17, 2025).

6 Inner Mongolia Autonomous Region People's Government. Available online at: https://www.manzhouli.gov.cn/OpennessContent/show/272422.html (Accessed June 28, 2025).

7 Ministry of Agriculture and Rural Affairs of the People's Republic of China. Available online at: https://www.moa.gov.cn/nybgb/2005/dsanq/201806/t20180617_6152408.htm (Accessed June 28, 2025).

3.2.2 Core independent variables

Implementation of the GECP. This paper investigates the impact of the GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment by constructing double difference variables. The interaction term combines the policy implementation stage with a dummy variable representing the herdsmen group. The policy implementation stage includes periods before and after the enactment of the policy, while the herdsmen group comprises both the experimental group affected by the policy and the control group that is not affected. Given that the GECP is implemented simultaneously for all herdsmen across the major pastoral areas of the country, there is no naturally existing control group. Drawing on existing research (Zhang et al., 2021; Liu et al., 2023a), this study constructs a control group using samples that are weakly affected by the policy. Specifically, this paper utilizes herdsmen whose family contracted pasture area is less than 1,500 mu as a control group. This is because herdsmen in the research area generally consider 1,500 mu to be the amount of pasture necessary for a family's subsistence. According to herdsmen with less than 1,500 mu of contracted pastureland, the annual ecological compensation of a few thousand yuan has made it difficult to influence their pastoral production activities, and even more difficult to mobilize their motivation to reduce livestock. Therefore, the pasture loading rate of these herding households is expected to be minimally impacted by the policy, making them theoretically suitable for constructing the control group. Furthermore, this paper draws on existing research to select "Ecological compensation subsidies" as a representation of the characteristics of the GECP (Zhou J. et al., 2022). The ecological compensation subsidies were defined as the cumulative total of the prohibition of grazing subsidies, grass-livestock balance reward subsidies, and seasonal rest grazing subsidies received by the herdsmen throughout the year.

3.2.3 Control variables

This paper selects the characteristics of the herdsmen and other policy factors as control variables (Ma et al., 2009; Le and Leshan, 2020). The characteristics of the herdsmen include health status and years of grazing experience, total household income, the number of laborers engaged in animal husbandry, grassland rent-in, cost of forage per sheep, and barn feeding. Other policy factors considered include the subsidies for covering farming costs, socialized services aimed at local livestock development and policy regulations. To mitigate issues of covariance and heteroscedasticity, total household income was subjected to logarithmic transformation in this study.

3.2.4 Moderating variable

3.2.4.1 Non-pastoral employment

This paper characterizes non-pastoral employment variable by utilizing the proportion of non-pastoral income (comprising household wages, business earnings, and other sources) relative to the total household income of herdsmen, as referenced in existing studies. This variable is continuous, with a value range of (0, 1) (Du et al., 2016).

3.2.5 Instrumental variables

Local non-pastoral employment conditions. In reference to existing studies (Tian and Li, 2014; Zhou et al., 2017), local non-pastoral employment conditions were selected as the instrumental variable to address the issue of endogeneity. This variable serves two primary functions: on one hand, it reflects the local non-pastoral employment conditions, indicating that areas with better non-pastoral employment prospects typically offer more job opportunities and higher non-pastoral income. On the other hand, the extent of herdsmen's overgrazing is not directly correlated with local non-pastoral employment opportunities, and there is no evidence linking this variable to macro compensation policies or individual or family-level overgrazing behavior. Moreover, by excluding personal information, the instrumental variable is theoretically not expected to influence the random error term, thus affirming its validity as an effective instrumental variable

Descriptive statistics of each variable are analyzed in Table 3.

3.3 Econometrics model

To test the hypotheses, a double difference model was constructed to analyze the mechanism of the GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment. The effect of policy implementation can be captured by estimating the difference between the treatment and control groups before and after the policy's implementation. The fixed-effects double-difference model constructed in this paper is as follows:

$$CZ_{it} = \alpha_0 + \alpha_1 Policy_{it} \times Treat_{it} + \alpha_2 Treat_{it} + \alpha_3 Policy_{it} + \beta Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (10)$$

In Equation 10, CZ_{it} is an explanatory variable indicating the degree of overgrazing of herdsmen. $Policy_{it}$ is a dummy variable for the implementation period of the third round of grassland ecological bonus policy, $Policy_{it}$ =0 for 2020 and $Policy_{it}$ =1 for 2023; $Treat_{it}$ is a dummy variable for the group of herdsmen, $Treat_{it}$ =0 for the control group, and $Treat_{it}$ =1 for the experimental group; α_1 is the coefficient of the double-difference estimate reflecting the impact of the GECP on the herdsmen's overgrazing behavior, and if α_1 is significantly positive, it indicates that the GECP has aggravated the overgrazing behavior of herdsmen; $Control_{it}$ is a set of observable control variables affecting the overgrazing behavior of herdsmen, including the characteristics of the head of the herdsmen, the characteristics of the herdsmen, and the conditions of the district, etc.; μ_i is the individual fixed effect reflecting the influence of the characteristics of the individual factors that do not change over time on the degree of overgrazing; γ_t denotes the year fixed effect reflecting the influence of the macro-factors, such as the economic growth and the economic environment, on the degree of overgrazing of herdsmen; and ε_{it} denotes the random error term.

Further, in order to test the moderating role of non-pastoral employment in the mechanism of the GECP's influence on the overgrazing behavior of herdsmen, a hierarchical regression analysis model is constructed with reference to the existing research results (Wen et al., 2005). The specific model is as follows:

$$CZ_i = \beta_0 + \beta_1 sub + \beta_2 inc + \beta_3 sub \times inc + \gamma_i \quad (11)$$

In Equation 11, sub denotes the amount of ecological supplemental subsidies; inc denotes the share of non-pastoral income of herdsmen in total household income; $sub \times inc$ denotes the interaction between the amount of ecological supplemental subsidies and the share of

TABLE 3 Descriptive statistical analysis of variables.

Type	Variable	Definition	2020		2023	
			Mean	S.D.	Mean	S.D.
Dependent variable	Degree of overgrazing	The difference between actual and theoretical livestock load (sheep unit).	84.24	137.49	101.49	155.89
Core independent variables	Ecological compensation subsidies	The sum of the amount of grazing compensation, balance of grass and livestock and seasonal grazing compensation (ten thousand yuan).	0.75	0.93	0.89	1.10
Controlled variable	Health status	Physical health level of the herdsman (1 = very poor, 2 = relatively poor, 3 = general, 4 = relatively good, 5 = very good).	3.80	1.01	3.53	1.00
	Years of grazing experience	Years of grazing (years).	23.49	10.23	26.44	10.30
	Total household income (logarithm)	The sum of animal husbandry income, non-pastoral income, property income and transfer income of pastoral families.	12.14	11.70	12.20	11.94
	The number of laborers engaged in animal husbandry	Number of labor force engaged in animal husbandry production (one).	1.86	0.75	1.80	0.74
	Grassland rent-in	Whether to rent the grassland in that year (1 = yes, 0 = no).	0.25	0.44	0.23	0.42
	Cost of forage per sheep	Total annual cost of feed for a single animal (yuan / sheep unit).	355.41	234.31	359.94	222.00
	Barn feeding	Whether to adopt barn breeding in that year (1 = yes, 0 = no).	0.16	0.37	0.24	0.43
	The subsidies for covering farming costs	Can the compensation amount make up for the income loss caused by the livestock reduction (1 = very low, 2 = relatively low, 3 = general, 4 = high; 5 = very high).	2.21	0.86	3.22	1.24
	Socialized services aimed at local livestock development	Socialized services for local animal husbandry development (1 = very poor, 2 = relatively poor, 3 = general, 4 = relatively good, 5 = very good).	3.35	0.95	3.73	1.01
	Policy regulations	The government supervision situation in that year (1 = no, 2 = looser, 3 = general, 4 = stricter, 5 = very strict).	3.02	1.12	3.059	1.13
Moderating variables	Non-pastoral employment	The proportion of the sum of non-pastoral income such as wage and business income in the total family income.	0.21	0.27	0.22	0.28
Instrumental variables	Local non-pastoral employment conditions	Local non-pastoral employment conditions (1 = no, 2 = relatively Low, 3 = general, 4 = good, 5 = very good).	2.01	1.03	2.30	1.18

non-pastoral income; β_0, β_1, β_2, β_3 denotes the parameter to be estimated, γ_i is a random perturbation term, and the meanings of the other variables are the same as those explained in Equation 10.

To ensure the validity of the results, it is essential to make the characteristics of the experimental and control groups as similar as possible prior to applying the double difference method. This entails satisfying the 'balanced trend test.' However, given that there are only two periods of sample data, conducting a parallel trend test is not feasible. To address this limitation, this paper draws on existing studies and employs the Propensity Score Matching-Difference in Differences (PSM-DID) method to evaluate the influence mechanism of the GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment (Wang et al., 2021; Tian and Wu, 2024). The specific models are as follows:

$$CZ_{it}^{PSM} = \alpha_0 + \alpha_1 Policy_{it} \times Treat_{it} + \alpha_2 Treat_{it} + \alpha_3 Policy_{it} + \beta Control_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (12)$$

The variables and their coefficients in Equation 12 have the same meaning as in Equation 11.

4 Analysis of results

4.1 Analysis of the influence mechanism of the GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment

Based on the theoretical analysis framework and research hypotheses, this paper utilized STATA 18.0 software to estimate the model. Table 4 presents the double difference estimation results regarding the impact of the GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment. After controlling for time and individual fixed effects, the specific results are as follows.

TABLE 4 Empirical analysis of the impact of GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment.

Variable	Model 1 (PH1 herdsmen)	Model 2 (PH2 herdsmen)	Model 3 (PH3 herdsmen)
Policy × treated	26.845***	27.157**	−29.313***
	(8.842)	(11.435)	(7.895)
Health status	41.394**	−5.430	18.285*
	(16.021)	(13.875)	(10.666)
Years of grazing experience	−28.019**	−11.939	−69.588***
	(11.312)	(23.566)	(11.525)
Total household income(logarithm)	−23.990***	43.263***	23.748*
	(8.468)	(11.923)	(13.636)
The number of laborers engaged in animal husbandry	50.820***	32.697***	45.424***
	(11.852)	(11.615)	(7.186)
Grassland rent-in	−94.397***	33.295**	−86.536***
	(12.375)	(12.972)	(19.452)
Cost of forage per sheep	−0.072***	−0.035	−0.026**
	(0.023)	(0.033)	(0.011)
Barn feeding	−25.197*	−35.428**	2.929
	(14.975)	(16.572)	(10.670)
The subsidies for covering farming costs	−17.269**	−81.855***	−5.803
	(7.518)	(20.171)	(3.647)
Socialized services aimed at local livestock development	10.148	−33.869*	−4.847
	(20.996)	(17.948)	(5.385)
Policy regulations	−12.235*	−15.733	−14.349***
	(6.636)	(9.634)	(5.044)
Constant	977.622***	272.373	749.597***
	(320.322)	(649.077)	(228.792)
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	560	296	228
R-squared	0.603	0.598	0.731

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

The results of model 1 demonstrates that the implementation of the GECP has a significant positive effect on the degree of overgrazing among PH1 herdsmen at the 1% significance level, with an impact coefficient of 26.845. This implies that the policy increases the degree of overgrazing for these herdsmen by 26.845 sheep units. The primary reason is that PH1 herdsmen are unable to bear the high costs associated with reducing livestock. Surveys indicate that over 70% of these herdsmen believe that the compensation and incentive subside do not adequately compensate for the income loss resulting from livestock reduction, the finding that aligns with empirical evidence. Furthermore, nearly 50% of PH1 herdsmen express a willingness to reduce livestock; however, due to the singular nature of their income structure and insufficient capacity for transforming livelihoods, they ultimately opt for overgrazing despite receiving compensation and incentives. Consequently, the findings suggest that the GECP does not significantly mitigate the overgrazing behavior of PH1 herdsmen, thereby confirming the hypothesis 1.

The results of model 2 indicate that the implementation of the GECP significantly and positively affects the degree of overgrazing among PH2 herdsmen at the 5% significance level, with an impact coefficient of 27.157. This implies that the policy increases the degree of overgrazing for these herdsmen by 27.157 sheep units, and there was no significant difference in the degree of overgrazing between PH1 herdsmen and PH2 herdsmen. The probable reason for this is that the policy has been implemented up to the third round and its impact on the pastoralists has weakened, while the lower non-pastoral income has not significantly affected overgrazing. In the actual research process, we also found that more than half of the PH2 herdsmen will use ecological subsidies to expand the scale of pastoral in order to pursue more economic benefits, even though this will destroy the grassland ecology. In addition, some herdsmen will use the grassland for grazing without restriction after renting the grassland, which undoubtedly worsens the ecological damage of the grassland (Wang et al., 2018; Ma et al., 2024). Those reflect the insignificant mitigating effect of GECP on the overgrazing behavior of PH2 herdsmen, and hypothesis 2 is verified.

The results of model 3 indicate that the implementation of the GECP has a significant negative impact on the degree of overgrazing

among PH3 herdsmen at the 1% level, with an impact coefficient of −29.313. This implies that the policy reduces the degree of overgrazing for these herdsmen by 29.313 sheep units, demonstrating that the implementation of the policy has effectively mitigated the extent of overgrazing in this group. The primary reason for this phenomenon is twofold. First, the low proportion of pastoral income results in a relatively low opportunity cost for PH3 herdsmen when reducing their livestock. Second, non-pastoral income offers these herdsmen a more substantial and stable source of income. Consequently, the combined effects of these factors lead PH3 herdsmen to respond more positively to the policy, thereby validating hypothesis 3.

In terms of control variables, the health statue, years of grazing experience, the number of laborers engaged in animal husbandry, and barn feeding have a significant effect on the overgrazing behavior of herdsmen and the direction of impact is in line with expectations. Specifically, as a labor-intensive industry, animal husbandry requires a substantial labor force (Zhou and Zhao, 2019). Consequently, the greater the labor investment in pure animal husbandry, the more pronounced the overgrazing issues become. Herdsmen with extensive grazing experience possess the knowledge to enhance grazing efficiency within a sustainable breeding range; thus, a longer grazing tenure correlates with a reduced degree of overgrazing. Furthermore, barn feeding is characterized by high production efficiency and intensification (Zhang et al., 2018). It allows for rational planning of breeding space, enhances breeding efficiency per unit area, and reduces reliance on natural grasslands compared to traditional livestock farming, thereby alleviating pressure on pastures. However, if the cost is greater than the benefit, the herdsmen will not expand the scale of production (Ma et al., 2016).

In addition, this paper also finds that some of the control variables do not have the expected impact on the overgrazing behavior of herdsmen. Such as total household income and grassland rent-in have a significant positive effect on the overgrazing behavior of PH2 herdsmen. There are two possible reasons for this, one is that higher household incomes provide the conditions for PH2 herdsmen to rent in grasslands or adopt the practice of barn feeding, but due to the lack of regulation of herdsmen's use of grasslands, some herdsmen may destroy grasslands in pursuit of short-term benefits (Ma et al., 2024); another is that the cost of forage has less impact on pastoralists, some of whom will expand their farming without limit after leasing in pasture, thus increasing grazing pressure on the grassland. Additionally, some PH2 herdsmen in areas with a higher level of socialized services for livestock farming can access the necessary financial and technical assistance for barn feeding (Qi et al., 2024). This support can, to some extent, help alleviate their challenges during the barn feeding, thereby reducing the degree of overgrazing.

4.2 Moderating effect of the proportion of the proportion of non-pastoral employment income on the GECP affecting the overgrazing behavior of herdsmen

To examine the moderating effect of the proportion of non-pastoral income employment on the mechanism of the GECP affecting the overgrazing behavior of herdsmen, this paper utilizes existing research and employs a hierarchical regression model to analyze the total sample data. The specific results are presented in Table 5, model 5. The estimation results indicate that the interaction term between the ecological compensation subsidies and the proportion of non-pastoral employment income significantly negatively impacts the overgrazing behavior of herdsmen at a statistical significance level of 1%. The regression coefficients for both ecological compensation subsidies and the proportion of non-pastoral employment income are negative, suggesting that a higher proportion of non-pastoral employment income among herdsmen corresponds to a greater inhibitory effect of the GECP on their overgrazing behavior. Furthermore, the R^2 value of the model after including the interaction term is 0.562, which exceeds the value prior to its inclusion, thereby reinforcing the conclusion that the proportion of non-pastoral employment income positively moderates the influence of the GECP on the overgrazing behavior of herdsmen and hypothesis 4 is verified.

In light of the potential reverse causality between the proportion of non-pastoral employment income and overgrazing, this study opted

TABLE 5 Moderating effect of non-pastoral employment on overgrazing behavior of herdsmen as influenced by GECP.

Variable	OLS		2SLS	
	Model 4	Model 5	Model 6	Model 7
Ecological compensation subsidies	−23.657***	−21.628***	−30.429***	−28.881***
	(4.006)	(3.893)	(4.105)	(4.075)
Non-pastoral employment	−281.533***	−306.029***	−35.885***	−35.651***
	(32.006)	(31.252)	(7.002)	(6.916)
Ecological compensation subsidies× non-pastoral employment		−75.508***		−11.687***
		(12.521)		(3.095)
Controlled variable	Controlled	Controlled	Controlled	Controlled
Observations	542	542	542	542
R-squared	0.532	0.562		
F value			275.7	265.352
DWH χ^2 test			0.9804	0.0563

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

to utilize an instrumental variable to replace the proportion of non-pastoral employment income, thereby addressing the potential endogeneity issue. Drawing upon existing research, the study introduced "local non-pastoral employment conditions" as the instrumental variable. The estimation results obtained after incorporating this instrumental variable into the 2SLS model are presented as Model 6 and Model 7 in Table 5. These results indicate that the hypothesis of the proportion of non-pastoral employment being an exogenous variable is valid. Furthermore, the F-statistic estimated in the first stage is 275.7, significantly exceeding the critical value of 10, which suggests that weak instrumental variable issues are not present. Consequently, this further substantiates the robustness of the estimation results from Model 5. The results of the analysis indicate that there is no endogenous relationship between the proportion of non-pastoral employment and overgrazing.

4.3 Robustness tests

In order to ensure that the previous analysis on the mechanism of the impact of the GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment is more convincing, this paper applies the PSM-DID model, the replacement of explanatory variables, and the reconstruction of the control group and the experimental group, respectively, to test the robustness of the previous findings. The test results show that the findings of the previous paper are robust, and that the GECP significantly affects the overgrazing behavior of herdsmen with varying levels of non-pastoral employment.

4.3.1 Double difference estimation after propensity score matching (PSM-DID)

The validity of the difference-in-differences model relies on the parallel trend assumption. However, this paper only uses data from 2020 and 2023, making it impossible to adequately test the parallel trend assumption. To solve this problem, we refer to existing studies and use the combination of Propensity Score Matching method (PSM) and Difference-in-Differences (DID) to try to minimize the differences between the treatment and control groups (Cheng et al., 2021; Han, 2019; Sun and Fan, 2017). The specific steps are as follows: firstly, this paper adopts the propensity score matching method to match the samples of the treatment and control groups for the three data sets respectively, to solve the problem of self-selection bias that may arise from the test results; secondly, the data that are not successfully matched are deleted; finally, the samples that are successfully matched are estimated again.

The specific steps of the Propensity Score Matching (PSM) method are as follows: (1) selecting all control variables as matching variables for near-neighbor matching with replacement; (2) estimating propensity scores based on the explanatory and control variable groups; (3) identifying control group individuals corresponding to the treatment group based on the propensity score values for all individuals. To evaluate whether the matched results improved the balance of the data, balance tests were conducted on the matched samples. The results of these balance tests are presented in Table 6. The mean deviation of the data across all three groups of pastoralists was reduced to approximately 10 percent. The value of Pseudo R^2decreased to about 0.02, and the probability value shifted from significant to insignificant. It can also be seen in Figure 2 that the deviation between the treatment and control groups for the matched variables is significantly reduced. In summary, the total errors of the samples after matching have been significantly reduced, and the characteristics of the samples among the groups are now more similar. Thus, the balance test is deemed successful.

The common support domain serves as a fundamental test target for evaluating the effectiveness of the Propensity Score Matching (PSM) method. Figure 3 demonstrates the common support domain before and after matching, and it can be seen that only a few observations are not within the common range of values, which indicates that there is less sample loss during the matching process and the matching effect is better.

Subsequently, unmatched successful samples were removed. Based on the refined sample data, a double difference model was employed to estimate the effect of the GECP on the overgrazing impacts attributed to herdsmen with varying levels of non-pastoral employment. The estimation results presented in Table 7 indicate that the direction and significance of the estimated coefficients regarding the impact of the GECP on the degree of overgrazing among PH1 herdsmen, PH2 herdsmen, and PH3 herdsmen remained largely unchanged. Furthermore, in order to avoid the impact of using different matching methods on the estimation results, this paper replaces the matching method and matches again to check the robustness of the results, and the results again verify the robustness of the benchmark regression.

4.3.2 Replacing the explained variables

In order to test the robustness of the baseline estimation results, this paper utilizes previous research to incorporate "livestock stock" as an explanatory variable in estimating the impact of the GECP on

TABLE 6 The results of the balance test after variable matching.

Type of herdsmen	Matching methods	Pseudo R^2	LR Statistic	*p* Value	Mean deviation	Median deviation
PH1 herdsmen	Before matching	0.35	135.73	0.00	34.90	28.90
	After matching	0.02	8.78	0.55	11.00	12.40
PH2 herdsmen	Before matching	0.33	127.47	0.00	30.80	24.40
	After matching	0.02	5.43	0.86	9.80	5.30
PH3 herdsmen	Before matching	0.21	68.03	0.00	33.10	29.80
	After matching	0.03	9.61	0.47	10.90	8.30

***Refer to the significance levels of 1%.

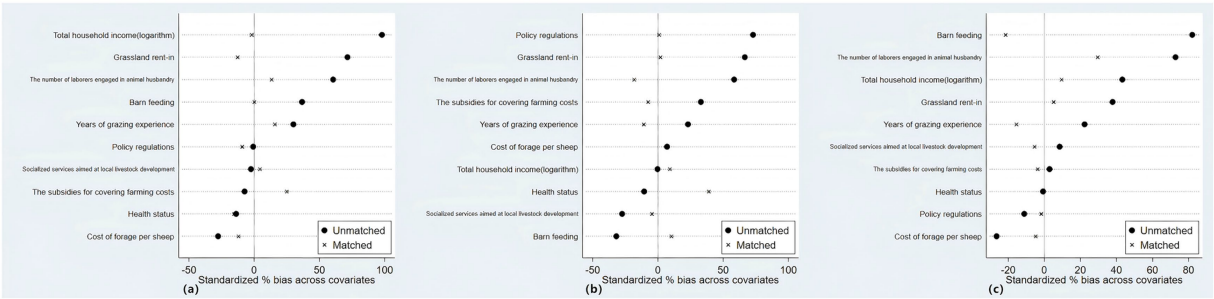


FIGURE 2
The result of the balance test of the PSM method: **(a)** PH1 herdsmen; **(b)** PH1 herdsmen; **(c)** PH1 herdsmen.

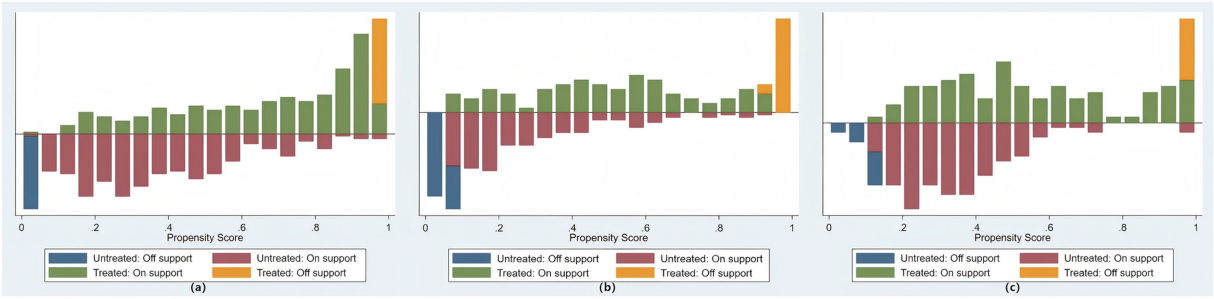


FIGURE 3
The common support domain of the PSM method: **(a)** PH1 herdsmen; **(b)** PH1 herdsmen; **(c)** PH1 herdsmen.

the overgrazing behavior of herdsmen with varying levels of non-pastoral employment (Ding et al., 2022). The results presented in Table 8 indicate that, after substituting the explanatory variables, the GECP has a significantly positive effect on the livestock stock of both PH1 and PH2. Conversely, it exerts a significant negative impact on PH3 herdsmen, which aligns with the findings in Table 4 and further substantiates the robustness of the previous results.

4.3.3 Reconstructing the control and experimental groups

To mitigate selection bias and the bias of omitted variables, this paper draws upon existing research and employs the criterion of "participation in barn feeding or artificial forage programs" to reconstruct both the control and experimental groups, thereby enhancing the accuracy of the estimation results (Zhang et al., 2018). "treat = 0" indicates that the herdsmen did not participate in the policy, and "treat = 1" indicates that the herdsmen participated in the policy; The specific regression results presented in Table 9 are largely consistent with those in Table 4, further reinforcing the robustness of the previous conclusions.

5 Discussion

This paper based on the farmer model to provide a more scientific analysis of the influence mechanism of the GECP on the overgrazing behaviors of pastoral herdsmen. By analyzing the empirical results, we find that GECP does not seem to be able to mitigate the overgrazing behavior of herdsmen. In fact, the implementation of this policy has resulted in an exacerbation of overgrazing issues. These findings align with existing literature, reinforcing the notion that the GECP does not effectively curtail the overgrazing behavior of herdsmen (Zhou S. et al., 2022; Xie X. et al., 2018; Liu et al., 2023b). The fundamental reason for this result is that the ecological compensation policy at this stage cannot effectively alleviate the contradiction between the government's ecological goals and the economic needs of herdsmen. Specifically, PH1 herdsmen have a single income structure and low risk tolerance, making it difficult for them to protect the ecosystem by reducing livestock, and even more difficult for them to reduce grazing pressure on grasslands by adopting barn feeding or renting in grasslands (Chang et al., 2022; Zhang et al., 2021). In addition, too low a compensation standard makes it difficult to compensate for herders' livestock reduction losses, which further undermines the effectiveness of the policy (Zhang et al., 2019). While PH2 herdsmen have the means for barn feeding and rent-in grassland, high transfer and breeding costs compress profit margins (Dong et al., 2023). Consequently, rational economic behavior drives them to make production decisions that contradict the policy.

However, we also found that the GECP has significantly mitigated the overgrazing behavior of PH3 herdsmen. The possible reason is that non-pastoral employment exerts a significant negative moderating effect on the mechanism of the GECP concerning herdsmen's overgrazing practices. Specifically, the effectiveness of the GECP in mitigating overgrazing can be substantially enhanced by increasing the proportion of income derived from non-pastoral employment among herdsmen. This enhancement occurs because the 'income effect' generated by non-pastoral employment can improve herdsmen's

TABLE 7 Results of PSM-DID estimation of the mechanism of the impact of GECP on the overgrazing behavior of herdsmen with varying levels of non-pastoral employment.

Variable	Nearest neighbor matching (K = 1)			Radius matching (0.01)		
	PH1 herdsmen	PH2 herdsmen	PH3 herdsmen	PH1 herdsmen	PH2 herdsmen	PH3 herdsmen
Policy × treated	21.359**	23.893*	−28.530***	21.359**	24.755*	−19.893**
	(9.071)	(14.215)	(8.268)	(9.071)	(14.581)	(8.979)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
constant	978.724***	388.395	792.645***	978.724***	240.038	−412.345**
	(326.383)	(1104.936)	(234.540)	(326.383)	(1099.498)	(164.347)
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	448	198	202	448	188	174
R-squared	0.626	0.584	0.740	0.626	0.570	0.601

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

TABLE 8 Test results for replacement of explanatory variables.

Variable	PH1 herdsmen	PH2 herdsmen	PH3 herdsmen
Policy × treated	23.523***	31.976***	−19.432***
	(8.620)	(11.305)	(6.948)
Control variables	Yes	Yes	Yes
constant	1020.306***	350.538	367.964*
	(312.274)	(641.731)	(201.338)
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	560	296	228
R-squared	0.534	0.618	0.799

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

household income, thereby enabling them to offset the income loss associated with livestock reduction (Huang et al., 2024). Additionally, labor diversion reduces the labor supply available for pastoral production, which compels a contraction in the scale of livestock production (Wang et al., 2024). Consequently, the combined effects of these factors result in a stronger inhibitory effect of the GECP on the overgrazing behavior of herdsmen. Field research data indicated that the response to the livestock reduction policy among PH3 herdsmen was 38.12% higher than that of PH2 herdsmen, with their livelihood conversion capacity index being 42% greater than that of PH1 herdsmen. This data further substantiates the critical role of non-pastoral employment in alleviating overgrazing.

In addition, through the systematic analysis of the research data, this paper finds that the types of herdsmen show obvious regional distribution characteristics: PH1 herdsmen are mainly concentrated in the eastern region, PH2 herdsmen are mainly in the central region, while PH3 herdsmen are mainly distributed in the western region. This spatial distribution pattern reflects, to some extent, that the implementation of the GECP has a more significant effect in the western region, and its inhibiting effect on overgrazing behavior is more prominent than in the eastern and central regions. It is worth noting that although the eastern and central regions have higher quality grassland resources, the unitary industrial structure exposed during the process of economic development has led to an over-dependence of the regional economy on animal husbandry. This monolithic economic development model makes it difficult for herdsmen in the region to realize effective livelihood transformation, thus exacerbating the risk of overgrazing. In contrast, the western region has benefited from a more diversified economic structure, and under policy guidance, most herding households have successfully transitioned to non-herding employment. This structural transformation has not only effectively alleviated grazing pressure on the grasslands, but has also provided an important guarantee for the sustainable conservation of grassland ecosystems.

6 Conclusion

This paper focuses on the overgrazing behaviors of herdsmen and explores in depth the influence mechanism of the GECP on these behaviors. Firstly, based on the farmer model, this paper constructs theoretical analytical frameworks to examine the influence mechanism of the GECP on the overgrazing behaviors of PH1, PH2, and PH3 herdsmen, respectively. The conclusions of the paper are as follows: (1) The GECP appears to be ineffective in reducing the degree of

TABLE 9 Test results after reconstructing the control and experimental groups.

Variable	PH1 herdsmen	PH2 herdsmen	PH3 herdsmen
Policy × treated	26.685***	31.776***	−22.276***
	(8.847)	(10.947)	(8.218)
Control variables	Yes	Yes	Yes
constant	946.655***	−33.604	707.123***
	(319.791)	(648.983)	(234.807)
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	560	296	228
R-squared	0.603	0.605	0.724

***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

overgrazing among both PH1 and PH2 herdsmen due to serious incentive incompatibility between the ecological requirements of the government and the economic needs of herdsmen. In fact, the implementation of this policy has led to an increase in overgrazing. (2) The GECP has significantly mitigated the overgrazing behaviors of PH3 herdsmen, resulting in a reduction of overgrazing by 29.313 sheep units. This indicates that PH3 herdsmen have actively responded to the policy by decreasing their livestock numbers. (3) Non-pastoral employment exerts a significant negative moderating effect on the mechanism of the GECP regarding herdsmen's overgrazing practices. Specifically, the effectiveness of the GECP in mitigating overgrazing can be substantially enhanced by increasing the proportion of non-pastoral employment income among herdsmen. (4) In terms of control variables, grassland rent-in, barn feeding, and socialized services aimed at the local community have a significant dampening effect on the overgrazing behaviors of herdsmen. Based on these conclusions, the policy recommendations are as following:

(1) Optimize the subsidy standard and the form of payment. First of all, the Government can, on the basis of comprehensive consideration of grassland ecological protection inputs and benefits, moderately raise the ecological subsidy standard in order to incentivize herdsmen to protect the ecological environment; at the same time, the Government should implement a differentiated form of funding, based on the amount of livestock carried to determine whether overgrazing have occurred during herdsmen's grazing, so as to decide whether to issue subsidies to herdsmen, in order to reduce the likelihood of the subsidy failing to be effective.
(2) Strengthening policy regulation and improving the efficiency of supervision. The government should strengthen the supervision of the grazing behavior of PH1 herdsmen and PH2 herdsmen, and raise the default cost of overgrazing, so as to increase the binding force on the overgrazing behavior of herding households. At the same time, the government should set up a reasonable supervisory organization, optimize the structure of the team, and improve the efficiency of supervision.
(3) Developing the pastoral labor transfer market and giving full play to the livestock-reducing effects of non-pastoral employment. The government should broaden the non-pastoral employment channels, through the employment market to lead more pastoral labor to non-pastoral employment market transfer, reducing herdsmen's dependence on traditional pastoral production; at the same time, should improve the non-pastoral employment market, to ensure that herdsmen can obtain stable non-pastoral employment income.
(4) Give full play to the roles of barn feeding and grassland rent-in. The Government should strengthen policy support, help herdsmen build the infrastructure needed for barn feeding, encourage herdsmen to reduce the number of livestock grazing on natural grasslands through barn feeding, and promote the transformation of natural grassland grazing into barn feeding and semi-barn feeding; at the same time, it should improve the market for the transfer of grasslands and encourage herdsmen to transfer their grasslands, so as to optimize the allocation of grassland resources and achieve the sustainable development of a balance between grasses and animals.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

WO: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing, Formal analysis, Visualization. FJ: Funding acquisition, Methodology, Visualization, Writing – review & editing. JH: Writing – review & editing, Data curation, Investigation, Software. ZG: Writing – review & editing, Conceptualization, Funding acquisition, Supervision. BZ: Methodology, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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EDITED BY
Chengqi Wang,
University of Nottingham, United Kingdom

REVIEWED BY
Guoxiang Li,
Nanjing Normal University, China
Xiaodong Yang,
Shihezi University, China
Xiaokai Li,
North China University of Water Conservancy and Electric Power, China

*CORRESPONDENCE
Jinghui He,
hejh@dgu.ac.kr

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Digital rural construction and agricultural green total factor productivity: the role of land finance, land resource misallocation, and agricultural technology innovation

Zhenyang Zhang[1,2], Tianxiang Hu[3] and Jinghui He[1]*

[1]Department of Law, Dongguk University, Seoul, Republic of Korea, [2]School of Humanities and Law, Nanchang Hangkong University, Nanchang, China, [3]Department of Business Administration, Jeonbuk National University, Jeonju, Republic of Korea

Prior studies on whether and how digital rural construction (DRC) contributes to enhancing agricultural green total factor productivity (AGTFP) remain limited. This study uses Difference-in-Differences method and panel data comprising 18,543 observations from 2,128 counties (districts) between 2012 and 2022 to examine the impact of DRC on AGTFP and its underlying mechanisms. The findings indicate that DRC significantly boosts AGTFP, a result that holds after conducting several robustness checks and endogeneity test, including replacing the dependent variable, excluding other policy impacts, adjusting the sample period, and propensity score matching method. The mechanisms through which DRC enhances AGTFP include improving land finance, alleviating land resource misallocation, and fostering agricultural technology innovation. The effects of DRC on AGTFP are notably more pronounced in the central and western regions of China, non-major grain-producing areas, and regions with lower land transfer efficiency. Our insights clarify the influence pathways through which DRC facilitates the enhancement of AGTFP, offering fresh theoretical insights and practical implications for further guiding DRC and leveraging the efficiency of AGTFP.

KEYWORDS

digital rural construction, agricultural green total factor productivity, land finance, land resource misallocation, technology innovation

1 Introduction

Agricultural green total factor productivity (AGTFP) is defined as the production efficiency in agriculture under resource and environmental constraints, aiming to enhance economic efficiency while reducing environmental impacts (Wang X. et al., 2024). Such a focus underscores the essential principles of sustainable agricultural progress (Chu et al., 2024; Jiang et al., 2024; Xu et al., 2025). Historically, constrained by various factors, the development of agriculture in China has faced bottlenecks such as low production efficiency, economic benefits, and significant ecological and environmental pressures (Hu et al., 2024). It is imperative to pinpoint new focal points that leverage digital elements and technological innovation to empower agriculture, promoting a

transformation towards intensive, efficient, and greener high-quality development. Recently, the swift proliferation of the internet and smartphones, along with the expansion of e-commerce channels, has laid a solid foundation for digital rural construction (DRC) (Wu and Liu, 2025). DRC is defined as the acceleration of information infrastructure construction in rural areas, the integration of information technology into rural production and life, the promotion of applications such as remote education and telemedicine, and the establishment of a digital governance system for rural areas.[1] As a confluence point of a network powerhouse, digital China, and the rural revitalization strategy, DRC has garnered substantial attention from the Chinese government. The 2018 Central No. 1 Document proposed the implementation of a digital rural strategy, marking a new stage of comprehensive enhancement in the informatization construction of China's agriculture and rural areas. In 2019, the General Office of the Communist Party of China Central Committee and the State Council issued the "Digital Rural Development Strategy Outline,"[2] which clearly outlined a comprehensive plan for DRC, providing more robust support for rural digital development. In 2020, the Central Cyberspace Affairs Commission, in collaboration with seven other agencies, released the "Notice on Conducting National Digital Rural Pilot Work," followed by the announcement of the "National Digital Rural Pilot Regions List," which designated 117 counties (cities, districts) as the inaugural group of national digital rural pilot areas.[3] Despite these policy documents closely following the new changes faced by the informatization development of China's agriculture and rural areas and playing a guiding role, whether DRC can act as a catalyst for enhancing AGTFP remains an issue to be explored.

The academic consensus currently underscores multiple critical viewpoints: First, the digital economy enhances agricultural production efficiency and transforms agricultural growth modes by providing platform technologies, thereby influencing agricultural development patterns (Fabregas et al., 2019; Hu et al., 2024; Ye, 2025). Second, digital rural initiatives utilize digital technologies as the most significant variable to improve agricultural economic benefits and as a new form of productive power in agricultural industry development (Li et al., 2025; Wang and Tang, 2023). These technologies optimize resource allocation and integration, leading to creative destruction and disruptive innovation in traditional agriculture (Zhao Li et al., 2024), thus constructing an intensive, efficient, and green modern agricultural industry. Third, digital technologies exert strong spillover effects and empowering functions on resources, industries, and agricultural entities (Du et al., 2023; Subramanian, 2021). This influence optimizes the rural labor structure, enhances the technological content within agriculture, transforms agricultural production modes (Li et al., 2023; Musajan et al., 2024), and stimulates the endogenous development momentum of agriculture, which significantly enhances agricultural modernization. Fourth, digital technologies reduce the costs for farmers to access goods and market information (De la Peña and Granados, 2024), thereby improving farmers' abilities to connect with markets (Sarku and Ayamga, 2025). Additionally, these technologies enhance the level of rural human capital and drive the upgrading of the agricultural industry (Liu B. et al., 2023; Zhao Liyang et al., 2024).

However, limited research has directly explored the impact of DRC on AGTFP (Cai and Han, 2024; Lu et al., 2024; Xu et al., 2025), leaving open the question of whether DRC can significantly enhance AGTFP. Moreover, given the relatively recent introduction of DRC, the transmission mechanisms through which it influences AGTFP remain unclear. Additionally, the potential heterogeneous effects of DRC on AGTFP have been underexamined. Addressing the identified research gaps, this study recommends these RQs:

RQ1: Does DRC enhance AGTFP?
RQ2: What is the impact mechanism of DRC on AGTFP?
RQ3: Does the impact of DRC on AGTFP exhibit potential heterogeneity?

The answers to these questions could provide decision-making insights for effectively unleashing the potential of DRC, fostering the economic upgrading of agriculture, and creating a new engine for high-quality agricultural development. In our study, we treat the DRC pilot policy as a quasi-natural experiment and empirically evaluate the impact of the implementation of DRC on AGTFP using a panel data set of 2,128 counties (districts) from 2012 to 2022. We employ a Difference-in-Differences (DID) model to assess the effects and their underlying mechanisms. Our findings confirm that DRC significantly enhances AGTFP. Robustness checks further validate the reliability of our results. Additionally, we identify three mediating mechanisms through which DRC impacts AGTFP: land finance, land resource misallocation, and agricultural technology innovation. Our analysis reveals that DRC improves levels of land finance and agricultural technology innovation, and reduces land resource misallocation, all of which contribute to the enhancement of AGTFP. Finally, we observe significant heterogeneity in the impact of DRC on enhancing AGTFP in agriculture across different geographic locations, grain functional areas, and land transfer efficiency. This impact is stronger in central and western China, non-grain-producing areas, and regions with lower land transfer efficiency.

This study extends the marginal contributions in three significant areas: First, it empirically investigates the influence of DRC on AGTFP at the level of Chinese county and district, enriching the quantitative research on how DRC influences high-quality agricultural development. Second, the study delineates the transmission mechanisms through which DRC enhances AGTFP, focusing on land finance, land resource misallocation, and agricultural technology innovation. This analysis provides empirical support and policy guidance for optimizing DRC policies and advancing high-quality agricultural growth. Third, we discuss the DRC's diverse impacts on AGTFP by geographical location and grain functional areas, this research offers experiential evidence for coordinated regional agricultural development.

1 Available online at: https://www.cac.gov.cn/rootimages/uploadimg/1632875491344223/1632875491344223.pdf

2 Available online at: https://www.gov.cn/xinwen/2019-05/16/content_5392269.htm

3 Available online at: https://www.cac.gov.cn/2020-10/23/c_1605022250461079.htm

This study is organized as follows: Section 2 delves into the theoretical analysis and constructs the hypotheses. Section 3 describes the dataset, variables, and empirical method. Section 4 offers an in-depth examination and discussion of the empirical results. Section 5 concludes the study.

2 Theoretical analysis and hypotheses development

2.1 DRC and AGTFP

With the accelerated advancement of DRC, agricultural operators are progressively enhancing their ability to collect, transmit, and process data. This progress enables them to optimize resource allocation, improve production efficiency, reduce costs, and lower agricultural pollution and carbon emissions. As a result, it facilitates a shift away from extensive farming practices and addresses challenges arising from fragmented management (Lu et al., 2024; Xu et al., 2025), making DRC a catalyst for AGTFP. Specifically, advancing green technology and improving its efficiency achieves this promotion effect (Chen et al., 2020; Zhao Li et al., 2024).

First, regarding green technology advancement: (i) The accelerated adoption of digital technologies such as 5G, artificial intelligence, and the agricultural Internet of Things has significantly driven innovation in agricultural production technologies. This innovation contributes to reduced agricultural pollution and carbon emissions, leading to green technological progress (Hao et al., 2022; Li et al., 2024). (ii) DRC facilitates data sharing between agricultural research institutions and enterprises, greatly enhancing the precision of agricultural R&D. Such data sharing not only expedites the development of new pesticides and fertilizers but also improves their effectiveness and environmental safety, further advancing green technologies (Guo, 2024; Zhao S. et al., 2024; Zhu and Li, 2021). (iii) DRC supports the establishment of an interconnected agricultural technology extension system, reducing the costs of learning new technologies. This system boosts farmers' adoption of green technologies, accelerating their diffusion and implementation (De la Peña and Granados, 2024; Sarku and Ayamga, 2025; Zhao Liyang et al., 2024).

Second, focusing on green technology efficiency: (i) DRC accelerates agricultural information flows and eliminates informational barriers. For instance, digital technologies allow farmers to access real-time information on advanced production techniques, market demand shifts, and updated government policies. Such timely and comprehensive access promotes efficient resource allocation and enables producers to adjust strategies in response to market and environmental changes. This process particularly encourages farmers to focus on reducing the environmental impacts of agricultural activities, thereby enhancing green technology efficiency (Xu et al., 2025). (ii) By fully digitizing the agricultural value chain—including production, management, and sales—DRC significantly optimizes production processes. This transformation spans not only production and processing stages but also extends to distribution, achieving supply chain digitalization. Such extensive digitization reduces information costs, enhances transparency across markets and management, and boosts transaction efficiency. More importantly, this process minimizes resource waste and optimizes input utilization, directly improving green technology efficiency (Cai and Han, 2024). Drawing on the above discussion, an assumption is as follows:

H1: DRC enhances AGTFP.

2.2 DRC, land finance, and AGTFP

Studies have demonstrated that regions with better DRC and integrated land finance systems exhibit higher levels of productivity and sustainability in agriculture. These regions benefit from streamlined land management processes that facilitate the optimal use of agricultural land, leading to improvements in AGTFP (Wang Y. et al., 2024; Jiang et al., 2022).

First, digital technologies such as Geographic Information Systems (GIS), blockchain, and big data analytics are transforming land records and transaction management. For example, GIS offers important location-based information for accurate land-use planning, improving farming efficiency, and protecting the environment, which greatly helps AGTFP. Also, blockchain technology ensures the transparency and security of land transactions, minimizing fraud and disputes over ownership (Hou R. et al., 2021). This clarity in ownership encourages investments in sustainable agricultural practices and technologies. Moreover, the use of big data analytics in rural areas enables more informed decisions on land use. By analyzing extensive data on soil quality, climate patterns, and crop yields, farmers and local governments can align land-use decisions with sustainable agricultural practices (Bennett et al., 2019). These technologies further enhance land finance by ensuring accurate assessment and efficient collection of land taxes and revenues (Ma et al., 2020). This fiscal enhancement provides rural communities with the resources necessary to invest in infrastructure and services that promote sustainable agriculture (Deng et al., 2023). Second, improved land finance supports the implementation of targeted agricultural policies (Zhou et al., 2018). With strengthened fiscal capacity, governments can subsidize green technologies and sustainable farming practices (Hou S. et al., 2021), such as precision agriculture, which reduces waste and maximizes AGTFP. Thus, DRC integrates advanced digital technologies into rural management and development, unlocking substantial potential to improve AGTFP through enhanced land finance mechanisms. Based on the above discussion, we proposed:

H2: DRC enhances AGTFP by improving land finance.

2.3 DRC, land resource misallocation, and AGTFP

DRC holds transformative potential for enhancing AGTFP by reducing the land resource misallocation (Cai and Han, 2024; Xie et al., 2022). Digital technologies such as artificial intelligence (AI), big data analytics, and remote sensing can dramatically improve the accuracy of land assessment and ensure that agricultural practices

are optimally aligned with land capabilities (Liu C. et al., 2023). For instance, remote sensing technology offers the advantage of monitoring land use changes in real time, providing data that can help prevent overuse of land and facilitate sustainable farming practices (Rogan and Chen, 2004; Mashala et al., 2023). Big data analytics can process vast amounts of information from these technologies to predict trends, optimize crop rotation, and enhance land use planning (Yin et al., 2021). The application of these technologies in the DRC leads to a more precise understanding of land characteristics, which is essential for correcting misallocations (Wang et al., 2025). By ensuring that each piece of land is used according to its optimal agricultural potential, not only are yields improved, but resources such as water and fertilizers are used more efficiently, reducing waste and environmental impact. Moreover, empirical evidence supports the notion that reducing resource misallocation through digital means enhances rural land use efficiency (Fan et al., 2025). Thus, these findings show that regions implementing DRC in land resource misallocation management observe marked improvements in AGTFP. Accordingly, the subsequent hypothesis is advanced:

H3: DRC enhances AGTFP by mitigating land resource misallocation.

2.4 DRC, agricultural technology innovation, and AGTFP

As digital rural development progresses, local governments are enhancing the infrastructure for digital technologies such as 5G networks, data centers, and platform systems (Tim et al., 2021). This enhancement provides better public infrastructure support for various entities to engage in innovative activities, reducing the costs and risks associated with these activities, thereby aiding regional agricultural technology innovation. Agricultural technology innovation introduces new concepts and knowledge into traditional agriculture, improving agricultural production efficiency and the utilization of input factors, reducing waste emissions and environmental pollution, and facilitating a shift towards agricultural growth with lower resource consumption (Zhang et al., 2023). This shift significantly contributes to the AGTFP improvement.

On the other hand, the DRC also promotes a digital transformation in local rural governance models and public service methods in transactions and finance (Malik et al., 2022). This transformation encourages agricultural entities to enhance their innovation awareness and capabilities, fosters learning and technical spillovers among innovators, and creates a "demonstration and incentive effect" for agricultural technology innovation (Zhang and Zhang, 2024). Moreover, agricultural technology innovation facilitates more rational allocation and tighter integration of factors among various rural industries, promoting the penetration and extension of rural industrial chains. This extension expands traditional agriculture from a single production stage to encompassing production, sales, and services within the entire industrial chain (Limpamont et al., 2024). Consequently, this leads to an optimized upgrade of the agricultural industry and the emergence of new sectors such as leisure agriculture and biotechnology (Zhang et al., 2022), further enhancing AGTFP. Based on the analysis above, the following hypothesis is proposed:

H4: DRC enhances AGTFP by fostering agricultural technology innovation.

Figure 1 presents our theoretical framework.

3 Methodology

3.1 Empirical strategy

As a convergence point of strategies focused on building a network powerhouse, digital China, and rural revitalization, the development of digital rural areas has received significant attention at the national level in China. In 2018, China introduced the digital rural strategy in its "No. 1 Document," followed by the publication of the "Digital Rural Development Strategy Outline" in 2019, and the announcement of the "National List of Digital Rural Pilot Areas" in 2020, designating 117 counties (cities, districts) as the initial batch of national digital rural pilot areas. The construction goals of these pilot areas encompass seven main aspects: (i) Undertake comprehensive planning and design for digital rural development, tailoring construction plans to local conditions. (ii) Enhance rural information infrastructure, actively exploring new applications for digital infrastructure. (iii) Explore new business models in the digital rural economy, vigorously fostering high-information-intensity production and business organizations with strong demonstration effects and tapping into the potential applications of emerging digital technologies in agricultural production. (iv) Promote the deep integration of informatization and rural governance, fully leveraging grassroots governance roles. (v) Improve the information service system, precisely addressing the real needs of agriculture and rural areas. (vi) Establish mechanisms for the integration and sharing of facility resources, promoting information integration. (vii) Stimulate market enthusiasm, nurturing a digital rural ecosystem.

The selection of these pilot areas and the structured rollout of the policy allow us to treat the introduction of the digital rural pilot policy as an exogenous policy shock. This setup is ideal for employing a DID model to robustly determine the causal effects of DRC on the AGTFP across varied regions. Because the use of the DID methodology is underpinned by the exogeneity of the policy implementation, which is assumed not to be influenced by prior trends in AGTFP within the selected counties. We selected the intervention (digital rural policy) because it is externally imposed and not a result of internal factors within the pilot areas. This aligns with the characteristics of a quasi-natural experiment. Consequently, we are consistent with established methodologies (Wang Z. et al., 2024) and treat the introduction of the digital rural pilot policy as an exogenous policy shock and employ a DID model, as delineated in Equation 1, to ascertain the causal impacts of DRC on AGTFP.

$$AGTFP_{ct} = \alpha + \beta DID_{ct} + \delta Controls_{ct} + \sum Year + \sum County + \varepsilon_{ct} \quad (1)$$

Where t represents a given year and c denotes a specific county. $AGTFP$ refers to agricultural green total factor productivity. DID_{ct} indicates if county c was influenced by the DRC pilot policy in year t. The coefficient β is the primary coefficient of interest, with a

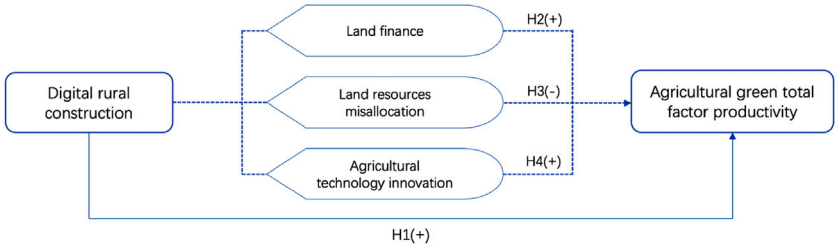


FIGURE 1
Theoretical framework.

significantly positive β indicating that the DRC positively impacts AGTFP. The model includes control variables at the county level, detailed in Table 2. Fixed effects for year and county are incorporated as '*Year*' and '*County*' to adjust for time-specific and county-specific variations. The stochastic error term is represented by ε_{ct} and α is a constant term in the model.

3.2 Variables declaration

3.2.1 Dependent variable: agricultural green total factor productivity (AGTFP)

Drawing from the study by Wu and Zhang (2024), we employ the non-desired output Slack-Based Measure (SBM) model and the Global Malmquist Luenberger (GML) model to measure AGTFP. The specifical steps are outlined as follows:

Step 1: Calculate the current year's AGTFP for each county using the non-desired output SBM model. The calculations are detailed in Equations 2–6:

$$AGTFPSBM = min \frac{1 - \frac{1}{m} \times \sum_{i=1}^{m} \frac{\bar{s_i}}{X_i}}{1 + \frac{1}{S1+S2} \times \left(\sum_{r=1}^{S_1} \frac{S_r^g}{Y_r^g} + \sum_{k=1}^{S_2} \frac{S_k^b}{Y_k^b} \right)}$$
$$(i = 1, 2, \ldots, m; r = 1, 2, \ldots, S_1; k = 1, 2, \ldots, S_2) \quad (2)$$
$$\text{Subject to } X_0 = X \times \lambda + S^- \quad (3)$$
$$Y_0^g = Y^g \times \lambda - S^g \quad (4)$$
$$Y_0^b = Y^b \times \lambda + S^b \quad (5)$$
$$S^- \geq 0, S^g \geq 0, S^b \geq 0 \quad (6)$$

Where $AGTFPSBM$ denotes the AGTFP for each county. m represents the number of input indicators. S_1 and S_2 denote the number of desired and non-desired outputs, respectively. S^- and X_i represent the input slacks and input variables, while S_r^g and Y_r^g refer to the shortfalls in desired outputs and the variables for desired outputs, respectively. S_k^b and Y_k^b are the excesses in non-desired outputs and the variables for non-desired outputs, respectively. λ is the vector of weights. X_0, Y_0^g, and Y_0^b are the actual values of input variables, desired output variables, and non-desired output variables associated with the decision-making unit (DMU). Additionally, X, Y^g, and S^g represent the estimated input quantities, estimated desired output variables, and estimated non-desired output variables required by the DMU. S^-, S^g, and S^b correspond to the input slacks, shortfalls in desired outputs, and excesses in non-desired outputs, as observed in the DMU.

Step 2: Utilize the GML index to measure changes in AGTFP, which serves as our dependent variable in this study. The specific model is as follows in Equation 7.

$$AGTFP^{t,t+1} = (x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1})$$
$$= \frac{1 + D_t(x^t, y^t, b^t)}{1 + D_{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \left[\frac{\frac{1+D^G(x^t, y^t, b^t)}{1+D_t(x^t, y^t, b^t)}}{\frac{1+D^G(x^{t+1}, y^{t+1}, b^{t+1})}{1+D_{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}} \right]$$
$$= \frac{TE^{t+1}}{TE^t} \times \frac{BPG_{t+1}^{t,t+1}}{BPG_t^{t,t+1}} = GEC^{t,t+1} \times GTC^{t,t+1} \quad (7)$$

Where $AGTFP$ denotes the index of agricultural green total factor productivity. An index value greater than 1 indicates an improvement in productivity. GEC and GTC represent technology efficiency and technology progress, respectively. t denotes the year, x, y, and b represent the inputs, desired outputs, and undesired outputs, respectively. TE stands for overall technology efficiency. BPG denotes the distance between the global technology reference set and the effective production frontier, where $D^G(x^t, y^t, b^t)$ is the reference set directional vector. This vector indicates that the input x and the production structure can adjust the output in the direction of the output vector, potentially increasing production up to a maximum factor of λ.

Table 1 below illustrates the components that constitute the AGTFP index. The calculation of agricultural carbon sequestration is shown in Equation 8.

$$Carbon\ Sequestration_i = \sum_{k=0}^{n} (C_k \cdot D_k) = \sum_{k}^{n} (C_k \cdot Y_k / H_k) \quad (8)$$

Where $Carbon\ Sequestration_j$ represents the total carbon sequestration of major crops in a i county (city, district); k denotes the k-th crop; C_k is the carbon absorption rate, referring to the amount of carbon absorbed per unit of dry organic matter synthesized by k-th crop; D_k is the biological carbon content of k-th crop; Y_k is the economic yield of k-th crop; H_k is the economic coefficient of k-th crop. Following Tian and Zhang (2013), Appendix B provides the economic coefficients and carbon absorption rates for major crops.[4]

4 This study calculates carbon sequestration based on grain yield converted to carbon absorption, without accounting for the effects of changes in planting area or farming practices (e.g., planting density) on agricultural carbon absorption.

TABLE 1 Components of the AGTFP index.

Primary indicator	Secondary indicator	Description
Inputs	Labor input	Number of people employed in farming
	Land input	Total area of crop sowing
	Agricultural machinery input	Total power of agricultural machinery
	Fertiliser input	Amount of agricultural fertilisers used
	Pesticide input	Amount of pesticides used
	Agricultural film input	Usage of agricultural plastic film
	Irrigation input	Effective irrigated area in agriculture
Desired Outputs	Total agricultural output	Gross value of farming output with 2011 as the base year
	Agricultural carbon sequestration	Total carbon sequestration of main crops
Undesired Outputs	Agricultural carbon emissions	Total carbon emissions from agriculture
	Agricultural non-point source pollution	Amount of non-point source pollution emissions from agriculture

Data source: China Statistical Yearbook (2013–2023).

The specific calculation of agricultural carbon emissions is shown in Equation 9.

$$E = \sum E_i = \sum T_i \cdot \delta_i \tag{9}$$

Where E represents the total carbon emissions from agriculture; E_i denotes the carbon emissions from each type of agricultural input (also referred to as carbon sources, hereafter); T_i is the quantity of the i-th carbon source; δ_i is the carbon emission coefficient of the i-th carbon source. Appendix C summarizes the carbon emission coefficients from agriculture.

The calculation of agricultural non-point source pollution is shown in Equation 10.

$$E_{non-point\ source} = \sum_i PE_i(1-\eta_i)C_i(EU_i, S) \tag{10}$$

Where $E_{non-point\ source}$ represents the amount of non-point source pollution emissions from agriculture. i denotes a county (city, district). PE represents the agricultural and rural pollution generated, which refers to the maximum potential pollution caused by agricultural production and rural life without considering resource utilization or management factors. η is the coefficient of resource utilization efficiency. C is the pollutant emission coefficient, determined by unit and spatial characteristics (S), reflecting the combined effects of regional environment, rainfall, hydrology, and various management practices on agricultural and rural pollution. EU represents the statistical value of the indicator.

3.2.2 Independent variable: digital rural construction (DID)

Digital rural construction is defined as DID, is the interaction term between the treatment group ($Treat$) and the treatment period ($Post$), denoted as $Treat \times Post$. Here, '$Treat$' is a dummy variable for pilot counties or districts. If a county or district c is in a DRC pilot area (treatment group), it is assigned a value of 1; if it is outside the DRC pilot area (control group), it is assigned a value of 0. '$Post$' is a binary variable that delineates the timeframe relative to the implementation of the pilot policy, with a value of 1 assigned to the years 2020 and beyond, and a value of 0 to earlier years.

3.2.3 Mechanism variables

(1) Land finance (LF). Following the study of Cheng et al. (2022), we employ the ratio of land sale transaction price to local GDP, multiplied by 100, as a measure of land finance. Land sale revenue accurately reflects the scale of fiscal revenue local governments garner from land concessions. This metric differs from net land revenue in that it does not deduct the cost compensation for land concession. Additionally, from a fiscal management perspective, cost compensation projects represent a form of government expenditure. Excluding these cost items would undeniably result in an underestimation of land concession revenues.

(2) Land resource misallocation (LRM). In China, local governments often supply industrial land below the minimum price standard or even at zero cost on a large scale, while restrictively leasing commercial and residential land at high prices. Although this strategy has accelerated industrialization and urbanization, it has also led to vicious competition and redundant construction. As a result, the proportion of industrial land in the supply structure of state-owned construction land is excessively high, leading to a distortion in the allocation of land resources. The issue of land resource misallocation can be investigated through several dimensions: the allocation among different purposes of state-owned construction land, between agricultural and construction land, across regional construction land quotas, and the ratios of land lease prices for different land types. To accurately reflect the distribution of land resources among different industries and uses in various cities, this paper utilizes the method of Du and Li (2021), measuring land resource misallocation by the ratio of industrial land to total

TABLE 2 Variable description.

Variables	Name	Symbol	Description
Dependent	Agricultural green total factor productivity	AGTFP	Refer to Equation 7
Independent	Digital rural construction	DID	$Treat \times Post$, where $Treat$ = 1 if the county is within the digital rural construction pilot region, 0 otherwise; $Post$ = 1 if the time is the year 2020 or later, 0 otherwise
Mechanisms	Land finance	LF	$\frac{Land\ sale\ transaction\ price}{Local\ GDP} * 100$
	Land resource misallocation	LRM	$\frac{Industrial\ land}{Total\ construction\ land} * 100$
	Agricultural technology innovation	ATI	Ln(Agricultural invention patent applications)
Controls	City size	Size	$Ln(City's\ permanent\ population)$
	Industrial structure	Instructure	Value added by the primary industry as a share of GDP * 1 + secondary industry as a share of GDP * 2 + tertiary industry as a share of GDP * 3
	Per capita GDP	GDP	$Ln(\frac{GDP}{City's\ total\ population})$
	Per capita government expenditure	Expenditure	$Ln(\frac{Fiscal\ expenditure}{City's\ permanent\ population})$
	Per capita FDI	FDI	$\frac{Actual\ foreign\ direct\ investment\ used}{GDP}$

construction land, multiplied by 100. A higher value indicates greater misallocation of land resources, signifying severe misallocation; conversely, a lower value indicates lesser misallocation.

(3) Agricultural technology innovation (ATI). Drawing on the methodology of Liu et al. (2014), we calculated agricultural technology innovation using the natural logarithm of agricultural patent applications. This metric reflects the level of technological advancement and innovation within the agricultural sector.

3.2.4 Control variables

According to the study by Cheng et al. (2022), we used several urban-level control variables that were designed to statistically control for the potential confounding factors that impact the underlying relationships we examined in this study. The control variables include: (i) City size, measured as the natural logarithm of the permanent population of the city (in 10,000). (iii) Industrial structure: It is calculated as value added by the primary industry as a share of GDP * 1 + secondary industry as a share of GDP * 2 + tertiary industry as a share of GDP * 3. (iii) Per capita GDP: The log of GDP over total population. (iv) Per capita government expenditure: A measure of fiscal expenditure per unit of the total permanent population and logged. (v) Per capita FDI—the ratio of the aggregate foreign direct investment in actual to GDP. Table 2 summarizes the measurements of all variables.

3.3 Samples and data sources

Based on a panel dataset of Chinese counties and districts from 2012 to 2022, this study examines the link between DRC pilot policy and AGTFP. The reasons for selecting this sample period are as follows: (i) Although DRC was first proposed in the 2018 "No. 1 Document," rural internet development in China has grown rapidly since 2012. (ii) Considering data availability and consistency, 2022 is the latest year with updated data for the indicators used in this study. The final dataset included 18,543 observations on the individual events in 2,128 counties and districts from 32 provinces (this includes autonomous regions and direct-controlled municipalities under the Central Government, excluding Hong Kong, Macau, and Taiwan) after excluding counties with extensive data gaps. The data of AGTFP, DRC, land finance, and land resource misallocation and other control variables were collected from the "China City Statistical Yearbook," "China Rural Statistical Yearbook," and "China Agricultural Yearbook." The data source regarding agricultural technology innovation was obtained from the "China National Intellectual Property Administration" by patent classification number A01.

Table 3 shows the descriptive statistics for the main variables. The standard deviation (SD) of $AGTFP$ is 0.227, diverging from the mean value of 0.646. Also, the minimum value of $AGTFP$ stands at 0.245, while the maximum value is 1.039. This demonstrates that the significant disparity in $AGTFP$ is among different counties (cities/districts). Meanwhile, the SD of $treat$ is 0.172, while the SD of $Post$ is 0.440, verifying that DRC has a marked variation across counties. The distribution patterns of other control variables largely match those documented in the literature.

4 Results

4.1 Baseline regression

We adopt a sequential regression approach to analyze the effects of DRC on AGTFP, with the results illustrated in Table 4. Column (1) presents initial findings without incorporating control variables or fixed effects for counties and years and demonstrates the coefficient for DRC (DID) is considerably positive at the 1% level, indicating a beneficial impact on

TABLE 3 Descriptive statistics.

Variable	Obs	Mean	SD	Min	p25	p50	p75	Max
AGTFP	18,543	0.646	0.227	0.245	0.462	0.581	0.840	1.039
Treat	18,543	0.0306	0.172	0	0	0	0	1
Post	18,543	0.262	0.440	0	0	0	1	1
Size	18,543	6.070	0.578	4.657	5.659	6.096	6.509	7.475
Instructure	18,543	2.317	0.126	2.041	2.232	2.308	2.393	2.635
GDP	18,543	10.76	0.532	9.529	10.38	10.74	11.10	12.03
Expenditure	18,543	9.090	0.371	8.234	8.839	9.099	9.341	10.09
FDI	18,543	0.0139	0.0145	−0.00100	0.00240	0.00920	0.0200	0.0601

TABLE 4 Bassline regression.

Variables	(1)	(2)	(3)
	AGTFP	AGTFP	AGTFP
DID	0.2859***	0.2262***	0.0772***
	(9.9420)	(8.3335)	(2.7555)
Size		0.0784***	0.0742***
		(10.5222)	(2.8389)
Instructure		−0.3340***	0.0026
		(−9.4111)	(0.1062)
GDP		0.1143***	−0.0050
		(12.9522)	(−0.5950)
Expenditure		0.1869***	0.0501***
		(16.6099)	(4.4819)
FDI		−2.3195***	0.1228
		(−11.7910)	(0.8772)
_cons	0.6462***	−1.9516***	−0.2137
	(190.4778)	(−20.3728)	(−0.9318)
County	No	No	Yes
Year	No	No	Yes
Obs	18,543	18,543	18,543
Adjusted R^2	0.0011	0.1903	0.8397

Notes: *p < 0.1, **p < 0.05, ***p < 0.01. T-statistics presents in parentheses.

AGTFP. Column (2) extends the model to include control variables, albeit still omitting county- and year-specific fixed effects. Here, the coefficients for *DID* remain positively significant at the 1% level. Column (3) further refines the analysis by integrating both control variables and fixed effects for each county and year, where *DID* consistently shows a positive effect on AGTFP, significant at the 1% level. Specifically, a 1% increase in *DID* correlates with a 2.7% enhancement in AGTFP (coefficient = −0.027, p < 0.01). These findings substantiate the significant contribution of DRC to the improvement of AGTFP, thereby supporting the study's hypothesis (H1).

4.2 Robustness tests

We perform multiple robustness tests to validate the findings concerning the impact of the DRC on AGTFP.

(1) Parallel trend test. Since the validity of the DID methodology depends on the assumption of parallel trends, it is essential to check this assumption. This assumption implies that AGTFP trends in both treatment and control groups were parallel prior to the introduction of the DRC pilot policy. We carefully test the parallel trends with dynamic heterogeneity methods, following the strategy of Beck et al. (2010), we use the econometric model in Equation 11.

$$AGTFP_{ct} = \alpha + \beta_1 DID_{ct}^{-8} + \cdots + \beta_9 DID_{ct}^{2} + \delta Controls_{ct} + \sum Year + \sum County + \varepsilon_{ct} \tag{11}$$

where the superscript on DID_{ct} denotes the lead or lag term relative to the DRC pilot policy shock. For example, DID_{ct}^{-8} implies a value of 1 if it is 8 years before policy implementation for county *c*, and 0 otherwise; DID_{it}^{2} signifies a value of 1 if 2 years post-policy for county *c*, and 0 otherwise. To avoid multicollinearity, the variable D_{ct}^{-1} representing 1 year before the DRC pilot policy shock, is excluded from Equation 11. The responses from DID_{ct}^{-8} to DID_{ct}^{2} are compared against the baseline at DID_{ct}^{-1}. Definitions for other variables are consistent with those in the baseline model.

Figure 2 illustrates the outcomes of the parallel trend assessment. Before the execution of the DRC pilot policy, the β coefficients approximate zero, and their confidence intervals include zero, suggesting that the pre-policy trends were similar in both the treatment and control groups, with no significant deviations. From the effective date of the policy, the β coefficients increasingly show significance, and their confidence intervals exclude zero, indicating a notable increase in AGTFP within the treatment group after the policy's implementation. These findings confirm that the DRC pilot policy effectively enhances AGTFP, satisfying the criteria of the parallel trend test.

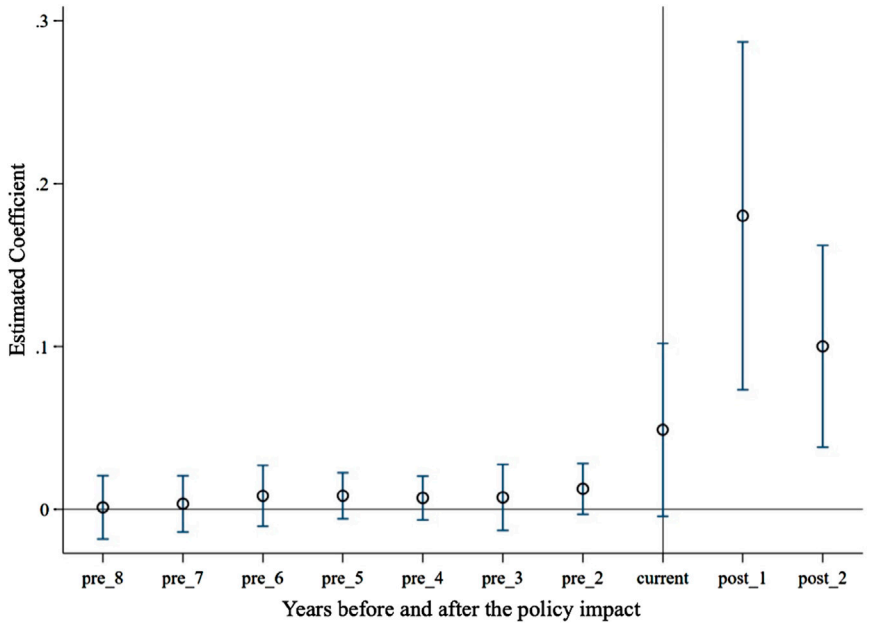


FIGURE 2
Parallel trend test.

(2) Placebo test. To reinforce the reliability of our results, we use Chetty et al. (2009)'s placebo test. This involves randomly picking the treatment group 500 times and replicating the analysis multiple times to generate placebo outcome coefficients, which are then depicted using a kernel density plot in Figure 3. If the actual policy effects are markedly different from those observed in the placebo tests, it suggests that the effects are not due to random variation. The kernel density plot reveals that the distribution of placebo estimates is roughly bell-shaped and centers around zero. This indicates that most estimates from these "pseudo" policy implementations are negligible. Furthermore, the p-values are predominantly clustered around these zero-centered estimates, reinforcing that the impacts from the "pseudo" policy implementations are statistically insignificant. Therefore, the significant impacts of the DRC on AGTFP observed in our study are likely not attributable to random factors or other unaccounted variables, affirming the robustness and validity of the actual policy effects.

(3) Replacing the dependent variable. As stated by Wang X. et al. (2024) and Long et al. (2023), we adopt the scale-invariant SBM-GML model that accounts for undesirable outputs as an alternative measure for AGTFP, denoted as *AGTFPGML*. The data are sourced from the annual editions of the *China Statistical Yearbook*, *China Rural Statistical Yearbook*, and various local statistical yearbooks. Equation 12 calculates and decomposes this variable for unexpected output:

$$AGTFPGML^{t,t+1}\left(x^t, y^t, a^t, x^{t+1}, y^{t+1}, a^{t+1}\right) = \frac{1 + E^G\left(x^t, y^t, a^t\right)}{1 + E^G\left(x^{t+1}, y^{t+1}, a^{t+1}\right)} \tag{12}$$

Where the factor vectors x, y, and a show the inputs, the desired outputs, and the not-desired outputs, respectively. AGTFP indicators include agricultural labor, land, water, machinery, fertilisers, diesel, plastic film, and pesticide; desired output, such as agriculture, forestry, animal husbandry, and fishery gross output value; and non-desired output, such as agricultural carbon emissions. Appendix A lists input–output indicators.

The findings presented in Column (1) of Table 5 reveal a statistically significant positive correlation between *DID* and *AGTFPGML* at the 5% significance level. This suggests that the DRC has a positive effect on AGTFP, thereby reinforcing the main conclusion's robustness and consistency.

(4) Excluding COVID-19 impacts. Given the significant disruptions caused by the COVID-19 pandemic in 2020 and 2021, we followed the approach advised by Qing et al. (2024) to exclude these years from our dataset to avoid potential biases in our regression analysis. Column (2) of Table 5 shows the re-estimated findings, still indicate a robust benefit impact of *DID* on *AGTFP*, with a coefficient of 0.1102 ($p < 0.01$). This consistency underscores the robustness and reliability of our findings.

(5) Controlling city fixed effects. To control for the possibility of biases owing to city-level heterogeneity, we included city-fixed effects in our regression model. This approach takes into consideration the differences across cities, generating a more accurate estimate of the actual effect of DRC over AGTFP. Column (2) of Table 5 presents our updated results, which show that the link remains statistically significant at the 1% level, implying that DRC's exerted influence was effectively applicable across cities despite their diverse characteristics.

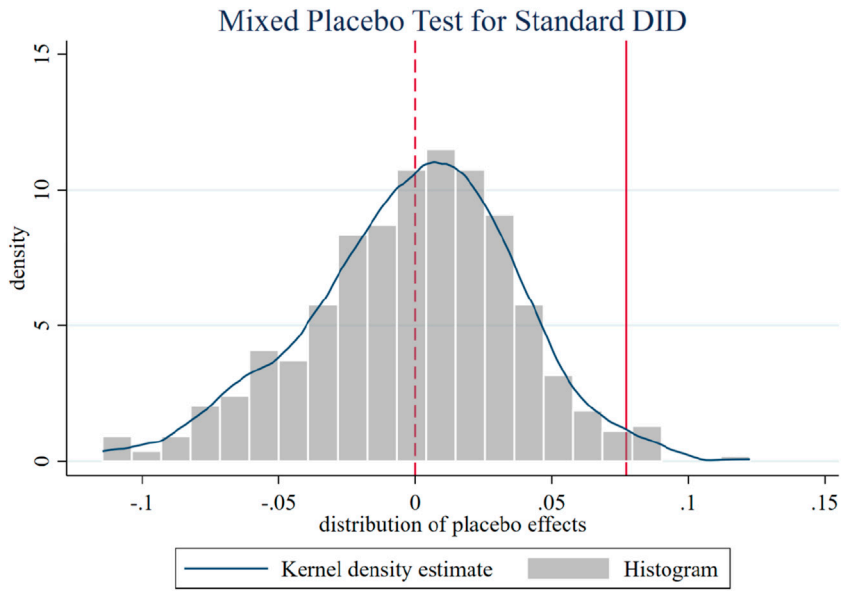


FIGURE 3
Placebo test.

(6) Excluding other policies in the same period. To avoid that other concurrent policies may confuse our potential effect, we accounted for the Chinese smart city pilot policy, which was implemented from 2012 (details can be found in "Ministry of Housing and Urban-Rural Development").[5] By 2024, the policy had designated 289 cities as smart city pilots. Previous studies, such as Wang et al. (2022) and Song et al. (2023), reported its beneficial impacts on urban green total-factor productivity and carbon productivity in China. In our model, we introduce the smart city policy variable (Smartcity) so that the impacts can be disentangled. As shown in Column (4) of Table 5, the smart city variable is negatively significant, but the coefficient continues to be negatively significant as well, and at the 1% level. This result reinforces the robustness of our results, showing that DRC has a separate impact on AGTFP from those of other simultaneously instituted policies.

4.3 Endogeneity tests

Even though the digital rural pilot policy is considered an outside influence, the choice of pilot areas might still be linked to hidden factors (e.g., political influence, regional development goals, or local government capacity) that also affect AGTFP. If not properly controlled, these unobservable factors could bias the estimated treatment effects. Moreover, pilot and non-pilot areas may systematically differ in observable characteristics (e.g., infrastructure quality, technological readiness, or economic development level) before the policy is implemented. If these differences are not adequately addressed, they could confound the causal relationship between DRC and AGTFP. To address potential issues from hidden factors and existing differences, we use the propensity score matching (PSM) method, following Li et al. (2023) and Ma et al. (2020). Using nearest-neighbor matching, counties (cities/districts) in the treatment group are paired with similar counties (cities/districts) in the control group. The matching process incorporates all control variables and county- and year-fixed effects, ensuring a 1:4 match based on the DID treatment variable. After PSM, we re-estimate the regression model using the matched dataset. The primary independent variable (*DID*) remains significantly and positively correlated with AGTFP, as shown in Table 6. These results, consistent with the benchmark regression, further confirm the robustness and reliability of the conclusions.

4.4 Mechanism analysis

To further understand the impacts of DRC on AGTFP, it is essential to investigate the potential mechanisms involved. This study examines three possible channels: land finance, land resource misallocation, and agricultural technology innovation. We adopt the two-step mechanism analysis method proposed by Qing et al. (2024) to empirically assess these impacts.

First, our research delved into how land finance mediates the effect of DRC on AGTFP. Column (1) of Table 7 reveals that *DID* has a positive effect on land finance, as indicated by a coefficient of 1.7702 with a significance level of 5% ($p < 0.05$). This finding reinforces that DRC enhances land finance,

5 Available online at: https://www.gov.cn/gzdt/2013-01/31/content_2323562.htm

TABLE 5 More robustness checks.

Variables	Replacing the dependent variable	Excluding COVID-19 impacts	Controlling city fixed effects	Excluding other policies in the same period
	(1)	(2)	(3)	(4)
	AGTFPGML	AGTFP	AGTFP	AGTFP
DID	0.0519**	0.1102***	0.0651***	0.0780***
	(2.3181)	(2.8652)	(2.7975)	(2.7925)
Smart-city				−0.0156***
				(-2.8297)
Size	−0.0397***	0.0943***	0.0851***	0.0734***
	(−2.7674)	(3.7941)	(3.4720)	(2.8087)
Instructure	0.0014	0.0212	0.0142	0.0008
	(0.1188)	(0.9887)	(0.6030)	(0.0335)
GDP	−0.0326***	−0.0111	−0.0055	−0.0035
	(−6.2969)	(−1.3693)	(−0.6733)	(−0.4141)
Expenditure	0.0692***	0.0748***	0.0558***	0.0486***
	(10.5185)	(6.8074)	(5.0596)	(4.3535)
FDI	−0.2130***	−0.3526**	0.1504	0.1412
	(−3.4222)	(−2.5114)	(1.1061)	(1.0069)
_cons	0.9879***	−0.5392***	−0.3530	−0.2026
	(8.3373)	(−2.6706)	(−1.6089)	(−0.8819)
County	Yes	Yes	No	Yes
City	No	No	Yes	No
Year	Yes	Yes	Yes	Yes
Obs	18,543	16,836	18,543	18,543
Adjusted R^2	0.2506	0.8668	0.8504	0.8398

Note: same as a footnote under Table 4.

subsequently promoting an improving AGTFP, thus supporting H2.

Second, DRC and AGTFP should have a significant and positive relationship, and land resource misallocation plays a mediating role in this association. As shown in Column (2) of Table 7, the data suggest that has a vastly negative impact on land resource misallocation (coefficient = −2.7688, $p < 0.01$) These data suggest that DRC is important for land resource misallocation, which leads to improvement in AGTFP, thus providing evidence for supporting H3.

Third, we investigated how DRC and AGTFP are connected through agricultural technology innovation. Column (3) of Table 7 shows that it has a substantial favorable impact on agricultural technology innovation, with a coefficient of 0.2368 at the 5% significance level ($p < 0.05$). This implies the mechanism by which DRC contributes to the improvement of AGTFP through promoting agricultural technology innovation, which is an adequate way to corroborate H4.

4.5 Heterogeneity analysis

To deepen our understanding of how the DRC influences AGTFP, we conducted three heterogeneity analyses. These analyses focus on the differences across geographical locations, grain production functionality, and the context of land transfer efficiency.

First, regional heterogeneity analysis of the impact of DRC on AGTFP in different regions of China (eastern, central and western). The results, which we outline in Table 8, reflect nuanced regional effects. Column (1) displays the results for the eastern region, where the influence of DRC on AGTFPG is insignificant, indicating that the region's higher economic status and relatively greater agricultural productivity may reduce the observable benefits from DRC. Conversely, Columns (2) and (3) of Table 8 highlight a benefit influence of DRC on AGTFP in central and western China, respectively. These findings indicate that DRC markedly boosts AGTFP in these less economically developed regions.

TABLE 6 Endogenous test: PSM-DID approach.

Variables	(3)
	AGTFP
DID	0.0820***
	(3.6834)
Size	0.1803***
	(7.0578)
Instructure	0.0883***
	(3.1845)
GDP	0.0015
	(0.1576)
Expenditure	0.0195
	(1.4894)
FDI	1.0311***
	(5.8672)
_cons	−0.9211***
	(−4.0355)
County	Yes
Year	Yes
Obs	7,382
Adjusted R^2	0.8676

Note: same as a footnote under Table 4.

TABLE 7 Mechanisms analysis.

Variables	(1)	(2)	(3)
	LF	LRM	ATI
DID	1.7702**	−2.7688***	0.2368**
	(2.1132)	(-3.1461)	(2.1922)
Size	3.7854***	−3.9601***	−0.5019***
	(6.4350)	(-3.5030)	(-4.4717)
Instructure	0.8571	0.2601	−0.0731
	(1.4181)	(0.1669)	(−0.4320)
GDP	−0.1573	−2.4036***	0.1102***
	(−0.8290)	(−5.5410)	(2.6642)
Expenditure	3.6033***	2.0663***	0.3649***
	(10.3424)	(4.5547)	(5.5973)
FDI	9.1936***	21.0422***	5.2400***
	(2.8296)	(3.2212)	(7.0916)
_cons	−51.4179***	113.7868***	3.6270***
	(−10.0068)	(10.7962)	(2.9810)
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
Obs	18,543	18,543	18,399
Adjusted R^2	0.6009	0.7976	0.8927

Note: same as a footnote under Table 4.

Second, move from DRC to AGTFP heterogeneity across functional perspectives of grain production. We identify counties as part of major grain-producing regions and non-major grain-producing regions.[6] The outcomes are given in Table 9, which shows significant differences in the effect of DRC on AGTFP for the two groups. Specifically, Column (1) shows that DRC does not significantly improve AGTFP in major grain-producing regions, suggesting that its implementation in major grain-producing regions may face limitations in driving substantial AGTFP improvements. Conversely, Column (2) demonstrates a statistically significant positive effect of *DID* on *AGTFP* at the 1% significance level, indicating that the benefits of DRC on AGTFP are more pronounced in non-major grain-producing regions.

Third, we further examine the heterogeneous impact of land transfer efficiency. We divided the sample into high and low groups based on the median of land transfer efficiency. The results are presented in Table 10. Column (1) shows that DRC has a positive impact on AGTFP at the 1% significance level. This evidence indicates that in counties (or cities/districts) with lower land transfer efficiency, DRC effectively improves AGTFP. In contrast, Column (2) shows that DRC has no statistically significant effect on AGTFP.

5 Discussions

5.1 Main findings

In light of the twin challenges posed by global environmental pollution and resource constraints, enhancing AGTFP is critical. Our research investigates the impacts of China's DRC pilot policy, treated as a quasi-natural experiment. Utilizing a DID technique, we analyze how the DRC affects AGTFP across 2,128 counties and districts from 2012 to 2022. Below, we outline the principal findings of our study:

i) Our results confirm that the DRC significantly enhances AGTFP. Robustness checks consistently support this finding. Notably, a 1% increase in DRC implementation is associated with an approximate 7.72% rise in AGTFP. Our results are consistent with Hu et al. (2024), who used balanced

6 The major grain-producing areas include 13 provinces: Hebei, Shandong, Jiangsu, Anhui, Liaoning, Jilin, Heilongjiang, Inner Mongolia, Jiangxi, Henan, Hubei, Hunan, and Sichuan. The non-major grain-producing areas include 18 provinces: Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong, Hainan, Shanxi, Guangxi, Chongqing, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

TABLE 8 Geographic heterogeneity.

Variables	Eastern	Central	Western
	(1)	(2)	(3)
	AGTFP	AGTFP	AGTFP
DID	−0.0341	0.2351***	0.0402**
	(−0.9429)	(5.6368)	(2.4570)
Size	−0.0226	−0.1359**	0.0853***
	(−0.9610)	(−2.4938)	(2.9584)
Instructure	0.1967***	−0.3279***	0.2173***
	(8.4683)	(−5.3683)	(7.4388)
GDP	0.0096	−0.0534***	0.0935***
	(1.2076)	(−3.3035)	(7.8616)
Expenditure	−0.0600***	−0.1251***	0.0748***
	(−5.0051)	(−6.2070)	(4.8473)
FDI	0.4220**	2.2086***	−0.3564**
	(2.0520)	(5.6616)	(-2.1291)
_cons	0.7521***	3.8876***	−2.0402***
	(3.5753)	(7.8368)	(-7.7928)
County	Yes	Yes	Yes
Year	Yes	Yes	Yes
Obs	5,781	6,477	6,285
Adjusted R^2	0.8910	0.8301	0.8893

Note: same as a footnote under Table 4.

panel data from 1,503 counties in China and similarly found that digital rural development significantly enhances AGTFP. However, our findings differ from Zhou et al. (2023), who analyzed panel data from 30 Chinese provinces between 2011 and 2019 and found an inverted U-shaped relationship between digital agriculture growth and AGTFP growth.

ii) The results elucidate several mechanisms through which DRC indirectly aids in the improvement of AGTFP. These include increasing land finance, alleviating land resource misallocation, and fostering greater agricultural technology innovation. Our findings align with those of Fan et al. (2025), who discovered that digital rural development alleviates land resource misallocation, thereby indirectly improving rural land use efficiency. Also, our result confirms the findings of Zhang et al. (2023), whose empirical analysis shows that the digital economy primarily promotes agricultural technological innovation, thereby enhancing AGTFP.

iii) The influence of the DRC on AGTFP exhibits regional disparities. Our findings show that the impact of DRC on AGTFP is more significant in China's central and western regions, non-major grain-producing areas, and regions with lower land transfer efficiency. Several factors may explain these findings: (i) The central and western areas, characterized by their relatively lower economic development and agricultural productivity, are likely to benefit more distinctly from the integration of digital technologies, underscoring a regional disparity in the effectiveness of DRC. (ii) Major grain-producing regions often have well-established agricultural practices and infrastructure. This maturity might limit the incremental benefits that digital interventions can provide, as these regions may already operate at or near optimal efficiency levels. The introduction of digital tools in these areas might not lead to significant improvements in productivity due to diminishing returns on already advanced techniques and technologies. In contrast, non-major grain-producing regions may have more to gain from DRC due to less optimized agricultural processes and a greater need for technological innovation. These regions might represent areas where current productivity levels are lower, thus the introduction of digital technology could lead to substantial improvements. The significant impact observed in these regions suggests that digital tools are effectively addressing specific inefficiencies or gaps in agricultural practices. (iii) In regions with lower land transfer efficiency, DRC likely addresses structural inefficiencies, such as fragmented land use, enabling better resource integration and productivity gains, which enhances AGTFP. However, in areas with higher land transfer efficiency, existing systems may already operate near optimal levels, leaving limited room for DRC to further enhance AGTFP.

5.2 Theoretical contributions

This study makes three key theoretical contributions. First, it advances the literature on integrating digitalization with sustainable agriculture by providing empirical evidence of how DRC policies enhance AGTFP. Second, it enriches the understanding of policy-driven mechanisms by revealing how DRC promotes AGTFP through land finance, resource allocation efficiency, and agricultural technology innovation, offering insights into the indirect pathways of impact. Third, it highlights the heterogeneity of DRC's impact on AGTFP, particularly based on the distinct characteristics of major and non-major grain-producing areas. It explores the regional disparities in how digital rural construction empowers AGTFP improvement from a new perspective. This deepens the theoretical discussion on spatial differences in policy implementation and their effects on sustainable agricultural development.

5.3 Practical implications

Based on the insights derived from our assessment of China's DRC pilot policy and its impact on AGTFP, the following recommendations are proposed to guide policymakers in enhancing the efficacy and reach of similar initiatives: (i) Policymakers should consider allocating more resources towards

TABLE 9 Heterogeneity from the perspective of grain-producing function.

Variables	Major grain-producing region	Non-major grain-producing region
	(1)	(2)
	AGTFP	AGTFP
DID	0.0020	0.1679***
	(0.0733)	(4.7210)
Size	0.0716***	0.3676***
	(3.4870)	(8.7083)
Instructure	0.0550*	−0.5023***
	(1.7829)	(-8.8207)
GDP	0.0161*	0.0278*
	(1.8715)	(1.8769)
Expenditure	0.0289**	0.1451***
	(2.4830)	(8.4849)
FDI	−0.0813	0.2510
	(−0.5381)	(0.8509)
_cons	−0.3279*	−2.0311***
	(−1.6979)	(−4.5243)
County	Yes	Yes
Year	Yes	Yes
Obs	10,603	7,940
Adjusted R^2	0.8632	0.8631

Note: same as a footnote under Table 4.

enhancing digital infrastructure in less developed regions, particularly in central and western China, non-major grain-producing areas and lower land transfer efficiency. Our study indicates that these regions benefit significantly from digital interventions, suggesting that targeted investments could yield substantial improvements in AGTFP. (ii) Local governments should have the flexibility to design and implement digital agriculture strategies that address their unique environmental conditions and agricultural challenges. For example, in more developed areas, particularly in eastern regions and major grain-producing zones, the incremental benefits of digital initiatives are less pronounced. Here, policymakers should focus on optimizing current digital practices and technologies, pushing for advancements in high-precision agriculture and data analytics to squeeze additional productivity gains. (iii) Given the positive correlation between DRC and agricultural technology innovation, it is paramount to create a setting that encourages innovation. This can be achieved through subsidies for research and development, partnerships between tech companies and agricultural sectors, and facilitating access to new technologies for small to medium-sized farms. Meanwhile, it serves to guarantee that the rural laborers have the requisite skills. Implementing comprehensive training programs that focus on digital literacy and modern agricultural techniques will help farmers effectively utilize new technologies.

5.4 Limitations and future research

Our study identifies several limitations that pave the way for further exploration in this field. First, while the investigation provides initial insights into the effects of DRC on AGTFP within China, broadening this study to include comparisons with developed nations and other emerging markets could improve the applicability of these results. Second, while the mechanisms of land finance, land resource misallocation, and agricultural technology innovation are crucial in understanding the effects of DRC on AGTFP, there are additional potential mechanisms that merit exploration, such as financial services and environmental monitoring or management. Third, it is crucial for future research to explore the non-linear dynamics between DRC and AGTFP. Investigating these relationships could reveal critical thresholds and potential saturation points of DRC's effectiveness. This insight is essential for optimizing the distribution of green resources in rural areas, ensuring that DRC initiatives are both effective and sustainable.

6 Conclusion

This study investigates the impact of digital rural construction (DRC) on agricultural green total factor productivity (AGTFP) by using

TABLE 10 Heterogeneity from the land transfer efficiency perspective.

Variables	Lower land transfer efficiency	Higher land transfer efficiency
	(1)	(2)
	AGTFP	AGTFP
DID	0.1582***	0.0056
	(3.4652)	(0.2780)
Size	0.2059***	−0.0211
	(4.0895)	(−1.1373)
Instructure	−0.4821***	0.4199***
	(−8.1107)	(13.2485)
GDP	−0.0231	−0.0799***
	(−1.3929)	(−6.4307)
Expenditure	0.1236***	−0.0505***
	(6.0001)	(−5.2398)
FDI	2.9211***	−1.4832***
	(12.6382)	(−12.3229)
_cons	−0.3897	1.1641***
	(−0.7618)	(6.0019)
County	Yes	Yes
Year	Yes	Yes
Obs	8,861	9,682
Adjusted R^2	0.8232	0.9126

Note: same as a footnote under Table 4.

China's DRC pilot policy as a quasi-natural experiment and employing a difference-in-differences (DID) approach with data from 2,128 counties and districts between 2012 and 2022. The results demonstrate that DRC significantly improves AGTFP, with a 1% increase in DRC leading to a 7.72% rise in AGTFP. This improvement occurs through three main channels: enhanced land finance, reduced land resource misallocation, and the promotion of agricultural technology innovation. The analysis further shows that the effects of DRC on AGTFP vary across geographical regions, grain production function, and land transfer efficiency. Stronger impacts are observed in regions with China's central and western, non-major grain-producing, and lower land transfer efficiency. These findings underscore the pivotal role of digital governance in advancing green agricultural development and provide actionable insights for policymakers and practitioners aiming to establish rural digital governance systems and achieve sustainable agricultural outcomes.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

ZZ: Conceptualization, Investigation, Methodology, Resources, Writing – original draft. TH: Data curation, Formal Analysis, Software, Visualization, Writing – review and editing. JH: Conceptualization, Methodology, Resources, Software, Project administration, Investigation, Validation, Writing – review and editing.

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Supplementary material

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Wu Haoqiang,
Wuhan Polytechnic University, China
Chaozheng Zhang,
Hunan Agricultural University, China
Changming Wang,
Northwest University, China

*CORRESPONDENCE
Manman Qu,
19712571727@163.com

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Digital economy, transfer of agricultural labor force and agricultural land production efficiency

Liuyan Li and Manman Qu*

School of Economics, Henan Normal University, Xinxiang, China

The digital economy has emerged as a new driving force and engine for China's economic growth. However, given the current shortage of production factors, whether the digital economy positively impacts agricultural land productivity remains to be further confirmed. This study employs balanced panel data from 31 Chinese provinces between 2009 and 2023, constructs a three-tier indicator framework, and measures China's digital economy development level using the entropy method. The research explores the impact and mechanisms of the digital economy on agricultural productivity. Key findings include: (1) Bidirectional fixed-effects models demonstrate that the digital economy significantly enhances agricultural productivity, supported by endogeneity tests, robustness checks, and threshold analysis. (2) Heterogeneity analysis reveals stronger productivity improvements in eastern, central, and northeastern regions, particularly in major grain-producing areas. (3) Mediation tests confirm that the digital economy boosts agricultural productivity by facilitating labor mobility. Based on these conclusions, policy recommendations are proposed: fundamentally improving rural digital infrastructure, establishing region-specific development frameworks, and strengthening support for digital agriculture entities. These measures provide practical pathways to enhance agricultural productivity.

KEYWORDS

digital economy, agricultural labor transfer, agricultural land production efficiency, two-way fixed effects, threshold effect testing

1 Introduction

As of 2024, China's urbanization rate has reached 67%, an increase of 55.52 percentage points compared with the end of 1949, with an average annual increase of 0.75 percentage points. Since the founding of the People's Republic of China, remarkable achievements have been made in China's urbanization construction. The growth of China's traditional agriculture has mainly relied on factors such as the economies of scale brought about by the innovation of the land system and the demographic dividend brought about by the labor force resources (Lin et al., 2018). The rapid development of urbanization has brought two direct impacts on China's agricultural production: The reduction in arable land and the outflow of agricultural labor. Therefore, promoting the growth of the agricultural economy requires the exploration of new avenues. The Third Plenary Session of the 20th Central Committee of the Communist Party of China emphasized that "we should improve the system for promoting the in - depth integration of the real economy and the digital economy. We should accelerate the establishment of a system and mechanism to promote the development

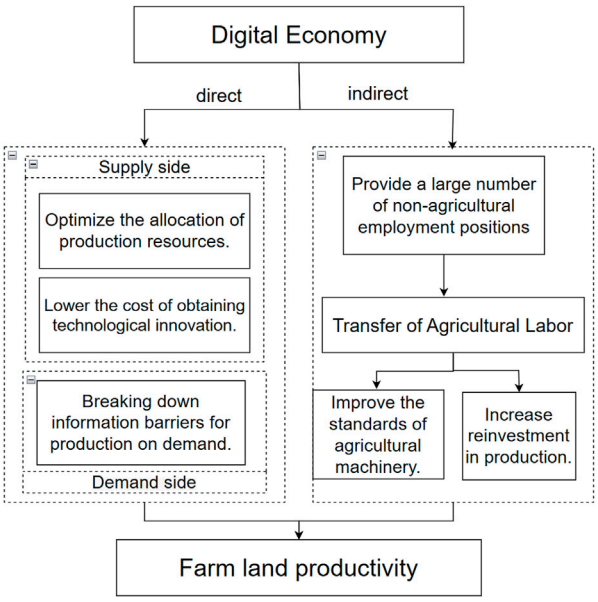


FIGURE 1
Theoretical mechanism analysis diagram.

of the digital economy and improve the policy system to promote the digitalization of industries and the industrialization of digital technology". This shows the country's emphasis on the development of the digital economy, which lays a foundation for comprehensively transforming the agricultural development model and realizing the in - depth integration of the digital economy and agriculture. With the rapid development of global digitalization, the digital economy promotes the digital transformation of agriculture by integrating big data, the Internet of Things, blockchain, and 5G communication technologies into agricultural development. It empowers facilities, data, and technology, alters the internal structure of the agricultural industry, triggers the reallocation of production resources, and improves agricultural production efficiency. Thus, the digital economy has pointed out a new direction for agricultural development and has created the possibility of enhancing quality and efficiency in agriculture. As a new engine and driving force for high - quality economic growth, can the digital economy's role in promoting economic growth be extended to the agricultural industry to improve the production efficiency of agricultural land, and what is the mechanism of this effect? This paper attempts to answer the above questions and provide policy suggestions for further realizing the modernization of agriculture and rural areas.

The concept of "digital economy" was put forward by American economist Tapscott, who believes that the digital economy has ICT infrastructure and various e-commerce models with ICT as the carrier (Tapscott, 1996). As the digital economy spreads around the world, Domestic scholars believe that the digital economy is a series of new - format economic and social activities that take digital information as resources, the Internet platform as the carrier, and digital technology innovation as the driving force (Chen et al., 2022). Its specific characteristics can be divided into three aspects: first, the characteristics of low - cost, standardization, and dynamism; second, the characteristics of low - cost, standardization, and dynamism; third, the characteristics of low - cost, standardization, and dynamism (Xiang and Wu, 2018). To further identify the impact of the digital economy, Many scholars have used the index method, the value - added method, the method of compiling satellite accounts, and methods related to national economic accounting,and the specific subdivision of measurement dimensions are also different. Liu and Meng (2019) divided the digital economy into two parts: the basic industries of the digital economy and the integration effect of the digital economy, and constructed a measurement model of the digital economy by aggregating these two parts. Hong (2019) used the value - added measurement method and the index method to conduct measurements from two dimensions: digital industrialization and industrial digitization. In addition, many studies have shown that the digital economy can make use of the information and intelligent characteristics of the digital economy to transform and upgrade traditional industries, and give birth to new industries, new business forms and new business models, improve production efficiency, and lay a theoretical foundation for improving agricultural land production efficiency.

Agriculture has always been considered as a land-and labor-intensive industry, in which the efficiency of agricultural land production plays a vital role in the overall development of agriculture. At present, the research on agricultural land production efficiency mainly focuses on the measurement and influencing factors of agricultural land production efficiency. From the perspective of input factors, the indicators to measure agricultural land production efficiency can be divided into: agricultural land output efficiency, agricultural labor productivity and total factor productivity, among which agricultural land output efficiency and agricultural labor productivity use the single factor productivity method. In order to further explore how to improve the productivity of agricultural land, many scholars have studied the impact of the current situation of labor force on the productivity of agricultural land and concluded that the transfer of migrant workers, non-agricultural employment and occupational differentiation can significantly improve the productivity of agricultural land (Sun, 2021; Qian and Hong, 2016; Chen, 2020). In addition, some scholars believe that agricultural machinery socialized services have a positive correlation with agricultural land production efficiency by expanding the scale of production (Ling et al., 2022). Since agricultural land can be exchanged and circulated as a commodity, the ownership of agricultural land can also affect the production efficiency of agricultural land. Studies have shown that the confirmation of agricultural land rights can significantly improve the production efficiency of agricultural land after more than 1 year (Gao et al., 2021).

Through the analysis of the existing literature, it can be concluded that: (1) there are abundant literature on the measurement and economic effects of digital economy, and the research on agricultural land production efficiency is still based on the traditional perspective, and there is a certain gap in the existence of digital economy on agricultural land production efficiency. (2) Some studies have shown that labor transfer can improve the productivity of agricultural land, but whether the transfer of agricultural labor force will have the same effect on the productivity of agricultural land remains to be proved. Therefore, this paper constructs an indicator system for the digital economy and conducts measurements from four dimensions: digital fundamental, digital application, digital innovation, and digital transformation. It

establishes a bidirectional fixed effects model to examine the impact of the digital economy on agricultural land productivity. Furthermore, it introduces the transfer of agricultural labor as a mediating variable to explore the pathways through which the digital economy affects agricultural land productivity. Finally, by considering the digital economy as a threshold variable, the study examines the threshold effect between the two factors and investigates whether the impact of the digital economy on agricultural land productivity varies across different geographical regions.

2 Theoretical analysis and research hypothesis

2.1 Direct effects

As a new economic form, digital economy can combine data, a new factor of production, with land, labor and other traditional factors of production to be used in agricultural production, realize the digital production mode of agriculture, and then improve the efficiency of agricultural land production. From the perspective of supply side, digital economy integrates digital technologies such as Internet and modern information technology into agricultural production process, implements accurate and efficient operation and management, establishes scientific modern agricultural production system, optimizes the rational allocation of production resources, and improves agricultural output efficiency (Li et al., 2025). At the same time, with the development of digital economy and the emergence of big data, producers can break through the obstacles of information circulation, obtain the information of cutting-edge technology in time, reduce the input cost of technological innovation, solve the problem of farmers to achieve innovation, and then expand the scale of production and improve the overall agricultural land production efficiency (Wen, 2024). From the demand side, the primary application of the digital economy in agriculture is to integrate information technology into agricultural production, thereby achieving a digital transformation in agriculture. This digitalization effectively breaks down the information barriers between consumers and producers, enabling producers to promptly and accurately capture the diverse needs of consumers for customized production. Additionally, based on consumer feedback from the APP, producers can optimize products and then formulate production plans. This approach maximizes the satisfaction of consumer demands, prevents supply and demand imbalances that could lead to overproduction or shortages, and ensures the efficient allocation of limited resources, thus enhancing the efficiency of agricultural land use (Liu, 2020).

Hypothesis 1. The digital economy can improve the production efficiency of agricultural land.

2.2 Indirect effects

2.2.1 The digital economy facilitates the transfer of agricultural labor

The dual economy theory holds that workers engaged in traditional agricultural production tend to pursue more efficient modern industries (Lewis, 1954). Among them, economic factors are also important influencing factors in labor transfer (Jia and Cheng, 2024). On the one hand, the high informatization of the digital economy can effectively reduce the time for laborers to collect job - related information, break the traditional employment information cocoon, provide a wide range of job options, achieve effective reallocation of resources, and promote labor transfer (Li and Gu, 2025). On the other hand, the digital economy attracts modern production factors such as capital, technology, and talent to establish a series of non - agricultural industries, forming new - mode industries with high levels of mechanization and digitization. It extends the industrial chain both vertically and horizontally. The emergence of new industries creates a large number of non - agricultural jobs, which require new employees as human capital support. This increases the labor demand, improves the employment rate of surplus labor, and promotes the transfer of farmers to non - agricultural industries (Tan et al., 2024).

2.2.2 The transfer of agricultural labor promotes the productivity of agricultural land

Based on the new theory of migration economics, labor transfer can increase investment in agricultural mechanization and deepen agricultural capital intensification in the short term. In the long run, it can improve the production efficiency of agricultural land (Woute, 2010). This is mainly because, on the one hand, labor transfer reduces the competitiveness of the agricultural and rural labor force. The elderly, the weak, women, and children gradually become the main body of the rural labor force (Huang and Hu, 2019), which stimulates increased investment in mechanization technology and promotes the substitution effect of agricultural machinery for labor, thereby improving the production efficiency of agricultural land (Wang et al., 2016). On the other hand, labor transfer can significantly increase the income level of families. To maximize the expected family income, family members will re - allocate production factors, causing some production factors to shift to non - agricultural industries. This increases the income of farmers from non - agricultural industries, thereby raising the overall family income level and increasing the possibility of reinvestment in production, so as to improve the production efficiency of agricultural land (Teng and Li, 2020; Wang, 2015).

Hypothesis 2. The digital economy improves the production efficiency of agricultural land by promoting the transfer of agricultural labor.

The specific theoretical mechanism diagram can be seen in Figure 1.

3 Research design

3.1 Data source

Based on the availability and scientific nature of the data, this paper selects panel data from 31 provinces in China from 2009 to 2023 for empirical analysis. The main data come from the annual "China Statistical Yearbook", "China Agricultural Statistical Yearbook", and "China Population and Employment Statistical Yearbook" published by the National Bureau of Statistics. Considering price fluctuations, this paper deflates the output

TABLE 1 The comprehensive index system for the level of the provincial digital economy.

Composite indicators	Primary indicator	Secondary indicator	Tertiary indicators
Level of digital economy	Digital fundamental	Mobile infrastructure	**X1**Capacity of Mobile telephone exchange
			X2Mobile phone penetration rate
		Fixed facility foundation	**X3**Internet broadband access port
			X4Number of domains
			X5Number of websites
			X6Long-distance optical fiber cable
			X7The total length of the limited television transmission trunk network
	Digital application	Personal application	**X8**Digital television
			X9The proportion of actual users of cable broadcasting and television
		Enterprise application	**X10**Number of websites owned by the enterprise
			X11 The number of websites owned by every hundred enterprises
			X12 Proportion of enterprises engaged in e-commerce transactions
		Social application	**X13**Total network retail sales/Total retail sales of consumer goods
	Digital innovation	Innovation investment	**X14**Full-time equivalent personnel in industrial enterprises above designated size for R&D
			X15R&D expenditures of industrial enterprises above a designated size
		Innovation output	**X16**The proportion of invention patent applications from industrial enterprises above a designated size accounts for the total number of patent applications
			X17 Transaction volume in the technology market
	Digital transformation	The transformation of e-commerce development	**X18**Revenue from software business/GDP
			X19E-commerce sales/GDP
			X20E-commerce procurement value/GDP
		Transformation of benefits from new products	**X21**Number of new product development projects
			X22 Expenditure on new product development funds
			X23 Sales revenue from new products

Note: The bold letters in the table denote the variable labels for the third-level indicators.

value of each year using the constant price index of 2009. For some missing values, linear interpolation is used in this paper.

3.2 Description of the variable

3.2.1 Dependent variable: agricultural land production efficiency (Eff)

In the existing literature, there are mainly two proxy variables for land production efficiency: yield per mu and profit per mu. The difference between the two is that the vector of input factors is no longer included in the profit per mu model (Wang, 2015). Based on the research purpose of this paper, considering that it is difficult to standardize the yields of different crops, the output value per mu is selected as the proxy variable for agricultural land production efficiency. The output value per mu of regional agricultural land is calculated by dividing the total regional agricultural output value by the sown area. Since the multiple cropping index of land varies across different regions, this paper uses the sown area instead of the cultivated land area.

3.2.2 Explanatory variable: digital economy (Dig)

The development of the digital economy relies on the theory of "four requirements": digital foundation, digital application, digital innovation, and digital industry. Referring to the approach of Jiao and Sun (2021), based on the availability, comparability, and comprehensiveness of data and in combination with the above-mentioned "four requirements" theory, this paper constructs the indicator system shown in Table 1 below and uses the entropy method to measure the development level of the digital economy.

3.2.3 Control variables

To control the potential impact of the existence of other factors on the production efficiency of agricultural land, this paper draws on

TABLE 2 Descriptive statistics.

Variable name	Calculation methods	Sample size	Mean	Standard deviation	Minimum value	Maximum value
Agricultural land production efficiency (Eff)	Ln (Regional agricultural output value/ acreage)	465	7.834	0.574	7.313	8.269
Digital economy (Dig)	—	465	0.824	0.090	0.169	0.912
The educational level of residents. (Edu)	Ln (Average years of education for rural residents.)	465	1.548	0.607	1.142	2.830
Economic development level (Dep)	Ln (Net income of rural residents)	465	8.961	0.473	8.381	10.728
Average Fertilizer Pure Quantity per Acre(Fer)	Ln (Regional fertilizer purity rate/cultivated area)	465	5.492	0.709	4.629	7.403
Average Pesticide Usage per Mu (Pes)	Ln (Pesticide usage amount/cultivated area)	465	9.349	1.942	5.561	10.188
Effective Irrigated Area Ratio (Irr)	Area of agricultural damage in the region/ Cultivated Area	465	0.169	0.235	0.032	0.217
Average film usage per mu (Agri)	Ln (Regional agricultural plastic film/ Cultivated Area)	465	8.989	1.232	5.756	9.713
Proportion of Disaster-Affected Area (Dis)	Effective irrigated area/cultivated area	465	0.829	0.114	0.573	0.962
Transfer of agricultural labor force (Lab)	Ln (Number of rural workforce-Number of employees in the primary industry)	465	6.730	1.427	2.943	7.891

the methods of Li et al. (2025) and Li and Bai (2018) to select the education level of residents (Edu), the level of economic growth (Dep), the average amount of pure - converted chemical fertilizers per mu (Fer), the average amount of pesticide used per mu (Pes), the proportion of effectively irrigated area (Irr), the average amount of agricultural film used per mu (Agri), and the proportion of disaster - affected area (Dis). Theoretically, in the process of agricultural production, these intermediate - input capital goods will improve the production efficiency of agricultural land. That is, the effects of the first six indicators are positive, while the proportion of disaster - affected area has a negative impact on agricultural production, and its effect is significantly negative. Of course, this needs to be verified later in the paper.

3.2.4 Mediator variable: transfer of agricultural labor force (Lab)

Through the above analysis of the theoretical mechanism, labor transfer can reduce agricultural competitiveness, improve the level of agricultural production mechanization, and thus enhance the production efficiency of agricultural land. This paper selects the level of labor transfer as an intermediary variable. Drawing on the research method of Wu (2016), it is measured by subtracting the number of employees in the primary industry from the number of rural employees.

The specific calculation methods and descriptive statistics for all variables used in this article can be found in Table 2.

3.3 Model setting

Based on the aforementioned theoretical analysis, to verify the impact of the level of digital economy development on agricultural land production efficiency, the following benchmark regression model is constructed:

$$Eff_{i,t} = \alpha_0 + \alpha_1 Dig_{i,t} + \beta Control_{i,t} + \lambda_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

(1) In the formula, λ_i represents the fixed effects of provinces, which are used to control individual factors that do not change over time (such as region - specific natural endowments: unobservable factors like soil quality, rainfall, temperature, etc. γ_t represents the fixed effects of years, which are used to control time factors that do not change with individuals (unobservable factors that affect agricultural land production efficiency as time changes). $\varepsilon_{i,t}$ represents the random disturbance term. α_1 reflects the impact effect of the development level of the digital economy on agricultural land production efficiency, which is the focus of this study.

To further examine the impact mechanism of the development level of the digital economy on agricultural land production efficiency, this paper draws on the approach of Baron and Kenny (1986) to construct the following mediating effect model:

$$Lab_{i,t} = \theta_0 + \theta_1 Dig_{i,t} + \beta Control_{i,t} + \lambda_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

$$Eff_{i,t} = \delta_0 + \delta_1 Lab_{i,t} + \beta Control_{i,t} + \lambda_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

Among them, $Lab_{i,t}$ is the mediating variable, and the rest are consistent with those in the above benchmark regression.

4 Empirical analysis

4.1 Benchmark regression results

This paper uses stata software to conduct a preliminary test of the benchmark Model (1). The regression results in columns (1)(2)(3)(4)

TABLE 3 Benchmark regression results.

Variable	Eff			
	(1)	(2)	(3)	(4)
Dig	0.691*** (12.65)	0.489*** (4.31)	0.646*** (11.06)	0.513*** (4.36)
Edu		1.238** (2.48)	0.252*** (2.84)	0.901* (1.77)
Dep		−0.150** (−2.20)	−0.037*** (−1.64)	−0.01*** (−1.30)
Fer		0.506*** (4.28)	0.540*** (4.74)	0.459* (4.16)
Pes		−0.060 (-1.00)	0.011 (0.20)	−0.10 (−0.15)
Irr		−0.029 (-2.51)	−0.006** (-3.01)	−0.01*** (−2.08)
Agri		0.146*** (4.27)	0.120*** (3.50)	0.125*** (3.61)
Dis		−0.002 (-2.84)	−0.002 (-2.42)	−0.001 (−2.28)
Constant term	−3.062 (-7.70)	0.214 (0.62)	−2.387*** (-5.67)	−1.377** (−1.55)
Fixed effects for regions	No	No	Yes	Yes
Time fixed effect	No	Yes	No	Yes
N	465	465	465	465
R^2	0.7490	0.7516	0.7494	0.7504

Note: * * *, * *, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for city level clustering are shown in parentheses. Same below.

of Table 3 all take the development level of the digital economy as the explanatory variable, and study its impact on the production efficiency of agricultural land by gradually adding control variables, regional fixed effects, and year fixed effects. Thus, Hypothesis H1 is verified. Column (1) of Table 3 shows that without adding control variables and without fixing effects such as regions and time, the coefficient of the digital economy is significantly positive at the 1% level. The results in columns (2) and (3) of Table 3 show that after adding control variables and fixing time and regions respectively, the coefficient of the digital economy is still significantly positive at the 1% level. The result in column (4) of Table 3 shows that after adding control variables and fixing regional and time effects, the coefficient of the digital economy is 0.513, and it passes the significance test at the 1% level. It can be seen that the digital economy can significantly improve the production efficiency of agricultural land, and Hypothesis 1 is verified. Among the control variables, we further observe that the per-mu pure amount of chemical fertilizers and the per-mu usage of plastic films are significantly positive, which indicates that the development of biotechnology represented by chemical fertilizers and plastic films can significantly improve the production efficiency of agricultural land. However, the logarithm of the per-mu usage of pesticides is negative but not significant. Nevertheless, it also shows that pesticides are not beneficial to the production efficiency of agricultural land in China, which is basically consistent with Lin (2011) research results. Finally, it is found that the disaster rate is not significant for agricultural land production, indicating that the disaster rate has little impact on the production efficiency of agricultural land, which shows that China's agriculture has strong disaster resistance.

4.2 Endogeneity test

Based on the above analysis, it can be concluded that the digital economy can significantly improve the efficiency of agricultural land production. However, the improvement of agricultural land production efficiency may also further promote the development of the digital economy. To eliminate this two-way causal relationship, this paper draws on the research of Li et al. (2024) and Wen (2023), and selects the interaction term between the one-period lagged term of the digital economy development level and the number of post and telecommunications offices per million people in each province in 1984 as the two instrumental variables in this paper. The reason is that the local communication level is related to the historical data of post and telecommunications offices. The number of post and telecommunications offices determines the current number of fixed-line telephones and Internet interfaces, which in turn affects the current local digital economy level, meeting the relevance condition of instrumental variables. Moreover, as a traditional communication facility, post and telecommunications offices have gradually faded out of people's lives, so they will not have an impact on the efficiency of agricultural land production, which also meets the exclusivity of instrumental variables.

TABLE 4 Results of the instrumental variable regression with the least squares method.

Variable	Model 1	Model 2	Model 1	Model 2
	Dig	Eff	Dig	Eff
Dig		0.535** (3.88)		0.530** (2.76)
L.Dig	0.852*** (4.49)		0.141*** (3.09)	
Control Variables	Yes	Yes	Yes	Yes
Fixed effects for regions	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
N	465	465	465	465
Cragg-Donald Wald F	1672.21		1081.25	
p-value	5.755 (0.7263)		3.872 (0.7244)	

This paper uses the two-stage least squares method to conduct an endogeneity test. To test the validity of the instrumental variables, Table 4 reports a series of test results for the instrumental variables. First, the estimated values and t-values of the two instrumental variables in the first-stage regression are reported. The regression coefficients of the two instrumental variables are significantly positive at the 1% level, indicating that the two instrumental variables used in this paper are significantly and positively correlated with the development level of the digital economy. In particular, the coefficient of the one-period lag of the digital economy level exceeds 0.8, indicating that this indicator has a very large impact on the current development level of the digital economy. The Cragg - Donald Wald F values obtained from the weak instrumental variable test are relatively large, which indicates that there is no problem of weak instrumental variables. The p-value of the over-identification test result is very large, indicating that we cannot reject the hypothesis that the two instrumental variables are exogenous. All these test indicators show that the two instrumental variables selected in this paper are appropriate.

In addition, according to the regression results in Table 4, after adopting the two-stage least squares instrumental variable regression, the coefficients of the digital economy level are all significantly positive at the 5% level, which further verifies the conclusion of the above benchmark regression in this paper. Therefore, it has passed the endogeneity test.

4.3 Robustness tests

4.3.1 Replace the measurement method

Considering that using different measurement methods may lead to certain deviations in the results, this paper uses the principal component analysis method to re - measure the digital economy level and uses it as a new explanatory variable. By adding control variables and fixing provinces and time, the above - mentioned model is used to conduct the benchmark regression again. The regression results are shown in column (1) of Table 5. The coefficient of the digital economy level is significantly positive at the 1% level, indicating that the digital economy growth level measured by the principal component analysis method instead of the entropy method still has a promoting effect on the agricultural land production efficiency. Therefore, the reliability of the benchmark regression results is verified.

4.3.2 Exclude special samples

The research sample in this paper consists of panel data from 31 provinces across the country, including four municipalities directly under the Central Government, namely Beijing, Tianjin, Shanghai, and Chongqing. Since municipalities directly under the Central Government in China are provincial-level administrative regions under the jurisdiction of the central government and have special political, economic, and cultural statuses, they have absolute advantages compared with other provinces, which may affect the results of this paper. Therefore, after excluding the sample data of these four municipalities directly under the Central Government, the model set in this paper is used for regression again, and the results are shown in Table 5 (2) below. The results in Column (2) of the TABLE show that the coefficient of the digital economy is 0.371 at the 1% significance level, which is consistent with the results of the benchmark regression, indicating that it has passed the robustness test.

4.3.3 Change the sample interval

The sample time interval selected in this paper is from 2009 to 2023, with a relatively large time span. Moreover, the digital economy was first proposed in China at the G20 Summit in 2016. Studying the impact of the digital economy on agricultural land production efficiency after 2016 is more referential. Therefore, this paper shortens the sample time interval to 2016–2023 and conducts regression again. The results are shown in column (3) of Table 5. The coefficient of the digital economy is still significantly positive, passing the robustness test. Compared with the benchmark regression results, the coefficient of the digital economy has increased significantly, indicating that the digital economy has a

TABLE 5 Results of the robustness check.

Variable	Eff				
	(1) Replace the measurement method	(2) Exclude special samples	(3) Change the sample interval	(4) One lag period	(5) Two periods of lag
Dig	0.592*** (7.14)	0.371*** (2.59)	0.691*** (6.91)		
L.Dig				0.535*** (5.18)	
L2.Dig					0.429*** (3.74)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant term	−2.197*** (-4.30)	−0.290** (-0.26)	−1.633*** (-3.07)	0.554*** (6.05)	0.414* (5.92)
Fixed effects for regions	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
N	465	405	248	434	403
R^2	0.7215	0.7254	0.7299	0.7289	0.6505

TABLE 6 Heterogeneity test results.

Variable	Eff					
	(1) Eastern	(2) Central	(3) Western	(4) Northeastern	(5) major grain - producing areas	(6) non - major grain - producing areas
Dig	1.105*** (5.01)	0.641*** (8.61)	0.517 (7.13)	0.662*** (3.29)	0.953*** (6.07)	0.716 (4.72)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant term	−7.996** (−4.10)	−3.708* (-4.35)	−3.272 (−3.85)	−3.876*** (−2.15)	−4.379* (−2.74)	−5.822 (−7.16)
Fixed effects for regions	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	165	90	165	45	195	270
R^2	0.8681	0.8580	0.8525	0.8580	0.7988	0.9397

greater role in improving agricultural land production efficiency in the recent period.

4.3.4 Consider the lag effect

The digital economy's impact on enhancing agricultural land productivity involves multiple stages and exhibits a certain degree of time lag. To investigate whether this impact is delayed, this study re-estimates the regression by using the digital economy's development level lagged by one period and two periods as new dependent variables, with the results presented in Table 5 (4) and (5). The findings indicate that the digital economy's effect on improving agricultural land productivity is significant both when lagged by one period and two periods, confirming the delayed nature of its impact.

4.4 Heterogeneity analysis

4.4.1 Analysis of heterogeneity in different regions

There are differences in the levels of economic growth, resource endowments, institutional environments, etc. among different regions. This paper draws on the practice of Zhang and Yang (2023), and divides the sample regions into four categories: eastern, central, western and northeastern regions according to

the classification standards of the National Bureau of Statistics, and conducts regression separately. The results are shown in Table 6 (1) (2) (3) (4). According to the results, the coefficients of the digital economy in the eastern, central, and northeastern regions are positively significant, indicating that the digital economy can effectively improve the agricultural land production efficiency in the eastern, central, and northeastern regions. The possible reason is that the eastern, central and northeastern regions have certain advantages in resource endowment compared with the western regions, and the high level of digital economy development can effectively combine with local sufficient agricultural land and labor force and other factors of production to improve the efficiency of agricultural land production. The reason why it is not significant in the western region lies in the lack of production resources due to remote geographical location and harsh climate environment, and it is easy to be affected by extreme weather in the production process, which hinders the improvement of agricultural land production efficiency.

4.4.2 Distinguish whether it is a principal grain producing area

Agricultural land is the fundamental resource for human survival and development. The quantity and quality of agricultural land are the foundation for enhancing agricultural production capacity and ensuring food security. The development of the digital economy has improved the production efficiency of agricultural land and may play a certain role in promoting the increase of grain output. This paper divides the sample into grain producing areas and non-grain producing areas by referring to Zhou et al. (2023).[1] As can be seen from columns (5) and (6) of Table 6, the coefficient of the digital economy in major grain - producing areas is significantly positive at the 1% level, while the coefficient of the digital economy in non - major grain - producing areas is not significant. This indicates that the digital economy has a more significant promoting effect on the production efficiency of agricultural land in major grain - producing areas. The possible reason is that the mechanization level in major grain - producing areas is relatively low. The development of the digital economy has invigorated the region, activating redundant local labor and production resources, optimizing the efficient allocation of these resources, and thus enhancing agricultural land productivity. For regions not primarily focused on food production, the scarcity of land resources is the most critical issue. Even with a high level of digital economy, this does not contribute to improving agricultural land productivity.

TABLE 7 Agent inspection results.

Variable	(1)	(2)
	Lab	Eff
Dig	0.236*** (3.57)	0.752*** (4.15)
Lab		0.316*** (3.29)
Control Variables	Yes	Yes
Constant term	−5.884*** (−4.43)	−2.397*** (−4.83)
Fixed effects for regions	Yes	Yes
Time fixed effect	Yes	Yes
N	465	465
R^2	0.8570	0.9821

4.5 Mechanism verification

The above regression results and robustness tests have verified that the digital economy significantly improves the production efficiency of agricultural land. But what is its mechanism of action? According to the theoretical analysis above, labor transfer is selected as the mediating variable, and regression is carried out using the mediation test Models 2, 3 constructed in this paper. The test results of the mediating effect of labor transfer are shown in Table 7. Through the analysis of the results, it can be seen that the digital economy can significantly promote labor transfer, and labor transfer can significantly improve the production efficiency of agricultural land, indicating that labor transfer can significantly play a mediating effect, thus verifying the validity of Hypothesis 2.

4.6 Threshold effect testing

In this paper, the Bootstrap method is used to conduct a threshold existence test with 500 self - samplings. The results are shown in Table 8. The results show that the model with the digital economy as the threshold variable has passed the single - threshold and double - threshold tests. From the estimation results in Table 9, it can be seen that the estimated coefficients of the digital economy within the three confidence intervals are all significantly positive at the 1% level and gradually increasing. Therefore, there is an increasing threshold effect.

5 Conclusions and policy recommendations

5.1 Conclusion

This paper uses the balanced panel data of 31 provinces from 2009 to 2023 and adopts the two-way fixed effects model to analyze the impact of the digital economy on the production efficiency of

1 Regarding the definition of major grain-producing areas, major grain-marketing areas, and areas with balanced grain production and marketing, this article adopts the classification method in the "Opinions on Further Deepening the Reform of the Grain Circulation System" issued by the State Council in 2001: Major grain-producing areas refer to 13 provinces (autonomous regions), namely Liaoning, Jilin, Heilongjiang, Inner Mongolia, Hebei, Shandong, Anhui, Jiangsu, Jiangxi, Henan, Hunan, Sichuan, and Hubei.

TABLE 8 Threshold value and confidence interval.

Inspection Methods	Threshold	RSS	MSE	F	P	10%	5%	1%
Single barrier	11.0184	0.0545	0.0002	57.22	0.0025	24.0013	28.4918	39.4310
Double threshold	11.2737 9.8103	0.0478	0.0002	40.27	0.0025	23.0409	26.4723	34.8923
Three doorsteps	11.7630	0.0457	0.0002	13.35	0.5300	31.7451	37.0121	56.3814

TABLE 9 Estimation results of the threshold effect.

Variable	Eff
Dig<9.8103	0.214** (5.86)
9.8103<=Dig<11.2737	0.493*** (3.72)
Dig>=11.2737	0.737*** (2.94)
Constant term	Yes
Fixed effects for regions	Yes
Time fixed effect	Yes
N	465
R^2	0.7416

agricultural land. The main conclusions are divided into the following aspects: First, the digital economy significantly boosts agricultural land productivity. After the endogeneity test and robustness test, the results remain robust. Second, the digital economy's impact on agricultural land productivity varies significantly. It notably enhances productivity in the eastern, central, and northeastern regions, as well as in major grain-producing areas. However, in western regions and non-grain-producing areas, the digital economy does not significantly improve agricultural land productivity. Third, mechanism analysis indicates that facilitating labor mobility is a key pathway for the digital economy to enhance agricultural land productivity.

5.2 Suggestion

Based on the research results of this paper, the following policy suggestions are put forward:

Firstly, To improve the digital infrastructure in rural areas, the digital economy needs a solid foundation of digital infrastructure to enhance agricultural productivity. This infrastructure ensures that digital technologies and resources are effectively integrated into the production process. Therefore, the government should increase investment in 5G networks, big data, and smart terminals, establish agricultural smart demonstration parks, provide policy subsidies and tax reductions for companies undergoing digital transformation, encourage individuals with digital expertise to contribute to agricultural digitalization, and offer free digital skills training to farmers, thereby enhancing the digital service level that aligns with the agricultural industry.

Secondly, construction systems should be formulated according to local conditions in different regions, and precise policies should be implemented. For the western region, the digital agriculture development guarantee system should be fundamentally improved first, good digital agriculture business entities should be introduced and cultivated, infrastructure construction should be improved, and the local digital development level should be enhanced. Then, the ways to improve the efficiency of agricultural land production can be broadened. For the eastern, central, and northeastern regions, platforms for the integration of the digital economy and agricultural production should be further constructed. Local available digital resources should be integrated to achieve in - depth integration of digital technology and agriculture. Starting from the real economy, a new batch of new business models and new business forms should be spawned relying on the digital economy to consolidate and strengthen digital development.

Thirdly, the cultivation of the digital agriculture business group should be strengthened. Digital skills training should be incorporated into the core content of the high - quality farmer cultivation project and the training of leaders of rural practical talents. Practical training such as Internet of Things operation, data analysis, e – commerce operation, and the use of intelligent management platforms should be carried out for family farm owners, cooperative leaders, and agricultural enterprise managers to improve the human capital level of those participating in the development of digital agriculture.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

LL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing. MQ: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Wang Zhang,
Northwest University, China
Xianhong Cheng,
Changzhou University, China
Xiaotan Zhang,
North China Institute of Aerospace Engineering, China

*CORRESPONDENCE
Xingang Wang,
wxg12431@163.com

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How can rural digital development activate agricultural land mobility? -Based on the dual perspectives of resource mismatch and labor mobility

Xingang Wang*

Yulin Normal University Business School, Yulin City, Guangxi, China

Introduction: Agricultural land transfer is crucial for achieving labor mobility and rational allocation of resources. The digital development of rural areas provides a new way to solve the dilemma of low level of agricultural land transfer in China.

Method: This article empirically tests the impact and mechanism of rural digital development on agricultural land transfer using a two-way fixed effects model and a mediation effects model, based on balanced panel data from 30 provinces in China from 2006 to 2023.

Conclusion: Firstly, the digital development of rural areas has significantly improved the transfer of agricultural land, and this impact is sustainable. After endogeneity and robustness tests, the results still hold true. Secondly, heterogeneity analysis found that the digital development of rural areas has a more significant impact on agricultural land transfer in central and western regions, the Yangtze River Economic Belt, provinces with lower levels of economic development and total factor productivity. Thirdly, mechanism analysis reveals that rural digital development improves agricultural land circulation by alleviating labor mismatch, land mismatch, and capital mismatch. At the same time, the digital development of rural areas has accelerated labor mobility and improved agricultural land transfer.

Discussion: The development of digital development in rural areas has a "latecomer advantage" and can balance regional imbalances. This article provides theoretical guidance for the relationship and future development between rural digital development and agricultural land transfer.

KEYWORDS

rural digital development, agricultural land transfer, labor mismatch, land mismatch, capital mismatch, labor flow

1 Introduction

China's rural areas have long been characterized by structural features such as small-scale land management and spatial distribution fragmentation. More than 90 per cent of the country's farming households operate on less than 10 acres of arable land, indicating that the current rural production pattern of small-scale farmers is still dominant (Zhu et al., 2025), leading to greater constraints on agricultural operations in terms of the efficiency of resource allocation, economies of scale and market responsiveness. Especially in the context

of agricultural modernization and high-quality development, the structural contradiction between "small farmers" and "big market" is becoming more and more prominent, which is not conducive to the realization of the core objectives of agricultural science and technology promotion, standardized production of agricultural products and the extension of the industrial chain (Aker, 2010; Aker, 2010). To address challenges in rural land use, the state has steadily advanced reforms to the rural land system. These efforts include reinforcing land ownership rights, improving the land transfer market, and encouraging the consolidation of land into the hands of agricultural operators with stronger managerial capabilities and technical expertise. According to the National Bureau of Statistics, agricultural land transfers in China increased substantially from 0.58 billion mu in 2004 to 532 million mu by 2020, indicating early progress in the market-oriented reform of land use rights. Nevertheless, the pace of growth in land transfers has slowed in recent years, suggesting ongoing issues within the rural land transfer market. These include weak alignment with labor migration across regions, the growing variety of agricultural business models, and broader development demands—factors that continue to hinder effective resource allocation and exacerbate the problem of land-use inefficiencies caused by the separation of people from land. In this context, the rapid development of digital technology to crack the inefficient allocation of agricultural land factors provides a new opportunity. Specifically, big data technology integrates land resources, farmer information, and market supply and demand data to achieve precise matching and price prediction of land supply and demand, significantly improving the efficiency and transparency of land transfer; Blockchain technology, with its decentralized and tamper proof characteristics, provides security guarantees for land ownership information registration, contract execution, and transaction traceability, enhancing the credibility of transactions; The Internet of Things technology utilizes sensors, remote sensing equipment, and other means to achieve real-time monitoring and dynamic management of land use status, ensuring the effective utilization of land resources; Artificial intelligence and intelligent algorithms can achieve intelligent matching, credit evaluation, and risk prediction between land supply and demand in the land information platform, improving transaction efficiency and reducing transfer risks; At the same time, the land transfer service platform and digital government system based on mobile Internet have widened the participation channels of farmers, lowered the transfer threshold, and stimulated the vitality of the rural land market. The comprehensive application of these digital technologies, from information symmetry, transaction matching to contract supervision, runs through the entire process of land transfer, providing solid support for building an efficient, transparent, and fair rural land transfer system. Along with the new round of scientific and technological revolution and industrial change, the digital economy has gradually become a key force to reshape the agricultural development model and enhance the efficiency of resource allocation. The 20th CPC National Congress clearly proposed to "accelerate the development of the digital economy and promote the deep integration of the digital economy with the real economy," pointing out the direction for the wide application of digital technology in the field of agriculture and rural areas. Given the obvious shortcomings in information infrastructure, digital talent and technology application in rural areas, especially in central and western and remote provinces, rural digital development has been elevated to a national strategic priority. Since 2018, when "vigorously developing digital agriculture" was first explicitly proposed, the central government has included digital rural areas as a key task in the "No. 1 Document" for five consecutive years, and has successively issued the "Outline of the Digital Rural Development Strategy," the "Plan for the Development of Digital Agriculture and Rural Areas (The Outline of Digital Rural Development Strategy, the Plan for Digital Agriculture and Rural Development (2019–2025), and the Key Points for Digital Rural Development in 2022 have been issued successively, forming a more systematic top-level design and strategic deployment. The digital development of rural areas can not only reshape the production organization and factor allocation logic of agriculture, but will also improve the relationship between supply and demand of agricultural land and stimulate the internal vitality of the land market by optimizing the flow of information, shortening the transaction chain, and improving the matching efficiency (Pirannejad and Janssen, 2019). While promoting the flow and efficient allocation of agricultural land, it also injects a lasting impetus for the realization of rural revitalization and the integrated flow of urban and rural factors, and provides institutional support and technical paths for the realization of the goal of common prosperity.

In recent years, with the rise of a new wave of digitalization, advanced information technologies such as big data, blockchain, and the Internet of Things have accelerated their penetration in the agricultural and rural fields, providing a practical path and technical support for solving the long-standing problems of information asymmetry, unclear property rights, and low transaction efficiency in agricultural land transfer. Among them, big data technology constructs an intelligent supply-demand matching platform through real-time integration and analysis of multidimensional data such as massive land resources, farmer attributes, market prices, and climate conditions. For example, some areas in Shandong rely on the "rural property rights trading platform + data center" model to achieve dynamic tracking and visual scheduling of village level land transfer information, significantly improving the efficiency of land supply and demand matching and market transparency. Blockchain technology, with its "decentralized" and "traceable" characteristics, has demonstrated unique advantages in land ownership confirmation, contract signing, and transfer transaction record management. Taking Deqing, Zhejiang Province as an example, the local pilot project of "blockchain + rural land ownership confirmation" embeds key data such as land ownership information, transfer contracts, and payment records into the chain, achieving verifiability and immutability of the entire transfer process, greatly enhancing the transaction trust between farmers and lessees. In addition, IoT technology has also played a key role in the management and utilization of land transfer. By deploying soil sensors, unmanned aerial vehicle monitoring systems, and agricultural meteorological stations, the cultivation status, input-output, irrigation and fertilization information of the transferred land can be collected in real time and fed back to land operators and regulatory agencies, achieving precise control and intelligent supervision of land use. In Jiangsu, Guangdong and other places, farmers rely on IoT systems for "remote agricultural management,"

greatly improving the efficiency of land use and the level of intensive agricultural management. The deep integration of these technologies not only optimizes the allocation of land elements, but also reshapes the operational logic of agricultural land transfer, providing solid digital support for China's agricultural modernization and rural revitalization.

At present, there are still fewer studies on the relationship between rural digital development and agricultural land transfer. Existing literature mostly focuses on the significance of the construction of digital villages, implementation paths and promotion strategies, as well as the construction of relevant indicator systems (Peng, 2019; Wang et al., 2021; Wen, 2022), and explores its association with digital divide (Cui and Feng, 2020), farmers' income (Qi et al., 2021), and high-quality development of rural areas (Xianli et al., 2019). Meanwhile, scholars have also focused on specific dimensions such as digital governance (Shen and Chen, 2021) and digital literacy (Chang Ling amidships, 2021). However, studies focusing on the direct relationship between rural digital development and agricultural land transfer are still relatively limited, mainly focusing on the specific application of digital technology in land transfer. In addition, some studies have explored the role of digital inclusive finance in land transfer transactions, pointing out that it helps to promote land transfer by alleviating information asymmetry and improving financial literacy (Zhang, 2022). The popularization of the Internet has also received widespread attention, and studies have shown that farmers' access to the Internet can significantly increase the likelihood of land transfer (Wenquan et al., 2022; Zhang and Zhang, 2020; Zhang et al., 2022; Cai et al., 2022). In addition, emerging technologies such as big data and artificial intelligence have also been shown to have a positive effect in enhancing the efficiency of land transfer (Liu et al., 2021). Despite the gradual increase in research on digital countryside and land transfer, the literature that systematically explores the relationship between the two is still insufficient, especially lacking in empirical analysis from a holistic perspective. Therefore, the purpose of this paper is to empirically examine the direct impact of rural digital development on agricultural land transfer and its functioning mechanism, so as to provide theoretical support and policy reference for promoting the development of digital countryside and land transfer practice.

The three innovations of this article are mainly reflected in the following aspects: firstly, based on balanced panel data from 30 provinces in China from 2006 to 2023, the direct impact of rural digital development on agricultural land transfer is empirically tested, and the reliability and sustainability of the results are ensured through endogeneity and robustness tests. Secondly, through heterogeneity analysis, the differential impact of rural digital development on agricultural land transfer under different regions, economic development levels, and productivity conditions has been revealed, enriching the existing theoretical research on regional differences in the effects of rural digital development. Thirdly, from the perspective of the mismatch of labor, land, and capital, a deep analysis was conducted on how rural digital development can improve the efficiency of agricultural land transfer by optimizing resource allocation and promoting factor flow. A theoretical innovation was proposed that rural digital development has a "latecomer advantage."

The other structural arrangements of the article are as follows: the second part is theoretical analysis and research hypotheses; Part Three: Data Sources and Empirical Design; Part Four: Empirical Results Analysis; Further analysis in the fifth part; Part Six Research Conclusions and Policy Recommendations; The seventh part is about research limitations and future research directions.

2 Theoretical analysis and research hypothesis

2.1 Rural digital development and agricultural land transfer

Agricultural land transfer is crucial for advancing agricultural modernization, optimizing rural resource allocation, and improving production efficiency. However, the process is often hindered by factors such as information asymmetry, complex transactions, and a lack of institutional frameworks, which limit its efficiency and scale. In traditional rural societies, the dissemination of land transfer information is restricted, and the transaction process lacks standardized procedures, increasing uncertainty and risk for farmers, thus discouraging participation in land transfer (Gao-Li et al., 2025).

With the in-depth implementation of the national "Digital China" strategy, the digital development of rural areas is an important part of it, and the gradual improvement of digital infrastructure in rural areas, the increasing popularization of digital technology, and the continuous expansion of digital public services provide new opportunities to solve the key bottlenecks restricting the transfer of agricultural land (Zhou et al., 2025). The construction of digital platforms and the promotion of agricultural information systems have enhanced the transparency and availability of rural land supply and demand information, shortened the information transmission chain, and effectively alleviated the information asymmetry between the two parties to the transaction. At the same time, the application of digital technological means such as blockchain and geographic information system in land ownership registration and contract management has improved the degree of standardization and security of land transactions, and reduced the transaction costs in the transfer process (Zhang et al., 2024). In addition, the onlineization of government services, financial resources and legal aid promoted by digital villages has broadened farmers' access to policy support, financing channels, and risk prevention and control tools, and further enhanced their willingness and ability to participate in the land transfer process (Su et al., 2023). This transformation not only optimizes the operating environment of the land market, but also provides institutional support for the construction of a standardized, efficient and transparent rural land transfer system.

2.2 Rural digital development, labor mismatch, and agricultural land transfer

Hypothesis 1: Rural digital development can significantly improve the level of agricultural land transfer.

TABLE 1 Construction of indicators for rural digital development

Level 1 indicators	Level 2 indicators	Definition of indicators	Weights
Digital Rural Infrastructure Development	Rural Logistics Coverage	Rural delivery routes/km	0.0337
	Logistics infrastructure investment	Fixed asset investment in transportation, storage and postal industry/billion yuan	0.0430
	Internet infrastructure development	Rural broadband access users/ten thousand	0.0829
	Agro-meteorological Observation Stations	Agricultural meteorological observation station/pc5	0.0242
Digital economization of the countryside	Level of agricultural digitization	Scale of digital agriculture/billion yuan	0.1095
	Rural E-commerce	Taobao village/one	0.1018
	Talent Support for Digital Rural Construction	Total economic enterprises and institutions specialized in agricultural technology professionals and technicians	0.0382
	Digital Technology Service	Employment in Information Transmission, Software and Information Technology Service Industry	0.0856
	E-commerce infrastructure capital investment	Local Financial Transportation Expenditure/billion yuan	0.0272
	Digital Finance Development Level	Digital Inclusive Finance Index	0.0816
Digitizing Rural Governance	Digital Rural Governance Capital Supply	Local Finance Urban and Rural Community Affairs Expenditure	0.0470
	E-government development level	Online government service capacity of provincial governments	0.0930
	TV Penetration Rate	Comprehensive population coverage rate of rural TV programs/%	0.0054
	Radio Penetration Rate	Comprehensive population coverage rate of rural radio programs/%	0.0048
Digitization of Rural Life	Information Service Consumption Level	Rural residents' *per capita* consumption expenditure on transportation and communication/Yuan	0.0312
	Information Technology Services	Total amount of telecommunication services/yuan	0.0925
	Smartphone Penetration Rate	Average number of cell phones per 100 rural households/unit	0.0991

Labor mismatch is a key structural issue that hinders the effective circulation and optimal use of agricultural land resources. This problem is evident in the persistence of a large number of low-efficiency workers in agriculture and rural regions, leading to underutilization of land and dampening both the motivation and scale of land transfer (Wang and Ran, 2022). Traditionally, barriers such as limited information access, inadequate employment services, and uneven urban-rural development restrict rural labor mobility, preventing the efficient reallocation of human capital across regions and industries (Wang and Ran, 2022).

The progress of rural digitalization offers a practical approach to addressing mismatches in rural labor allocation. On one side, digital platforms, online job services, and vocational training programs provide rural workers with more diverse and efficient means of accessing non-agricultural employment opportunities, thereby improving their capacity to seek jobs beyond their hometowns (Zhu et al., 2025). On the other side, the widespread adoption of digital infrastructure has strengthened the digital competence and information accessibility of rural residents, enabling households to respond more swiftly and adaptively to external labor market changes. Moreover, the digitization of public services and the refinement of social security systems have reduced institutional constraints on labor mobility, increasing farmers' willingness to leave agriculture without severing ties with their native communities (Liu, Weijiang and Hao, 2025). As labor outmigration accelerates, some rural residents withdraw from farming, freeing up land and boosting the supply of transferable land parcels. This facilitates the scaling up of land transfers and invigorates land markets. Consequently, the digital transformation of rural areas not only optimizes labor distribution across regions and sectors but also indirectly fosters land circulation through increased population mobility and the restructuring of production factors (Man-Yu and Xiao-Xing, 2022).

Hypothesis 2: Rural digital development promotes the level of agricultural land transfer by alleviating labor mismatch.

2.3 Rural digital development, land mismatch, and agricultural land transfer

Land mismatch is one of the important manifestations of the current low efficiency of agricultural resource allocation in China, which is specifically reflected in the irrational allocation of arable land resources, the rising proportion of abandoned land, and the serious fragmentation of land. TThe root causes lie in multiple factors such as information asymmetry, unclear land ownership, lack of transaction channels, and inconsistent perceptions of land use value among agricultural operators (Sun et al., 2022).

On the one hand, with the help of remote sensing, geographic information system (GIS) and other digital technologies, the precise identification and dynamic monitoring of land resources are realized, so that idle land and inefficiently utilized land can be incorporated into the transfer market in a timely manner; on the other hand, the digital platform enhances the visualization of land resources and the transparency of the transfer of land resources, and reduces the cost of matching between the supply and demand of land and the friction of the transaction (Huang and Ni, 2023). Therefore, rural digital development helps to alleviate the land mismatch problem by improving access to land information, enhancing the efficiency of land allocation, and optimizing the transfer mechanism, thus indirectly promoting the level of agricultural land transfer (Chen and Zhang, 2022).

Hypothesis 3: Rural digital development promotes the improvement of agricultural land transfer by alleviating land factor mismatch and thus promoting the improvement of agricultural land transfer.

2.4 Rural digital development, capital mismatch, and agricultural land transfer

Capital mismatch is one of the important factors restricting the efficient operation of the rural factor market, which is mainly manifested in the problems of insufficient supply of capital in the agricultural sector, restricted financing channels and the disconnection between the distribution of capital and actual demand. In the process of agricultural land transfer, operating entities often find it difficult to undertake new land due to insufficient capital, and potential land suppliers are reluctant to transfer land due to concerns about the lessee's lack of management ability, which in turn inhibits the activity of the land market and the scale of transfer (Chen et al., 2024).

The development of rural digital infrastructure has become a pivotal driver in mitigating capital mismatches within the agricultural sector by accelerating the digital transformation of rural financial systems. On the supply side, the widespread application of digital technology has significantly expanded the coverage of inclusive financial services, enabling agricultural entities to obtain more diversified and efficient financing channels *via* online platforms, thus easing capital constraints. Simultaneously, the integration of big data, artificial intelligence, and blockchain empowers financial institutions to conduct more precise assessments of farmers' credit profiles, land asset values, and operational capacities. This advancement enhances decision-making in credit allocation, optimizes risk management frameworks, and improves the efficiency of rural financial resource distribution. Moreover, the digital convergence of governmental and financial services further promotes the effective allocation and accessibility of agriculture-related funds, strengthening farmers' financial resilience and risk-bearing capacities in land transfer processes (Guo, 2024). Therefore, rural digitalization not only enhances financial accessibility and allocative efficiency but also fundamentally alleviates financing bottlenecks in agricultural production, thereby fostering the viability and sustainability of farmland transfer practices (Shen and Chen, 2021).

Hypothesis 4: Rural digital development contributes to the level of agricultural land mobility by mitigating capital mismatch and thus promoting agricultural land mobility.

2.5 Rural digital development, labor mobility, and agricultural land transfer

Labor mobility is one of the key drivers of agricultural land transfer. As the rural population transfers from agriculture to non-agricultural industries, the original farmers are no longer directly

TABLE 2 Variable definition table.

Symbol	Variable	Variable definition
fd	Agricultural land transfer	The ratio of the transferred area of household contracted farmland to the total area of household contracted farmland
dig	Rural digitalization	The entropy method is used to calculate the four dimensions of digital rural infrastructure, digitalization of rural economy, digitalization of rural governance, and digitalization of rural life
lre	Mismatch of land resources	$lre = (\frac{lre_i}{lre})/(\frac{s_i\beta_{ai}}{\beta_a})$
kre	Mismatch of capital resources	$kre = (\frac{kre_i}{kre})/(\frac{s_i\beta_{ai}}{\beta_k})$
bre	Mismatch of labor resources	$bre = (\frac{bre_i}{bre})/(\frac{s_i\beta_{ai}}{\beta_l})$
lab	migration	The proportion of employees in the secondary and tertiary industries to the total employed population in society
gdp	Per capita GDP	The regional GDP of each province divided by the number of permanent residents in the local area
rpo	Proportion of rural population	The proportion of rural population to the total number of permanent residents at the end of the year
wag	Proportion of agricultural water use	The proportion of total agricultural water consumption in the total social water consumption
dag	Degree of agriculturalization	The ratio of agricultural added value to regional gross domestic product
med	Agricultural machinery density	The ratio of total power of agricultural machinery to agricultural added value
psi	Proportion of primary industry	The ratio of added value of the primary industry to that of the secondary and tertiary industries

engaged in agricultural production, and their land resources holdings are gradually idled or inefficiently utilized, turning into the transfer market. This process not only releases the land supply, but also provides opportunities for specialized and large-scale agricultural management subjects to expand production, thus promoting the concentration and efficient use of agricultural land.

In this context, the advancement of rural digitalization has greatly facilitated labor mobility in rural areas by accelerating the establishment of information networks and expanding access to digital services (Cui and Feng, 2025). On the one hand, digital technologies have expanded rural laborers' access to non-farm employment information and improved their docking efficiency with the urban job market; on the other hand, digital platforms have lowered the cost of job matching and enhanced diversified forms of employment such as skills training, remote employment, and flexible employment (Liang et al., 2024). In addition, the digitization of government affairs and the improvement of the social security system have lowered the institutional barriers for migrant laborers in inter-regional migration, helping to increase their stability and willingness to go out for employment. As the rural labor force continues to move to the urban or non-farm sector, the separation of agricultural producers and land users has intensified, thus promoting farmers to transfer idle land to agricultural management bodies and realize the intensive use of land (Wang and Sun, 2023).

Hypothesis 5: Digital rural development indirectly enhances the level of agricultural land transfer by promoting rural labor mobility.

3 Research design

3.1 Variable selection

3.1.1 Explained variable

Agricultural land transfer (fd). This paper uses the ratio of the area transferred out of family-contracted cropland to the total area of family-contracted cropland area to measure agricultural land transfer. The use of this measure has strong scientific and rationality. This is because: first of all, the ratio can reflect the proportion of farmland owned by farmers for transfer, which can more accurately reflect the actual degree of land transfer, avoiding the scale bias brought about by the absolute area measurement. Secondly, measuring in the form of ratio can eliminate the interference caused by the differences in the total amount of contracted arable land among farmers, and make different farmers comparable to each other, which is convenient for horizontal comparison. Finally, this indicator can reveal the behavioral choices of farmers in the allocation of their own land resources, which helps to deeply understand the economic motivation and institutional influence behind their transfer behaviors. Therefore, the choice of this ratio indicator is both representative and practical, and also helps to improve the accuracy of land transfer research.

3.1.2 Explanatory variables

Current research lacks consensus on the evaluation system for rural digital development, with both single and composite indicators being employed. Single-index measurements often rely on variables such as the number of mobile devices used by farmers, while composite indices are typically constructed using methods like the entropy value approach or principal component analysis. Drawing on the methodologies of Lin et al. (2023) and Lei et al. (2023), this study establishes a multidimensional framework for assessing rural digital development across four aspects: digital infrastructure, digitalization of the rural economy, digital governance, and digital lifestyle. Based on data accessibility, 17 secondary indicators were selected and quantified using the entropy method. The construction of digital rural indicators is shown in Table 1.

3.1.3 Intermediary variable

3.1.3.1 Resource mismatch

From the perspective of resource factor allocation in the agricultural field, this paper focuses on the mediating role that agricultural resource factor mismatch may play between rural digital development and agricultural land transfer. Considering the diversity and structural characteristics of resource inputs in the agricultural production process, this paper classifies resource mismatches in three dimensions: i.e., land resource mismatch (lre), capital resource mismatch (kre) and labor resource mismatch (bre). This categorization aims to reveal more comprehensively the possible structural distortions in agricultural resource allocation and their potential impact on agricultural efficiency. In order to improve the scientificity and operability of the index, the construction of the resource mismatch index draws on the calculation method proposed by Chen et al. (2022), on the basis of which appropriate adjustments are made to better fit the data structure and analytical framework of the current study. The specific calculation methods for the indices are shown in Equations 1–3:

$$\mathrm{lre} = \left(\frac{\mathrm{lre_i}}{\mathrm{lre}}\right) \Big\backslash \left(\frac{\mathrm{s_i}\beta_{\mathrm{ni}}}{\beta_{\mathrm{n}}}\right) \tag{1}$$

$$\mathrm{kre} = \left(\frac{\mathrm{kre_i}}{\mathrm{kre}}\right) \Big\backslash \left(\frac{\mathrm{s_i}\beta_{\mathrm{ki}}}{\beta_{\mathrm{k}}}\right) \tag{2}$$

$$\mathrm{bre} = \left(\frac{\mathrm{bre_i}}{\mathrm{bre}}\right) \Big\backslash \left(\frac{\mathrm{s_i}\beta_{\mathrm{li}}}{\beta_{\mathrm{l}}}\right) \tag{3}$$

In this study, $\mathrm{s_i}\beta_{\mathrm{ni}}$, $\mathrm{s_i}\beta_{\mathrm{ki}}$, $\mathrm{s_i}\beta_{\mathrm{li}}$ are used to measure the input proportion of agricultural resource factors under optimal allocation, corresponding to the three categories of land, capital and labor, respectively. These parameters reflect the reasonable proportion that each resource should occupy under the condition of efficiency maximization. Meanwhile, the proportion of province i's agricultural output in the national agricultural output is also introduced into the model to reflect its relative importance in the national agricultural production. All the agricultural output data involved have been substantively adjusted by the GDP deflator to eliminate the interference of price changes and ensure the comparability of the data. In addition, β_{ni}, β_{ki}, β_{li} denote the output elasticities of land, capital, and labor, respectively, and these elasticity parameters are obtained through the estimation of the Cobb-Douglas production function, reflecting the marginal contribution of each factor to agricultural output. In order to measure the actual allocation of resources in each province, $\frac{\mathrm{lre_i}}{\mathrm{lre}}$, $\frac{\mathrm{kre_i}}{\mathrm{kre}}$, $\frac{\mathrm{bre_i}}{\mathrm{bre}}$ are also used to indicate the share of the province's land, capital, and labor inputs in the national total of the

TABLE 3 Descriptive statistics of variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
fd	360	32.706	16.883	3.353	91.111
dig	360	0.123	0.094	0.015	0.659
gdp	360	5.868	3.063	1.602	18.999
rpo	360	0.399	0.121	0.104	0.65
wag	360	0.596	0.182	0.065	0.952
dag	360	0.032	0.041	0.003	0.159
med	360	0.652	0.235	0.252	1.387
psi	360	0.112	0.068	0.002	0.348

corresponding factor inputs. Specifically, land resources are measured by the sown area of crops, capital is measured by the agricultural capital stock, which is estimated by the Perpetual Inventory Method (PIM), and labor resources are represented by the number of people employed in agriculture, which reflects the actual level of manpower inputs in each province. This method helps to systematically analyze the spatial distribution of agricultural resource mismatch and its impact mechanism.

3.1.3.2 Labor mobility (lab)

Labor force mobility is measured using the ratio of employees in secondary and tertiary industries to the total employed population of the society in the statistical yearbooks of each province and city. There is a strong rationality in using this ratio for measurement. In the process of China's economic structural transformation, the transfer of labor from the primary industry to the secondary and tertiary industries is the main manifestation of the flow of agricultural labor, and is also an important symbol for measuring the degree of non-agriculturalization of the rural labor force, urban-rural integration, and industrial upgrading. Compared with other measurement methods, this indicator can reflect more intuitively the trend of labor transfer from traditional agricultural sector to non-agricultural industry in each region, which in turn reflects the optimization degree of labor resources allocation.

Labor force mobility is assessed through the proportion of workers engaged in secondary and tertiary sectors relative to the total employed population, based on data from provincial and municipal statistical yearbooks. This metric is highly appropriate, as during China's economic restructuring, a key indicator of agricultural labor migration is the shift from primary to secondary and tertiary industries. It also serves as a crucial measure of rural labor non-agriculturalization, urban-rural integration, and industrial advancement. Compared with alternative metrics, this ratio offers a clearer depiction of regional labor movement away from agriculture toward non-agricultural sectors, thereby highlighting the efficiency of labor resource allocation. The variable definition table is shown in Table 2.

Table 3 presents the descriptive statistical results of the variables, reflecting significant differences in rural digital development and agricultural land transfer between provinces. The average agricultural land transfer rate (fd) is 32.71%, but the maximum value is as high as 91.11% and the minimum is only 3.35%, indicating that there is a significant difference in the level of land transfer activity among different regions; The average value of the Digital Development Index (Digi) for rural areas is 0.123, with a standard deviation of 0.094, indicating a relatively low overall development level and significant regional imbalances in development. The average *per capita* regional gross domestic product (GDP) is 5.868, indicating uneven levels of economic development across different regions. The average proportion of rural population (rpo) is 39.9%, and agriculture still has a large population base. The average proportion of agricultural water use (wag) is 59.6%, indicating a strong dependence on water resources in agriculture; The degree of agriculturalization (dag) is relatively low, averaging only 3.2%; The density of agricultural machinery (med) and the proportion of the primary industry (psi) also show significant fluctuations. Overall, there is strong regional heterogeneity among variables, providing a solid mathematical foundation for subsequent analysis of how rural digital development affects agricultural land transfer.

3.2 Model building

3.2.1 Baseline regression model

In order to empirically analyze the actual effects of rural digital development on agricultural land transfer, this paper constructs and adopts a fixed-effects regression model that includes both time and individual dimensions. The model helps to accurately identify the effects brought about by rural digital development on the basis of controlling time-invariant individual characteristics and cross-individual invariant time factors. The specific measurement model setting is shown in Equation 4:

$$fd_{i,t} = \beta_1 dig_{i,t} + \beta_2 gdp_{i,t} + \beta_3 rpo_{i,t} + \beta_4 wag_{i,t} + \beta_5 dag_{i,t} + \beta_5 med_{i,t} + \beta_6 psi_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t} \quad (4)$$

Where $fd_{i,t}$ is the explanatory variable of this paper, i.e., agricultural land transfer, $dig_{i,t}$ is the explanatory variable of this paper, i.e., denotes digital rural construction, and the other variables are the selected control variables, u_i denotes the individual fixed effect, which is used to eliminate the effect of heterogeneity that is invariant across the research objects in the dimension of time, and ϱ_t denotes the time fixed effect, which controls for the macro temporal factors that do not change with the region and affect all the observed objects such as policies, economic cycles, *etc.*, α denotes a constant term, and $\varepsilon_{i,t}$ denotes a random perturbation term to reflect other random influences that cannot be explained by the model and is used to describe the error component.

3.2.2 Mediation effects model

In order to deeply study how rural digital development affects the internal mechanism of agricultural land transfer, this paper further introduces a mediated effects model to analyze the possible intermediate transmission paths. This paper draws on Wen (2014) view that the traditional single mediation effect test method has certain limitations and is prone to biased estimation or insufficient significance. Therefore, this paper introduces a more advanced mediation effect test strategy based on the classic mediation test method of Baron and Sobel. This method has

TABLE 4 Benchmark regression results of digital rural construction on agricultural land transfer.

Variables	(1)	(2)
	fd	fd
dig	29.66***	23.90**
	(2.806)	(2.194)
gdp		−1.585*
		(−1.796)
rpo		119.6***
		(3.242)
wag		−13.71
		(−0.995)
dag		21.63
		(0.671)
med		−0.0397
		(−0.00697)
psi		−16.57
		(−0.343)
Individual fixed effects	Yes	Yes
time fixed effect	Yes	Yes
Constant	17.64***	−23.27
	(17.60)	(−1.257)
Observations	360	360
R-squared	0.677	0.725

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

significant advantages in statistical performance: on the one hand, it can improve the statistical efficacy (power) of the estimation results, thus enhancing the model identification ability; on the other hand, it can effectively control the first type of error rate (i.e., misjudging the existence of the mediation effect) and the second type of error rate (i.e., failing to find the real mediation effect), so as to improve the accuracy and reliability of the test. Based on the above considerations, this paper constructs the following regression modeling system, which is used to investigate the mechanism of rural digital development affecting agricultural land transfer. The specific econometric model settings are shown in Equations 5, 6:

$$lre_{i,t}/kre_{i,t}/bre_{i,t}/lab_{i,t} = \beta_1 dig_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t} \quad (5)$$

$$fd_{i,t} = \beta_1 dig_{i,t} + \sigma_1 lre_{i,t}/kre_{i,t}/bre_{i,t}/lab_{i,t} + \beta_2 Z_{i,t} + u_i + \varrho_t + \alpha + \varepsilon_{i,t} \quad (6)$$

where $lre_{i,t}, kre_{i,t}, bre_{i,t}, lab_{i,t}$ denote land resource mismatch, capital resource mismatch, labor resource mismatch, and labor mobility, respectively. The remaining variables are consistent with the benchmark regression.

In the above model setting, variables $lre_{i,t}$、$kre_{i,t}$、$bre_{i,t}, lab_{i,t}$ represent different dimensions of resource mismatch and labor force mobility, respectively: where $lre_{i,t}$ is used to measure land resource mismatch, $kre_{i,t}$ reflects capital factor mismatch, $bre_{i,t}$ indicates labor force resource mismatch, and $lab_{i,t}$ depicts the volume co-composition of labor force between urban and rural representations of the domain, and the rest of the control variables in the model are set to remain consistent with the baseline regression model for controlling the individual fixed effects, time trends and other key factors that may affect rural land use efficiency to ensure the robustness and explanatory power of the results.

3.3 Data sources

In order to ensure the availability and integrity of data, this paper selects the panel data of 30 provinces in Chinese Mainland (excluding Hong Kong, Macao, Taiwan and Xizang Autonomous Region) from 2006 to 2023, and constructs a research sample with a long time span and wide regional distribution. The collected data covers the output and input in the agricultural field, resource allocation status, and multiple control variables. Among them, the total output value of agriculture, forestry, animal husbandry, and fishery mainly comes from the "Statistical Yearbook of the Third Industry," while the input-output data and control variables related to agricultural production are respectively taken from the "China Statistical Yearbook" and the "China Rural Statistical Yearbook." To compensate for the lack of indicator data for some years and provinces, this article further consulted the statistical yearbooks of various provinces and the statistical bulletins publicly released by the government for supplementation and verification, in order to improve the coverage and consistency of the data. In terms of data processing, considering that price changes may affect the comparability of data between different years, this article uniformly uses 2010 as the base year to adjust the GDP deflator index for all variables related to prices or output values, converting them into actual values measured at constant prices in 2010, in order to more accurately reflect the actual fluctuation trend and economic structural characteristics of variables. This series of processing measures has laid a solid data foundation for subsequent empirical analysis.

4 Empirical result analysis

4.1 Baseline regression resultse

This section conducts an empirical analysis of how rural digital development influences agricultural land transfer, employing a two-way fixed effects model. Table 4 presents the regression outcomes. In column (1), without control variables, rural digital development shows a significantly positive effect on land transfer at the 1% significance level. Column (2), which includes control variables, still demonstrates a positive and significant coefficient at the 5% level, confirming that digitalization in rural areas contributes meaningfully to promoting land transfer. This effect

TABLE 5 Regression results of the impact of digital countryside construction on the sustainability of agricultural land transfer.

Variables	(1)	(2)	(3)	(4)	(5)
	fd	fd	fd	fd	fd
L.dig	31.89***				
	(2.929)				
L2.dig		44.14***			
		(3.483)			
L3.dig			59.63***		
			(3.924)		
L4.dig				83.10***	
				(4.390)	
L5.dig					124.4***
					(5.448)
gdp	−1.780**	−1.923**	−1.801*	−1.642	−0.967
	(−2.058)	(−2.083)	(−1.884)	(−1.603)	(−1.163)
rpo	126.0***	123.7***	110.4**	104.4*	41.96
	(3.388)	(2.994)	(2.300)	(1.775)	(0.668)
wag	−15.00	−21.33*	−20.29	−15.16	−9.571
	(−1.127)	(−1.763)	(−−1.675)	(−1.232)	(−0.817)
dag	25.88	29.58	28.75	20.35	10.25
	(0.792)	(0.901)	(0.917)	(0.615)	(0.343)
med	1.672	5.285	6.530	7.297*	14.54***
	(0.330)	(1.085)	(1.601)	(2.032)	(3.170)
psi	−28.68	−41.34	−34.70	−14.54	9.580
	(−0.591)	(−0.865)	(−0.693)	(−0.254)	(0.166)
Constant	−20.35	−10.83	−2.927	−3.904	9.873
	(−1.099)	(−0.574)	(−0.151)	(−0.179)	(0.452)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	330	300	270	240	210
R-squared	0.680	0.606	0.498	0.409	0.366

can be largely attributed to the enhanced transparency and efficiency brought by increased informatization. firstly, digital technology promotes the accurate management of agricultural land information. Through big data, cloud computing, Internet of Things and remote sensing technology, rapid monitoring, assessment and recording of land resources can be realized, providing reliable data support for agricultural land transfer. Second, the digital platform breaks down information barriers and shortens the information docking cycle between supply and demand. Farmers and investors can quickly release and obtain land transfer information on the digital platform to enhance the efficiency of land transfer. In addition, the application of blockchain and other technologies increases the transparency and security of land transactions and reduces the conflicts that may arise in the process of land transfer. Finally, rural digital development optimizes the rural financial service system and provides financial support for agricultural land transfer, such as land management right mortgage, which further stimulates the vitality of land transfer. In summary, digital rural construction has realized the standardization, scale and market-oriented development of land transfer through technological empowerment, and significantly promoted the process of agricultural modernization. Prove that hypothesis 1 of this article holds true.

4.2 Sustained impact of rural digital development on agricultural land transfer

The previous section found that the digital development of rural areas has a significant improvement effect on agricultural land transfer. As is well known, the digital development of rural areas is a long-term construction process, and there may be lag effects in this process, which may have a sustained impact on the transfer of agricultural land. Therefore, this section empirically tests whether the digital development of rural areas has a sustained impact on the transfer of agricultural land. Table 5 presents the empirical results. From the empirical results in Table 5, it can be seen that the coefficients for the lag period of rural digital development from one to five are significant at the 1% level, indicating that rural digital development does have a sustained impact on agricultural land transfer. From the regression results of the lag period, it can be seen that the impact of rural digital development on agricultural land circulation shows a significant and continuous strengthening trend, reflecting the lag and cumulative effects of digital construction in activating the flow of land factors. This result reflects in terms of economic connotation that empowering agricultural land transfer with digital technology is not achieved overnight, but rather a gradual process from infrastructure construction to institutional reform and then to market behavior evolution. Firstly, in the short term, although the improvement of digital infrastructure and the initial establishment of platforms have increased the accessibility of land resource information, their impact on the decision-making of land supply and demand behavior still needs time to gradually manifest. Secondly, with the passage of time, the promotion of digitalization on the transfer of agricultural labor, improvement of resource mismatch, and standardization of transfer systems has gradually accumulated, thus releasing stronger promotional effects in the second, third, and even longer periods. For example, as farmers obtain more non-agricultural employment opportunities, their willingness to withdraw from land increases, and new business entities also have stronger land absorption capabilities supported by digital finance and platform matching, thereby promoting the steady expansion of transfer scale. In addition, the government's supervision and standardization of land transfer behavior through digital government systems also have obvious institutional lag characteristics, and it will take some time to translate into sustained improvement in transfer efficiency and farmer trust. Therefore, the digital development of rural areas, through multiple paths of information integration, institutional support, and behavioral incentives, has a sustained impact on the gradient enhancement of agricultural land circulation in multiple lag periods, demonstrating its strategic significance as an institutional infrastructure in the construction of rural land markets.

The main reason is that it has restructured the allocation of rural land resources. Firstly, the vigorous development of digitalization in rural areas, such as big data, blockchain, cloud computing, *etc.*, has made land resource information transparent, real-time, and accurate, providing a solid foundation for predicting the true value of agricultural land and more scientific circulation. Secondly, digital platforms have effectively broken down the information barriers between land supply and demand, achieving efficient integration and significantly improving the matching efficiency and market vitality of land transfer. At the same time, the government relies on digital government platforms to strengthen the supervision of land transfer behavior, promote process standardization and information traceability, and enhance the safety of land transfer and the trust of farmers. In addition, the embedding of digital finance, such as land management rights mortgage loans and other services, provides farmers with new financing channels, reduces economic pressure, and promotes the transformation of land circulation from passive to active. Finally, the digital development of rural areas has attracted new types of agricultural management entities to flow to rural areas, promoting the development of agriculture towards scale and intensification, and further stimulating the long-term stable demand for land transfer. In summary, the digital countryside has built a new ecology for the sustainable development of agricultural land circulation through multi-dimensional construction.

TABLE 6 Endogeneity test regression results.

Variables	(1)	(2)
	dig	fd
internet	0.0534***	
	(11.80)	
dig		61.54***
		(5.644)
gdp	0.0209***	1.090**
	(10.54)	(2.186)
rpo	−0.1120**	−45.36***
	(−2.34)	(−4.497)
wag	0.0737***	−20.27***
	(3.30)	(−5.994)
dag	0.339***	10.40
	(5.61)	(0.572)
med	0.0306**	−10.18***
	(2.64)	(−4.452)
psi	−0.2708***	13.67
	(−4.36)	(0.761)
Constant	−0.384	53.65***
	(−9.91)	(9.088)
Individual fixed effects	Yes	Yes
time fixed effect	Yes	Yes
Kleibergen Paaprk LM	139.212 [0.000]	
Cragg-Donald Wald F	247.505 [16.38]	
Observations	360	360
R-squared		0.657

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

TABLE 7 Indicator construction of rural digital development.

Primary indicators	Secondary indicators	Tertiary indicators	Definitions
Digital Rural Development	Rural Digital Infrastructure Development	Rural Internet Penetration	Rural broadband access subscribers/number of rural households
		Rural Smartphone Penetration Rate	Cell phone ownership per 100 rural households per year
		Agricultural Meteorological Observation Operations	Number of agricultural meteorological observation stations
	Digitalization of Rural Industries	Scale of Agricultural Digitization	Value added of digital economy in primary industry
		Agricultural digitalization transaction	Rural e-commerce sales and purchases
		Agricultural Production Investment Effort	Investment in fixed assets in agriculture, forestry, animal husbandry and fishery/total investment in social fixed assets
	Rural Digital Industrialization	Rural network payment level	Rural digital financial inclusion index
		Rural Information Technology Application	Average population served per business outlet
		Rural digital industry base	Number of Taobao villages

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

4.3 Endogeneity test

Although this paper can alleviate the possible endogeneity problem to a certain extent by selecting regional gdp *per capita*, rural population, and agricultural machinery density as control variables to be added into the model, the reverse causality between rural digital development and agricultural land transfer may also lead to endogeneity. On the one hand, there may be an endogeneity problem between rural digital development and agricultural land transfer (Shan et al., 2022). Agricultural land circulation may be affected by local digital infrastructure, digital village governance, and so on, and also affects the level of regional digitization, and there may be an interaction between the two. The rapid improvement of agricultural land transfer can easily obtain the economic effect of rural digital development, which can further promote agricultural land transfer. On the other hand, from the perspective of government governance, provinces with slower agricultural land flow receive more attention from the government and may receive more resources and digital governance information. Therefore, there may be an endogeneity problem between rural digital development and agricultural land transfer.

To address potential endogeneity, this study adopts the approach of Lin et al. (2023), using the average rural digital development level of neighboring provinces as an instrumental variable. Neighboring regions often share similar geographic, policy, and economic contexts, making their digital development levels correlated with that of the target province, thus satisfying the relevance condition. At the same time, their digital progress is unlikely to have a direct impact on the province's rural economic or social outcomes, fulfilling the exogeneity requirement. Therefore, this variable serves as a valid instrument for rural digital development.

Table 6 presents the regression outcomes of the endogeneity test. Column (1) reports the first-stage results, where the coefficient of the instrumental variable is significantly positive at the 1% level, confirming a strong association. Column (2) displays the second-stage regression, showing that both the null hypothesis of under-identification and the presence of weak instruments are rejected. Even after accounting for endogeneity, rural digital development continues to exhibit a significantly positive effect, aligning with the findings of the baseline regression.

4.4 Robustness tests

4.4.1 Replacement of explanatory variables

In the previous paper, we constructed the indicators of rural digital development from four dimensions, in order to have a more reasonable measurement, we refer to the research methods of Wang and Bai (2022) and Fan et al. (2025), and re-measure the rural digital development from three dimensions and measure it using the entropy value method. The specific construction indicators are shown in Table 7.

Column (1) of Table 8 presents the regression results using an alternative explanatory variable. The coefficient of rural digital development remains significantly positive at the 5% level, confirming the robustness of the findings. This consistency arises because, despite variations in measurement methods, different indicators of rural digital development commonly reflect key aspects such as infrastructure, information services, and digital applications. As a result, they offer a coherent and reliable representation of the true level of rural digital advancement.

4.4.2 Shrinking tail

In order to demonstrate again the robustness of the conclusions of this paper, the indentation process is carried out in this section, with the main purpose of reducing the impact of extreme values on the regression results. In the data counted, there are inevitably individual observations that may appear abnormal due to

TABLE 8 Robustness test.

Variables	(1)	(2)	(3)	(4)
	fd	fd	fd	fd
dig1	40.59**			
	(2.481)			
L.fd				
dig		24.44*	32.70**	9.735***
		(1.971)	(2.735)	(8.691)
gdp	−1.755*	−1.719*	−1.545	−1.154
	(−2.018)	(−2.037)	(−1.542)	(−0.947)
rpo	113.0***	115.9***	84.50	98.83**
	(3.002)	(3.232)	(1.402)	(2.521)
wag	−14.99	−14.71	−14.64	−16.41
	(−1.070)	(−1.101)	(−0.793)	(−0.980)
dag	23.12	23.67	8.194	29.91
	(0.718)	(0.737)	(0.226)	(1.225)
med	−0.454	0.177	3.208	−2.165
	(−0.0834)	(0.0311)	(0.458)	(−0.371)
psi	−17.05	−15.82	−14.85	−0.663
	(−0.358)	(−0.326)	(−0.287)	(−0.0171)
Constant	−19.02	−20.83	−14.67	−13.17
	(−0.989)	(−1.183)	(−0.490)	(−0.640)
Individual fixed effects	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes
Observations	360	360	312	270
R-squared	0.727	0.723	0.698	0.787

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

TABLE 9 Heterogeneity in East, Central and West regions.

Variables	(1)	(2)	(3)
	East	Central section	West
dig	16.46	169.8*	95.09***
	(1.714)	(2.120)	(4.026)
gdp	−1.467	3.695**	1.488**
	(−1.615)	(2.527)	(2.292)
rpo	67.41	−167.3	192.9**
	(1.445)	(−1.183)	(2.267)
wag	−21.71	82.88	−74.66***
	(−1.278)	(1.851)	(−3.302)
dag	21.51	21.95	−85.11
	(0.416)	(0.537)	(−1.571)
med	−8.629	19.82***	24.49
	(−1.582)	(4.091)	(1.686)
psi	135.3	−31.87	141.8
	(1.774)	(−0.775)	(1.702)
Constant	13.32	48.00	−75.03
	(0.558)	(0.730)	(−1.364)
Individual fixed effects	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	132	96	120
R-squared	0.844	0.870	0.708
Number of cnty	11	8	10

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

statistical errors, and these extreme values may cause bias in the overall estimation results and affect the robustness of the conclusions. Therefore, by shrinking the upper and lower 1% for rural digital development and agricultural land transfer, the interference of outliers can be effectively reduced to ensure that the estimation results are more representative and reliable. Column (3) of Table 8 shows the regression results after shrinking the tails. From the results, the coefficient of rural digital development on agricultural land transfer is significantly positive at the 10% level, indicating that the conclusions of this paper are robust.

4.4.3 Exclude municipalities directly under the central government

Given that China's four centrally administered municipalities differ markedly from other provinces in administrative status, economic structure, fiscal capacity, and digital development level, their inclusion may introduce sample heterogeneity. As highly urbanized entities, these municipalities often benefit from concentrated resources and stronger policy backing in advancing rural digitalization, potentially skewing the overall estimation. To test the robustness of the findings, this section excludes the four municipalities and re-estimates the model. The results, presented in column (4) of Table 8, indicate that rural digital development continues to have a significantly positive effect on agricultural land transfer at the 5% level, further validating the reliability of the paper's conclusions.

4.4.4 Exclude abnormal years

Since 2020, the COVID-19 pandemic has had a profound impact on various aspects of China's socio-economic landscape, particularly in rural areas. It disrupted digital infrastructure development, limited information accessibility, altered industrial structures, and placed additional pressure on public finances. In response, governments at all levels implemented a range of extraordinary

measures, including substantial fiscal investments and the rapid establishment of digital emergency management systems. These interventions may have temporarily altered the trajectory and spatial characteristics of rural digitalization. Furthermore, heightened data volatility and reduced availability during the later stages of the pandemic could compromise the accuracy of empirical analysis. To mitigate such distortions, this study confines the robustness test to the pre-pandemic period of 2006–2019, a phase of relative stability. As shown in column (5) of Table 8, the coefficient for rural digital development remains significantly positive at the 1% level, further confirming the robustness of the results.

4.5 Heterogeneity analysis

4.5.1 Regional heterogeneity

To explore potential regional differences in the effect of rural digital development on agricultural land transfer, China is divided into eastern, central, and western regions. This classification reflects notable disparities in economic status, social structure, infrastructure, and the extent of digitalization. The eastern region typically features more advanced economies, higher urbanization rates, and stronger digital and information infrastructure, with notable progress in rural digital initiatives. In contrast, the central and western areas, where agriculture remains a key sector, lag in economic and technological development, and face more obstacles in advancing digital transformation. The central region has received more policy support in recent years and has greater development potential, but the overall level is still lower than that of the east; while the western region is affected by geographic conditions and historical development differences, and has a weaker foundation for digital construction. Therefore, it is divided into east, center and west.

The detailed regression outcomes are presented in Table 9. According to the findings, rural digital development has a statistically significant impact on agricultural land transfer in the central and western regions—at the 10% and 1% levels, respectively—but shows no notable effect in the eastern region. This disparity may stem from the eastern region's already advanced economic development and high informatization level, where digital infrastructure is long-established and mature. Consequently, the scope for further improvement through digital development is limited, reducing its influence on land transfer activities.

In contrast, the central and western regions have historically lagged in development, with agriculture still playing a major role in the economy. These areas tend to rely on traditional land systems and face more pronounced issues such as information asymmetry and high transaction costs. Strengthening digital infrastructure in these regions can greatly improve transparency and coordination in the land transfer market, cut down transfer costs, and enhance land resource allocation efficiency, thereby more effectively facilitating land transfers.

Moreover, recent policy efforts have prioritized digital rural development in these less developed regions. This policy focus has accelerated the expansion of digital services and infrastructure, further amplifying the positive effects on agricultural land transfer. Therefore, the heterogeneity analysis highlights that digital rural initiatives have a more significant influence in the central and western areas, underscoring the varying policy impacts across regions due to differences in development conditions and policy responsiveness.

4.5.2 Yangtze River economy

To further investigate the regional heterogeneity in the influence of rural digital development on agricultural land transfer, we classify regions based on whether they fall within the Yangtze River Economic Belt. This classification is grounded in the Belt's distinctive role in China's economic and regional development. Stretching across multiple provinces, the Yangtze River Economic Belt encompasses some of the most dynamic and interconnected areas in the country. As a strategically prioritized zone, it generally outpaces other regions in infrastructure, industrialization, policy support, and digitalization—factors that highlight its greater potential in advancing rural digital initiatives.

Accordingly, we perform an empirical analysis using this regional division. The regression results, presented in Table 10, reveal that rural digital development significantly influences agricultural land transfer in provinces along the Yangtze River Economic Belt at the 5% significance level, while such influence is statistically insignificant in provinces outside the Belt. This demonstrates a clear heterogeneity in the impact of rural digital development based on regional classification.

Several factors may account for this variation. Provinces within the Yangtze River Economic Belt typically enjoy more advanced digital infrastructure, higher levels of informatization, and more robust governmental backing for rural digital transformation. The relatively rapid urbanization in this area, along with more developed rural land markets and wider digital applications, facilitates smoother land transfers. Additionally, the region's efficient transportation, logistics networks, and streamlined information flows help lower transaction costs and reduce information asymmetries in land transactions.

Thus, the stronger effect observed in the Yangtze River Economic Belt likely stems from its comprehensive digital readiness, economic maturity, and targeted policy support. These elements together enhance the spillover benefits of digital rural development, accelerating the evolution of the agricultural land transfer market in these areas.

4.5.3 Different levels of rural digital development

In order to comprehensively identify the potential differential impacts of rural digital development on agricultural land transfer, this section introduces panel quantile regression method for empirical testing. Compared with traditional OLS methods, quantile regression can estimate the marginal effects of the dependent variable at different distribution positions of the independent variable, thereby capturing the heterogeneous effects that may exist between variables under different conditions. Specifically, this article divides rural digital development into different levels of development for quantile analysis, aiming to systematically explore the distribution effects of rural digital development on agricultural land transfer and further explore its role characteristics at different stages of development.

The regression results are shown in Table 11. According to the estimation results, when the rural land transfer rate is at the 10%,

TABLE 10 Heterogeneity test whether in the Yangtze River Economic Belt.

Variables	(1)	(2)
	In the Yangtze River Economic Belt	Not in the Yangtze River Economic Belt
	fd	fd
dig	35.25**	−13.28
	(2.675)	(−0.702)
gdp	−1.933*	−1.273
	(−2.093)	(−0.488)
rpo	126.9**	67.51
	(2.534)	(0.749)
wag	−24.91	−11.65
	(−1.646)	(−0.431)
dag	−7.760	192.0*
	(−0.230)	(2.177)
med	−1.283	1.000
	(−0.212)	(0.114)
psi	24.85	−232.1*
	(0.561)	(−2.161)
Constant	−23.71	19.65
	(−0.940)	(0.650)
Individual fixed effects	Yes	Yes
time fixed effect	Yes	Yes
Observations	228	132
R-squared	0.759	0.770
Number of cnty	19	11

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

30%, and 50% percentile, the digital development of rural areas has a significant positive impact on agricultural land transfer, and the regression coefficient is statistically significant; This indicates that in the regions corresponding to these quantiles, rural digital construction can effectively improve land transfer rates and promote the reallocation of land resources. However, when the land transfer rate is at the high percentile of 70% and 90%, the impact of rural digital development on land transfer is no longer significant, and the regression coefficient tends to decrease or even lose statistical significance, indicating that the marginal promotion effect of digital policies in high-level development areas is no longer significant.

The reason for this result may lie in the phased characteristics of the level of digital development in rural areas. In regions where digitalization is in its early stages or development, the introduction of digital technology can greatly improve information asymmetry, reduce land transfer transaction costs, enhance farmers' willingness to participate, and significantly increase land transfer rates due to outdated information infrastructure, closed market information, and poor circulation channels. The policy promotion and infrastructure investment in this stage can quickly take effect, and the activation effect on the land market is particularly evident. However, in areas where the level of digital development in rural areas is already high, such as developed provinces along the eastern coast or pilot demonstration areas, the relevant infrastructure is relatively complete, the degree of institutionalization of land transfer markets is high, and the efficiency of information acquisition and matching among farmers has become mature. In this situation, the marginal contribution of further improving the level of digitization to land transfer becomes limited, exhibiting a typical diminishing marginal effect phenomenon.

From an economic perspective, this quantile regression result reveals that the impact of rural digital development on land circulation has stage and level characteristics. Digital technology plays the most significant role in filling the gap in the initial stage of imperfect market mechanisms, while in an environment where market mechanisms have matured, its "efficiency" space gradually narrows. This discovery has important implications for the formulation of relevant policies: in promoting rural digitization, the government should adhere to differentiated and precise policy guidance, focus on supporting the central and western regions and underdeveloped areas with low land transfer rates and low market activity, accelerate the construction of digital infrastructure and service capabilities, in order to maximize policy effectiveness; At the same time, for regions with higher levels of development, more attention should be paid to the integration of digitalization and institutional innovation, avoiding duplicate investment and resource waste, and promoting the formation of a sustainable and balanced digital rural pattern.

In summary, the empirical results of quantile regression not only verify the heterogeneous impact of rural digital development at different stages of development, but also provide empirical evidence on the trend of marginal effect changes, which helps us to better understand the differential impact paths of digital policies on land system reform and rural revitalization strategy implementation.

4.5.4 Differences in levels of economic development

To examine how varying economic development levels across provinces might influence the outcomes, this section categorizes regions into two groups—high and low economic development—based on the median *per capita* GDP. Given the stark contrasts in resource endowments, institutional settings, market maturity, and agricultural structures across regions, this classification facilitates a more nuanced understanding of the differential impacts of rural digitalization under diverse economic conditions.

The empirical evidence is presented in Table 12. Regression results indicate that rural digital development significantly promotes agricultural land transfer in both groups at the 5% significance level. However, the effect is more pronounced in provinces with lower economic development. This may be attributed to several factors. First, less developed areas tend to suffer from limited access to land

TABLE 11 Heterogeneity of different rural digital development levels.

Variables	(1)	(2)	(3)	(4)	(5)
	10%	25%	50%	75%	90%
	fd	fd	fd	fd	fd
dig	25.91*	25.18**	24.08***	22.49	21.68
	(1.797)	(2.301)	(2.779)	(1.599)	(1.170)
gdp	−1.614	−1.603**	−1.588***	−1.565	−1.554
	(−1.619)	(−2.120)	(−2.651)	(−1.610)	(−1.213)
rpo	124.5***	122.7***	120.0***	116.1***	114.2**
	(3.447)	(4.476)	(5.528)	(3.296)	(2.459)
wag	−18.80	−16.94*	−14.16*	−10.10	−8.069
	(−1.414)	(−1.678)	(−1.770)	(−0.779)	(−0.472)
dag	15.99	18.05	21.12	25.62	27.88
	(0.477)	(0.709)	(1.048)	(0.783)	(0.647)
med	−0.914	−0.595	−0.118	0.579	0.928
	(−0.147)	(−0.126)	(−0.0317)	(0.0957)	(0.116)
psi	−36.13	−29.00	−18.33	−2.728	5.095
	(−0.978)	(−1.032)	(−0.822)	(−0.0756)	(0.107)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	360	360	360	360	360

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

transfer information, high transaction costs, and weak organizational frameworks. The integration of digital platforms in these regions can help dismantle information barriers, reduce costs, and enhance transaction efficiency—thereby yielding greater policy benefits and institutional improvements.

Second, traditional agriculture still dominates these areas, with low land use efficiency and substantial room for reallocating land resources more effectively. Digital technologies can significantly enhance land circulation and optimize resource use. In contrast, economically advanced regions already have well-established land markets, efficient transfer mechanisms, and high levels of informatization and market activity. Thus, the marginal contribution of rural digital development in these areas is limited. As a result, digital infrastructure plays a more transformative role in underdeveloped regions by facilitating the flow of land to more productive entities and significantly boosting land transfer activity.

4.5.5 High and low levels of total factor productivity

To assess how varying levels of total factor productivity (TFP) influence the effect of rural digital development, provinces are classified into two groups—high and low TFP—based on the median TFP value. As an indicator of the efficiency with which inputs such as land, labor, and capital are utilized in agricultural production, TFP reflects both the technological advancement and modernization level of a region's agriculture. This grouping facilitates the identification of heterogeneous effects across regions at different development stages and offers guidance for formulating more tailored policy interventions.

The empirical outcomes are presented in Table 13. According to the regression analysis, rural digital development has a statistically significant effect on agricultural land transfer in both high- and low-TFP areas, with coefficients significant at the 10% and 5% levels, respectively. Notably, the effect is stronger in regions with lower TFP. This heightened impact may be explained by the "bottleneck compensation" mechanism: in low-TFP areas, digital infrastructure can bridge existing gaps by improving information access, lowering transaction costs, and enhancing farmers' capacity to engage with external markets. These improvements help facilitate land mobility and more efficient resource allocation.

Conversely, in high-TFP provinces, where production systems and market mechanisms are already relatively mature, the additional benefits brought by digital tools tend to be marginal. As such, the effect of rural digital development on land transfer is comparatively weaker in these more advanced regions.

4.5.6 Urban-rural differences

In order to analyze whether the digital development of rural areas will have differential impacts on the transfer of urban and rural

TABLE 12 Heterogeneity of differences in the level of economic development.

Variables	(1)	(2)
	High level of economic development	Low level of economic development
	fd	fd
dig	18.92**	141.5**
	(2.363)	(2.651)
gdp	−2.625**	−1.535
	(−2.503)	(−0.363)
rpo	151.6***	191.5***
	(3.781)	(3.938)
wag	−16.72	8.458
	(−1.109)	(0.388)
dag	57.31	29.04
	(1.361)	(0.791)
med	−0.652	3.296
	(−0.198)	(0.477)
psi	−28.90	23.22
	(−0.219)	(0.581)
Constant	−14.57	−105.5***
	(−0.798)	(−3.153)
Individual fixed effects	Yes	Yes
time fixed effect	Yes	Yes
Observations	180	180
R-squared	0.796	0.784
Number of cnty	29	25

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

land from the perspective of urban-rural differences. This article measures the heterogeneity of urban-rural structure based on the provincial panel data used in the paper and the existing variable of rural population proportion, and groups them according to the median rural population proportion. When the proportion of rural population to the total population is higher than the median of the sample, the province is considered a rural area; When the proportion of rural population is lower than the median of the sample, the provinces are urban areas.

The specific regression results are shown in Table 14. From the regression results, the effect of rural digital development on agricultural land transfer in urban areas is not significant, and the coefficient for agricultural land transfer in rural areas is significant at the 5% level. This indicates that the digital development of rural areas has a more significant impact on land circulation in rural areas. Possible reasons are: firstly, rural areas have a stronger dependence on digitalization and a greater marginal effect. In areas with a high proportion of rural population, traditional information dissemination and land transfer matching mainly rely on acquaintance networks or offline administrative means, and the problems of information blockage and high transaction costs are more prominent. The introduction of digital means such as online land trading platforms, digital government services, and remote finance in such areas can significantly improve the efficiency of land transfer and have stronger marginal effects. Therefore, the positive effect of rural digital development on land transfer is more significant in rural areas.

Secondly, rural land resources in urban areas are scarce and have limited circulation space. Urban provinces, due to their high level of urbanization and a large proportion of industrial and service industries, often have smaller rural areas and scarce land resources. The boundaries and demand space for agricultural land transfer are relatively limited, and even with the improvement of digitalization, the driving force for land transfer behavior may be constrained by the "land resource bottleneck." Thirdly, agriculture in urban areas is not dominant, and the diversification of land use weakens the motivation for land transfer. In urban dominated areas, agriculture is not the main source of income for non residents, and farmers have a lower willingness to engage in agricultural production, with insufficient incentives for land transfer. At the same time, some rural land is facing pressure to be converted to non-agricultural use, leading to a more non market driven "vacating" configuration of land transfer, and digital mechanisms are difficult to effectively intervene. Fourthly, policy resources should be more inclined towards rural areas. The current national rural digital development strategy (such as digital rural pilot projects, rural e-commerce projects, smart agriculture construction, *etc.*) often focuses on traditional agricultural provinces and rural population concentrated areas. Therefore, digital infrastructure, platform services, and institutional support are more centrally invested in rural areas, and the driving effect of digitalization on land factor flow is stronger in these areas.

4.5.7 Differences in industrial structure

Due to the vast territory of our country, there are significant differences in industries among different regions, and their industrial structures vary. These differences affect the use and value of land, as well as the way digital technology operates. If the industrial structure is not distinguished, it is possible to misjudge the role of digitalization in reforming the land system, leading to the failure or inefficiency of the "digitalization + land" policy. Therefore, in order to further verify the differential impact of industrial structure differences on rural digital development and land transfer, this article divides them into agricultural dominated regions: regions where the proportion of the primary industry is greater than 50%. Industrial dominated regions: regions where the proportion of the secondary industry is greater than 50%. Service oriented areas: areas where the proportion of the tertiary industry is greater than 50%.

The specific regression results are shown in Table 15. From the regression results, the effect of rural digital development on agricultural land transfer in agriculture dominated areas is

TABLE 13 Heterogeneity of total factor productivity differences.

Variables	(1)	(2)
	High total factor productivity	Low total factor productivity
	fd	fd
dig	17.70*	37.23**
	(1.864)	(2.630)
gdp	−1.936**	0.166
	(−2.398)	(0.0849)
rpo	146.0***	31.17
	(3.986)	(0.463)
wag	−23.23*	19.31
	(−1.814)	(0.773)
dag	−20.07	32.59
	(−0.467)	(0.839)
med	−8.704	5.555
	(−1.644)	(0.795)
psi	−12.75	15.03
	(−0.274)	(0.329)
Constant	−22.59	−16.58
	(−0.954)	(−0.635)
Individual fixed effects	Yes	Yes
time fixed effect	Yes	Yes
Observations	181	179
R-squared	0.698	0.774

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

significant at the 5% level, while its effect on industrial dominated areas and service-oriented areas is not significant. This indicates that the digital development of rural areas plays a more significant role in land transfer in agricultural dominated areas. Mainly due to the high dependence of agriculture on land. The application of digital technology in agriculture, such as intelligent agricultural machinery, precision planting, and agricultural technology service platforms, has improved the efficiency of large-scale operations, thereby enhancing the demand for centralized land transfer. Meanwhile, small farmers are more inclined to transfer their land to new agricultural management entities with technological and resource advantages when facing digital barriers. In areas dominated by industry and service-oriented owners, the rural economic structure has partially "de landed," and digital development is more focused on extending the industrial chain, building platforms, and non-agricultural employment. The core position of land in economic activities has weakened, so the driving effect of digitalization on land circulation is not significant.

5 Further analysis

5.1 Mechanism analysis of resource mismatch

5.1.1 Labor mismatch

Labor mismatch refers to the inefficient allocation of labor resources in the industry, region or skill dimension, which is often manifested in the fact that the rural labor force cannot effectively flow or fails to engage in positions that match their abilities. By providing information services, employment platforms, skills training and digital infrastructure, rural digital development can help break down information barriers and improve the efficiency of employment matching, thereby alleviating the labor mismatch problem. Given that labor may be a factor affecting the scale of agricultural land operation and transfer, for this reason, using it as a mediating variable helps to test how rural digital development indirectly affects land transfer through optimizing factor allocation.

Table 16 presents the results of the mediating effect test concerning labor mismatch. According to the regression in column (2), rural digital development has a significantly negative impact on labor mismatch at the 1% level, suggesting its effectiveness in mitigating such mismatches. In column (3), both rural digital development and labor mismatch exhibit statistically significant coefficients in relation to agricultural land transfer—at the 5% and 10% levels, respectively—indicating that labor mismatch functions as a mediating variable in this relationship.

This may be attributed to the role of digital tools in enhancing rural workers' access to employment information and broadening non-agricultural job opportunities, which encourages part of the agricultural labor force to exit farming and transfer land to more capable operators. Furthermore, digitalization strengthens ties between rural laborers and modern agriculture, improves both geographical and occupational mobility, and eases structural labor shortages in the agricultural sector. These improvements foster the conditions necessary for larger-scale land operations. Thus, by optimizing labor distribution, rural digital initiatives also facilitate more efficient land resource allocation. Prove that hypothesis 2 of this article holds true.

5.1.2 Land mismatch

Land mismatch is usually manifested in the fact that land is not allocated to the most capable farmers with the greatest potential for large-scale operation in accordance with the principle of efficiency, resulting in inefficient land utilization and insufficient incentives for agricultural production. By promoting informationization, digital services and the construction of land transfer platforms, the rural digital development effectively improves the information symmetry between land supply and demand sides, reduces transaction costs and optimizes the allocation efficiency of the land market. Therefore, the introduction of land mismatch as a mediating variable helps to test how rural digital development indirectly promotes the intrinsic mechanism of land transfer by improving the allocation of land resources.

Table 17 reports the mediating effect test results related to land mismatch. As shown in column (2), rural digital development exhibits a significantly negative coefficient on land mismatch at the 5% level, suggesting its capacity to reduce mismatches in land

TABLE 14 Heterogeneity test of urban-rural differences.

Variables	(1)	(2)
	城市	农村
	fd	fd
dig	26.01	48.90**
	(1.070)	(2.251)
gdp	−1.976	−0.629
	(−1.310)	(−0.807)
rpo	−52.87	191.2***
	(−0.557)	(4.387)
wag	−24.68	6.318
	(−1.333)	(0.420)
dag	171.9*	3.184
	(1.903)	(0.0775)
med	1.353	−5.112
	(0.206)	(−1.124)
psi	−225.2**	41.09
	(−2.367)	(0.723)
Constant	81.95	−60.23**
	(1.493)	(−2.336)
Individual fixed effects	Yes	Yes
time fixed effect	Yes	Yes
Observations	180	180
R-squared	0.763	0.802
Number of cnty	17	16

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

allocation. Column (3) further reveals that both rural digital development and land mismatch significantly affect agricultural land transfer at the 5% and 10% levels, respectively, implying that land mismatch acts as a mediating channel in this relationship.

This effect is primarily due to digital technologies enhancing the efficiency of land factor allocation. Through the establishment of information-sharing platforms for land transactions, the application of big data, and the use of remote services, digital villages have increased transparency in land markets and streamlined the transfer process. These efforts have contributed to a more market-oriented and precise allocation of land resources.

In addition, digital tools have reinforced oversight of land utilization, curbed underuse and inefficiency, and facilitated the reallocation of land to more productive operators. Thus, by mitigating land mismatch, rural digital initiatives not only improve the circulation of land elements but also enhance their overall allocation efficiency, promoting the orderly transfer of agricultural land. Prove that hypothesis 3 of this article holds true.

5.1.3 Capital mismatch

Capital mismatch primarily refers to the inability of agricultural entities to access financing aligned with their marginal productivity, largely due to information asymmetries, limited financial inclusion, and constrained lending channels. This restricts their capacity for production expansion and, in turn, hampers the efficient flow of land resources. Rural digital development—through the advancement of digital financial services, improved credit accessibility, and the optimization of capital supply—can bridge informational gaps between capital providers and users, thereby enhancing allocation efficiency. Introducing capital mismatch as a mediating factor allows for a more nuanced examination of how digital rural initiatives improve capital distribution and subsequently support land circulation.

Table 18 presents the results of the mediating effect analysis. Column (2) shows that rural digital development significantly reduces capital mismatch at the 5% significance level. In column (3), both rural digital development and capital mismatch exhibit significant coefficients in explaining agricultural land transfer, at the 5% and 10% levels, respectively—confirming the mediating role of capital mismatch.

This relationship may stem from the digital transformation of rural financial systems, which enhances farmers' access to financing—particularly for emerging agricultural enterprises—enabling them to acquire land and engage in scaled operations. Additionally, digital platforms have strengthened financial institutions' capacity to assess rural credit risks, directing credit resources toward more productive and creditworthy actors. This reallocation facilitates the aggregation of land into the hands of capable farmers, thereby raising land-use efficiency. In sum, by optimizing capital flows, rural digitalization not only activates agricultural productivity but also promotes the effective and orderly transfer of farmland. Prove that hypothesis 4 of this article holds true.

5.2 Labor force mobility

As a large number of rural laborers migrate and surplus labor declines, farmers increasingly prefer to lease their land to capable and specialized entities to achieve more efficient land utilization. The advancement of digital village initiatives has notably boosted rural labor mobility by offering more accessible employment information, promoting digital skill development, and expanding channels for working outside local areas. Consequently, using labor mobility as a mediating factor provides a framework to examine how digitalization in rural areas indirectly accelerates land transfer through the activation of population mobility.

Table 19 presents the empirical analysis of this mediating effect. In column (2), the coefficient for rural digital development on labor mobility is significantly positive at the 5% level, suggesting that digitalization fosters the movement of the rural workforce. Column (3) further demonstrates that both rural digital development and labor mobility have statistically significant impacts on land transfer—at the 5% and 1% levels respectively—highlighting labor mobility as a key intermediary. This outcome likely stems from enhanced access to online job platforms, remote employment opportunities, and vocational training, all of which enable rural

TABLE 15 Heterogeneity test of industrial structure differences.

Variables	(1)	(2)	(3)
	Agricultural dominated regions	Industrial dominated regions	Service oriented areas for homeowners
	fd	fd	fd
dig	41.84**	34.97	9.168
	(2.300)	(1.300)	(0.392)
gdp	−1.356	−1.332	−2.619
	(−1.078)	(−0.744)	(−1.560)
rpo	39.85	15.82	146.3*
	(0.315)	(0.102)	(2.099)
wag	−30.13	−35.92	−32.61
	(−1.705)	(−1.642)	(−1.396)
dag	−26.47	7.951	93.50
	(−0.606)	(0.0935)	(1.349)
med	2.913	−1.770	−6.205
	(0.342)	(−0.207)	(−0.581)
psi	−64.14	18.66	−154.5
	(−1.210)	(0.135)	(−0.837)
Constant	27.93	38.40	10.46
	(0.477)	(0.566)	(0.357)
Individual fixed effects	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	162	127	124
R-squared	0.762	0.756	0.750
Number of cnty	20	17	18

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

workers to shift away from farming to other sectors. As labor exits the agricultural field, the resulting labor shortage prompts farmers to contract out land to larger, more professional operators, facilitating land consolidation and efficiency. Thus, by reshaping the composition of the agricultural workforce, rural digital transformation indirectly propels the circulation and optimized use of land resources.

The digital development of rural areas has played a positive role in promoting labor mobility in various aspects, indirectly promoting the improvement of agricultural land transfer. Specifically, the improvement of digital infrastructure and the expansion of platform economy have provided more remote employment opportunities and non-agricultural positions for rural labor, such as e-commerce operations, online services, outsourcing processing, *etc.*, effectively expanding farmers' employment channels, reducing dependence on self owned farmland, and releasing more transferable land resources; At the same time, digital technology also provides convenient vocational skills training and information acquisition platforms for rural labor, enhancing farmers' employment ability and migration willingness, accelerating the transfer of rural labor to secondary and tertiary industries and urban areas, and further enhancing the driving force of land outflow. In addition, digital platforms have significantly improved the efficiency of land supply and demand matching by promoting efficient information integration between land resources and management entities; Technologies such as blockchain and big data have reduced transaction costs and risks in land ownership confirmation, contract signing, and credit evaluation, enhancing farmers' willingness and sense of security in land transfer. In summary, rural digitization indirectly promotes the effective circulation of agricultural land from multiple dimensions by promoting labor transfer, improving human capital levels, and optimizing the land market environment, providing strong support for the efficient allocation of rural land resources and the modernization of agriculture. Prove that hypothesis 5 in this article holds true.

TABLE 16 Mediating effect test o000f labor mismatch.

Variables	(1)	(2)	(3)
	fd	ler	fd
dig	23.90**	−0.259***	23.39**
	(2.194)	(−3.060)	(2.178)
ler			−1.612*
			(−1.789)
gdp	−1.585*	−0.0134	−1.991
	(−1.796)	(−1.284)	(−0.951)
rpo	119.6***	−0.0331	119.5***
	(3.242)	(−0.0784)	(3.226)
wag	−13.71	0.0603	−13.59
	(−0.995)	(0.394)	(−0.979)
dag	21.63	0.350	22.33
	(0.671)	(0.734)	(0.690)
med	−0.0397	−0.0163	−0.0722
	(−0.00697)	(−0.240)	(−0.0128)
psi	−16.57	−0.366	−17.29
	(−0.343)	(−1.134)	(−0.355)
Constant	−23.27	0.792***	−21.69
	(−1.257)	(3.901)	(−1.177)
Individual fixed effects	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	360	360	360
R-squared	0.725	0.230	0.726

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

TABLE 17 Mediating effect test of land mismatch.

Variables	(1)	(2)	(3)
	fd	dgmm	fd
dig	23.90**	−0.470***	24.37**
	(2.194)	(−3.090)	(2.259)
dgmm			−1.565*
			(−1.756)
gdp	−1.585*	−0.0200	0.987
	(−1.796)	(−1.504)	(0.590)
rpo	119.6***	−0.00805	119.6***
	(3.242)	(−0.0175)	(3.252)
wag	−13.71	−0.0202	−13.69
	(−0.995)	(−0.123)	(−0.993)
dag	21.63	0.122	21.51
	(0.671)	(0.318)	(0.667)
med	−0.0397	−0.110	0.0693
	(−0.00697)	(−1.267)	(0.0122)
psi	−16.57	−0.559	−16.01
	(−0.343)	(−1.470)	(−0.331)
Constant	−23.27	0.953***	−24.21
	(−1.257)	(4.718)	(−1.320)
Individual fixed effects	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	360	360	360
R-squared	0.725	0.304	0.725

Note: ***, **, * respectively indicate significance at the 1%, 5%, and 10% levels. The heteroscedasticity robust T-values adjusted for national level clustering are shown in parentheses.

6 Conclusions and policy recommendations

6.1 Conclusion

This article uses balanced panel data from 30 provinces in China from 2006 to 2023 to systematically analyze the impact and mechanism of rural digital development on agricultural land transfer. The research results indicate that the overall digital development of rural areas has significantly promoted the transfer of agricultural land and has strong sustainability. This conclusion remains robust after controlling for potential endogeneity issues and conducting various robustness tests. Further heterogeneity analysis shows that this driving effect is more significant in the central and western regions, the Yangtze River Economic Belt, and provinces with lower levels of economic development or total factor productivity, reflecting the potential of rural digitization in promoting regional coordinated development. Mechanism analysis further reveals that the digital development of rural areas has effectively promoted land circulation by alleviating the mismatch of labor, land, capital and other factors in agricultural production, optimizing resource allocation, and so on; At the same time, the construction of digital rural areas has accelerated the rational flow of rural labor and created a favorable environment for factor mobility. In summary, rural digitization is not only an important way to promote the market-oriented allocation of agricultural land factors, but also injects new development momentum into achieving rural revitalization and agricultural modernization.

6.2 Suggestion

6.2.1 Strengthening digital rural construction and strengthening the digital foundation of agricultural land transfer

Digital rural development is emerging as a key strategic approach to advancing agricultural and rural modernization, with

TABLE 18 Mediation effect test of capital mismatch.

Variables	(1)	(2)	(3)
	fd	ols	fd
dig	23.90**	−0.222***	23.14**
	(2.194)	(−3.024)	(2.123)
ols			−1.619*
			(−1.754)
gdp	−1.585*	−0.00970	−3.458
	(−1.796)	(−1.137)	(−0.386)
rpo	119.6***	−0.459	118.0***
	(3.242)	(−1.291)	(3.212)
wag	−13.71	−0.0102	−13.74
	(−0.995)	(−0.0978)	(−0.996)
dag	21.63	0.168	22.21
	(0.671)	(0.582)	(0.671)
med	−0.0397	−0.0603	−0.248
	(−0.00697)	(−1.452)	(−0.0442)
psi	−16.57	−0.465	−18.17
	(−0.343)	(−1.284)	(−0.356)
Constant	−23.27	1.086***	−19.51
	(−1.257)	(7.523)	(−0.986)
Individual fixed effects	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	360	360	360
R-squared	0.725	0.692	0.725

TABLE 19 Mediating effect test of labor mobility.

Variables	(1)	(2)	(3)
	fd	htd	fd
dig	23.90**	26.67**	23.71**
	(2.194)	(2.549)	(2.158)
htd			4.595***
			(6.644)
gdp	−1.585*	0.179	−1.586*
	(−1.796)	(0.174)	(−1.789)
rpo	119.6***	−74.18**	120.1***
	(3.242)	(−2.317)	(3.255)
wag	−13.71	54.99***	−14.11
	(−0.995)	(2.783)	(−1.008)
dag	21.63	123.9***	20.73
	(0.671)	(3.171)	(0.636)
med	−0.0397	−6.848	0.0100
	(−0.00697)	(−1.081)	(0.00175)
psi	−16.57	−49.47	−16.21
	(−0.343)	(−1.131)	(−0.337)
Constant	−23.27	63.29***	−23.72
	(−1.257)	(3.894)	(−1.293)
Individual fixed effects	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	360	360	360
R-squared	0.725	0.368	0.725

its role in enhancing resource allocation and agricultural productivity becoming increasingly evident. The study reveals that rural digitalization significantly facilitates agricultural land transfers, underscoring its growing influence in driving more efficient land use. To harness this potential, it is essential to reinforce the top-level design of digital strategies in rural areas, emphasizing strategic alignment and the integration of resources. Efforts should be made to ensure comprehensive deployment and effective use of information infrastructure, data systems, and smart technologies in rural regions. In particular, expanding rural broadband, IoT networks, satellite remote sensing, and other digital infrastructure—especially in central, western, and remote rural areas—will be crucial for improving connectivity and access to information. On the other hand, we should focus on deepening the application of digital functions, embedding digital technology into specific scenarios such as agricultural production, land management and labor mobility, and promoting "Internet + Agricultural Management," "Blockchain + Land Rights Confirmation," "Big Data + Land Monitoring" and other measures. Promote the implementation of "Internet + agricultural management," "blockchain + land rights confirmation," "big data + land monitoring" and other models. In addition, the investment in rural human capital should be strengthened, and farmers' knowledge and application of digital tools should be enhanced through regular training and skill certification, so as to narrow the "digital divide" and avoid the phenomenon of "digital exclusion." Through the construction of a wide-coverage, multi-level, strong synergistic digital rural ecosystem, it can provide a solid institutional foundation and technical support for agricultural land transfer, and improve the operational efficiency and service capacity of the rural land system.

6.2.2 Improve the agricultural land transfer system and promote the construction of a market-oriented allocation mechanism for land elements

This paper finds that the construction of digital countryside significantly improves the level of agricultural land transfer through multiple mechanisms, but the land transfer market itself is still facing constraints such as asymmetric information, unstandardized transactions, and insufficient legal protection. Therefore, it is necessary to take institutional construction as a hand to comprehensively improve the mechanism of agricultural land

transfer. First, the establishment of a unified and standardized land transfer information platform, the use of digital technology to realize the real-time release of land supply and demand information, matching and matching, to enhance the efficiency and transparency of the transaction. The second is to strengthen the registration and electronic management of land ownership, and improve the dynamic updating and cross-sector sharing mechanism of land ownership data, so as to reduce the transaction risks caused by unclear property rights. Third, promoting the standardization of land transfer contracts and the construction of a legal service system, providing both parties to the transfer with convenient and efficient legal consultation, dispute mediation and litigation services, and enhancing institutional trust and market vitality. Fourth, improve the land value assessment system and land financial support policies, and explore innovative modes such as land mortgages and pledge of income rights through financial technology means to enhance the financing function of land transfer. In addition, attention should be paid to the protection of the interests of farmers in the process of land transfer to prevent damage to the rights and interests of farmers caused by "involuntary transfer" or "adverse selection." By building a fair, efficient and safe land transfer market, we can better activate rural land resources and promote the optimal reorganization and efficient use of agricultural resource elements.

6.2.3 Strengthening the Government's role in resource allocation and forming a synergistic promotion mechanism

On the one hand, the evolution of rural digital development and land transfer system depends on the government's leading role in financial input, institutional supply and policy orientation. It is suggested that we should focus on financial support, policy innovation and institutional safeguard to enhance the government's governance capacity and guidance efficiency. Specifically, we should increase financial transfers to central and western regions and areas with weak rural infrastructure, and set up a special fund for the synergistic development of digital villages and land transfer, which can be used for infrastructure construction, technology promotion and talent training. At the policy level, cross-sectoral coordination should be strengthened, and data barriers and policy divisions in agriculture and rural areas, information and communication, natural resources, finance and financial services should be broken down to establish a synergistic mechanism for the policy of linking the construction of digital villages and the development of land circulation. In terms of system, we should promote the formulation and implementation of local laws and regulations to promote agricultural land transfer, clarify the boundaries of the rights and responsibilities of various types of subjects in the land transfer and the protection mechanism, and improve the operability and implementation of the system. At the same time, it is recommended to build a performance evaluation and incentive mechanism, set a quantifiable and traceable index system for digital rural development and land transfer, and incorporate it into the performance evaluation of local governments, so as to guide the local governments to strengthen the coordination and promotion of the integration of land system innovation and digital technology in their development strategies. By enhancing the government's system design capability and public service effectiveness, a multi-dimensional co-management pattern can be built up with government guidance, market-led, farmer participation and social synergy, providing strong support for the integration of the agricultural land system and the digital economy. Specifically, the construction of policy coordination mechanisms should start from the following aspects: firstly, the government should strengthen top-level institutional design, improve land transfer management regulations, promote local governments to formulate detailed measures tailored to local conditions, clarify land ownership confirmation, transfer procedure norms, contract performance supervision, and dispute mediation mechanisms. At the same time, a unified information service platform should be established to integrate land resources, policy information, and market supply and demand, and improve the transparency and service efficiency of the land transfer market. Secondly, fully leverage the role of market mechanisms, encourage the development of specialized intermediary service providers such as rural property rights trading centers and land custody companies, establish standardized price discovery mechanisms, and promote the market-oriented and standardized operation of land transfer; Simultaneously innovate land financial instruments to enhance the capital attributes of land management rights. Thirdly, it is necessary to fully safeguard the dominant position of farmers, promote the registration and certification of rural land rights, strengthen the predictability of farmers' land rights, and improve their awareness and participation in land transfer policies through policy promotion, skill training, and legal assistance. Finally, it is necessary to guide social forces to participate in collaborative governance, encourage social organizations, research institutions, digital platform enterprises, *etc.*, to provide technical support, policy consultation, and data services, and establish sound mechanisms for information disclosure, public opinion supervision, and risk warning. Through the coordination and cooperation of the above-mentioned multiple entities, a long-term mechanism for land transfer can be formed, which integrates interests, shares responsibilities, and jointly builds governance, thereby improving the efficiency of rural land resource allocation and the overall vitality of rural economy.

6.2.4 Promote regional differentiated development path and achieve precise implementation of regional policies

The heterogeneity analysis results of this article indicate that the digital development of rural areas has a more significant impact on agricultural land transfer in central, western, Yangtze River Economic Belt, and provinces with lower levels of economic development and total factor productivity. This discovery reveals the regional imbalance between digital rural development and land system reform, suggesting that policymakers should avoid a "one size fits all" policy expansion when promoting relevant strategies, and instead focus on building differentiated development paths. Firstly, for the central and western regions as well as economically underdeveloped provinces, rural digital development should be given priority deployment as a fundamental project, and efforts should be focused on breaking through key bottlenecks such as weak information infrastructure and shortage of technical services. On this basis, a collaborative mechanism between land transfer and rural factor integration should be explored. Secondly, for ecologically sensitive areas with relatively complete institutional foundations such as the Yangtze River Economic Belt, the integration of digital technology with ecological agriculture and green land use models can be focused on to promote the integrated

development path of "ecology + digital + system." Thirdly, for regions with low total factor productivity, digital means should be used to accelerate the reallocation of resources such as land, labor, and capital, improve agricultural production efficiency, and stimulate market vitality in land transfer. In addition, it is necessary to combine regional development strategies and functional positioning to clarify the functional boundaries and development priorities of digital rural areas and land transfer. For example, national grain producing areas focus on stabilizing the transfer order, while urban suburban areas focus on the development of urban agriculture and the extension of the industrial chain. By implementing precise, regional, and hierarchical policy combinations and mechanism innovations, it can effectively promote the deep integration of land system reform and digital strategies, and promote the efficient allocation of regional land resources and high-quality agricultural development.

6.2.5 The reference significance for other countries

Although this study uses China as an example for empirical analysis, digital development also has important reference value and practical significance for other countries, especially for developing economies. Firstly, the improvement of digital infrastructure is a key prerequisite for countries to promote economic modernization. There is still a significant digital divide between urban and rural areas, as well as between regions in many countries. It is recommended that governments increase investment in digital infrastructure according to local conditions and improve the penetration rate of digital access. Secondly, domestic enterprises should be encouraged to embrace digital technology, promote the digital transformation and innovation of traditional industries, and enhance overall industrial competitiveness. In addition, the shortage of digital talents is a global issue, and countries should strengthen education system and technical training reforms to cultivate a new type of workforce with digital skills. Finally, countries need to strengthen digital governance and international cooperation, develop unified data standards and cross-border regulatory frameworks to jointly address the opportunities and challenges brought by the digital economy. Through policy coordination and experience sharing, countries can achieve more inclusive and sustainable development in the global digitalization process.

7 Research limitations and future research directions

Firstly, in terms of research limitations, this article points out that due to the fact that the data used is mainly based on panel data at the provincial level, although it has a certain degree of wide representativeness, it is difficult to deeply reveal the specific impact of rural digitization on land transfer behavior at a more micro level (such as county, township, or farmer level), especially in terms of farmers' decision-making motivation, land transfer transaction costs, information acquisition methods, *etc.*, which lack direct observation. Therefore, there is a certain degree of "macro meso disconnect" in explaining the mechanism of the conclusion. Secondly, although the indicators of rural digital development used in the article are as comprehensive as possible, the indicator system constructed based on statistical yearbooks and public data may not fully reflect the true state of rural digital development, especially in measuring the quality and depth of digital use, which is still insufficient. In addition, although the empirical model of the article has undergone various robustness tests and endogeneity controls using instrumental variable methods, it may still be affected by unobserved variables (such as local policy implementation capacity, grassroots organizational efficiency, *etc.*), thereby affecting the external validity of the conclusions.

In terms of future research directions, the article may expand its research from two levels: first, strengthen micro level investigation research, especially using survey data from farmers or villages, to explore how digitalization affects farmers' willingness to transfer land, land pricing ability, and transaction matching efficiency through micro mechanisms, and further reveal the impact path; Secondly, from the perspectives of policy interaction and institutional environment, we will conduct in-depth research on the policy differences, land system arrangements, and the moderating effects of infrastructure investment on the digital effects of promoting digital rural construction by different local governments. In addition, the author also points out that further cross-country comparative research can be conducted to test the applicability and differences of the mechanism of rural digitalization promoting land transfer in different institutional environments and development stages, thereby enriching the theoretical connection and policy implications between digital agriculture and land system reform in developing countries.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

XW: Funding acquisition, Writing – original draft, Project administration, Conceptualization, Data curation.

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EDITED BY
Cunyi Yang,
Sun Yat-sen University, China

REVIEWED BY
Yingjun Qi,
China Agricultural University, China
Guijun Wang,
Beijing Institute of Technology, China

*CORRESPONDENCE
Chunlei Huang,
2101111212@stu.pku.edu.cn

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Inclusive land ecological benefits: assessing the eco-efficiency returns of China's green industrial policy based on a quasi-natural experiment

Yarong Li[1], Xinyou Xiao[2], Jiani Chen[2] and Chunlei Huang[3]*

[1]Xi'an University of Architecture and Technology Huaqing College, Xi'an, China, [2]School of Economics, Minzu University of China, Beijing, China, [3]School of Marxism, Guangxi University, Nanning, China

Green industrial policy (GIP) is a crucial instrument for driving a green, low-carbon transition. While prior research has predominantly examined its role in enhancing firms' green performance, its potential contribution to the ecological transformation of land use has been largely overlooked. This study uses panel data from 287 prefecture-level cities in China over the period 2007–2022 and employs a multi-period difference-in-differences (DID) framework, leveraging the quasi-natural experiment provided by the "Comprehensive Demonstration Cities for Energy Saving and Emission Reduction" pilot program, to investigate the impact of green industrial policy on urban land use eco-efficiency (ULUEE). Our findings show that GIP significantly improves ULUEE, and this result remains robust across various robustness checks. Mechanism analysis indicates that the policy stimulates urban green technological innovation and optimizes the energy consumption structure, both of which contribute to higher ULUEE. Heterogeneity analysis further reveals that the policy's positive effects are especially pronounced in resource-declining cities, small and medium-sized cities, old industrial base cities, cities with lower levels of scientific and educational development, and cities where public environmental concern is greater. These results imply that the ecological benefits of GIP are broadly inclusive, albeit contingent upon the public's environmental awareness. By examining GIP through the lens of land use, this paper uncovers its ecological value and offers a novel pathway for enhancing ULUEE.

KEYWORDS

green industrial policy, urban land use eco-efficiency, inclusive growth, green transformation, ecological value

1 Introduction

Over the past 40 years of reform and opening up, China has achieved remarkable economic growth through substantial resource investment and extensive industrial expansion. However, this has resulted in a development model marked by elevated energy consumption and significant emissions, facilitating short-term economic acceleration while confronting the long-term challenge of substantial ecological costs. In 2006, China overtook the United States to become the world's foremost carbon emitter (Zhang et al., 2017). Figure 1 illustrates the ongoing increase in carbon emissions and overall energy consumption within China's prefecture-level administrative units. China's coal

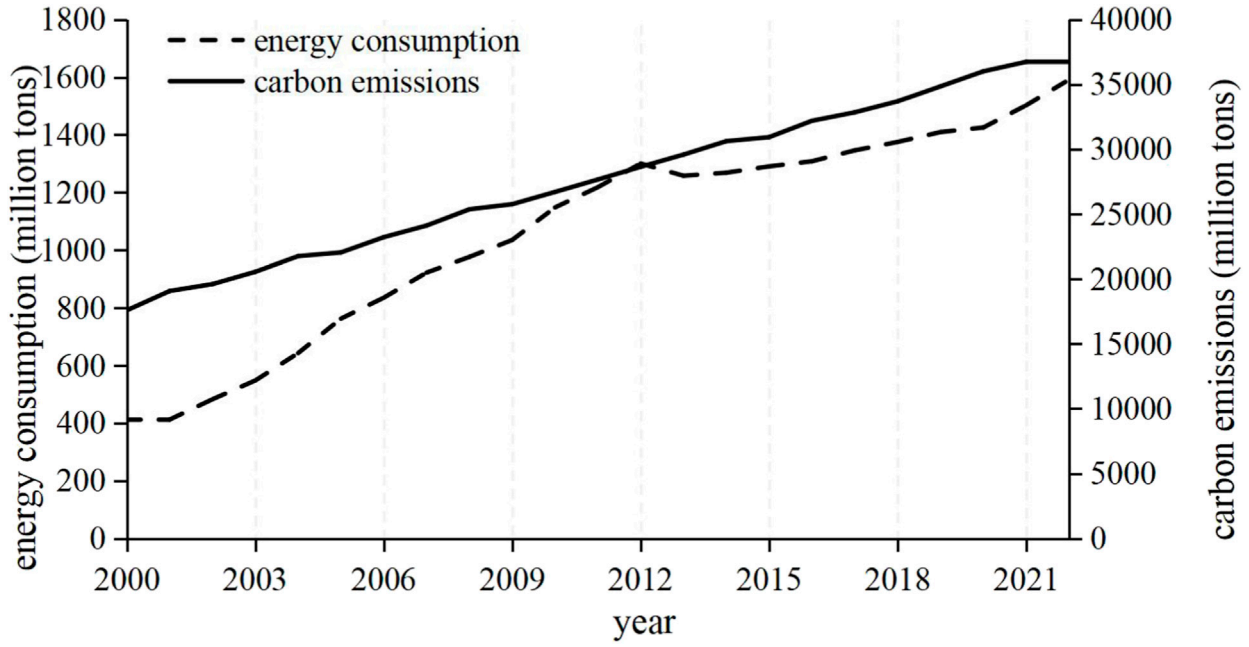


FIGURE 1
Variations in aggregate carbon emissions and overall energy usage in urban areas of China.

usage is 57.64% of total energy consumption, far surpassing that of the European Union (11.18%) and the United States (11.98%) (Zhao et al., 2022). Energy consumption per unit of GDP is 1.5 times the global norm, while energy intensity is 1.3 times the global average (Zhang et al., 2020), underscoring the dual challenge of energy use efficiency. This development pattern exhibits a dual negative impact in the spatial dimension. The extraction, transportation, and transformation of fossil energy sources like coal and oil result in ecological land encroachment, exacerbation of land pollution, and fragmentation of biological habitats, thereby impairing the ecosystem's self-repair capabilities (Haddad et al., 2015). Conversely, the unchecked growth of energy-intensive enterprises has exacerbated the inefficiency of industrial land utilization and contributed to issues of urban sprawl and irrational spatial organization (Seto et al., 2012), resulting in a misalignment of urban land resources. Inefficient land utilization consequently escalates energy consumption intensity due to redundant infrastructure development and heightened energy transmission losses. Land use eco-efficiency (ULUEE) has emerged as a crucial factor in resolving the development dilemma, encompassing not only the economic productivity of land resources but also influencing the carbon sequestration capacity of ecosystems and their potential for spatial transformation. The aforementioned model of high energy consumption and elevated emissions, along with the consequent low ecological efficiency in land use, can be largely attributed to the traditional industrial policy framework of the past. This framework has been characterized by a focus on scale expansion and cost competition (Rolfo and Calabrese, 2003). Such an orientation has led to the excessive development of resource-intensive industries while failing to effectively internalize environmental costs or promote a transition towards greener practices. Against this backdrop, ULUEE plays a crucial role in balancing economic growth with ecological protection. They are essential for promoting the green transformation of industries and improving ULUEE. The core idea is to redirect production factors from high-carbon, low-efficiency sectors to green, innovative ones through policy interventions, fundamentally transforming the industrial base and economic incentives that influence ULUEE. However, there is a lack of clear evidence about how it works and what results it produces. Global climate governance has reached a phase of heightened action intensity. As a responsible developing nation, China must navigate the dual challenges of economic development, land resource efficiency, and ecological protection through innovative green industrial policies and reforms in land governance. It is essential to identify a practical approach that reconciles developmental rights with environmental rights, which is crucial not only for its own ecological civilization but also for broader ecological considerations. This is not only relevant to the development of its own ecological civilization but also has a significant impact on the equity and efficacy of global climate regulation (Huang et al., 2025). So, under the dual-carbon goal, explaining how green industrial policy (GIP) affects land use eco-efficiency can help balance conservation and development.

In recent years, the emergence of green development has led to a growing focus on ULUEE. ULUEE involves analyzing the input and output systems of various resources in urban areas, guided by sustainable urban development principles (Tan et al., 2021). As a key indicator for measuring the coordination of urban human-environment systems, this concept establishes a "input-process-output" framework: At the input end, it focuses on the intensity of production factors such as land, capital, and labor; at the process end, it emphasizes optimizing industrial layout and applying ecological technologies; at the output end, it balances economic value creation, social welfare enhancement, and ecological impact.

Tan et al. (2021) characterize it as a thorough delineation of the synergistic optimization of the urban system concerning resource inputs, economic outputs, and environmental repercussions. While research on the determinants of ULUEE is very extensive, it needs further expansion (Chen Q. et al., 2023). The primary issues of ULUEE in the present study stem from the natural environment, economic development (Wang, 2023), industrial structure (Chang et al., 2023), regional economic collaboration, and the degree of urbanization (Zhang et al., 2021). Vergurg et al. examined ULUEE through ecological and sociological lenses (Verburg et al., 2010), whereas Halleux et al. examined the determinants of ULUEE in the Netherlands, Poland, and Belgium (Halleux et al., 2012). Moreover, scant work has concentrated on the function of GIP within this context. Given the adverse externality of pollution, the beneficial externality of governance, and the public goods characteristics of ecosystems, policy direction is paramount in the management of environmental pollution and the mitigation of climate change (Chu et al., 2024). Dependence only on market systems presents difficulties. The concept of central-local teamwork in governance emphasizes the need for collaboration between central and local governments on green industry policies and environmental management. GIP is crucial for this cooperation, providing guidance, regulation, incentives, and synergy to achieve dual-carbon goals and restructure the economic framework (Anzolin and Lebdioui, 2021).

GIP is a pertinent sectoral strategy that employs environmental objectives to shape the methods and framework of economic production (Busch et al., 2018). This is a set of governmental interventions designed to facilitate the transition of economic structural objectives towards green and sustainable development, primarily aimed at expediting the transformation and enhancement of green production (Matsuo et al., 2019). Unlike traditional industrial policies that primarily focus on economic growth, the green industrial policy framework considers environmental costs by strategically planning institutions, allocating resources, and guiding the market. This approach directs resources toward areas that generate lower carbon emissions. The carbon tax mechanism can restrain the uncontrolled growth of high-carbon businesses through price leverage (Metcalf, 2009), while the renewable energy subsidy program can expedite the commercialization of clean technology (Grubb et al., 2021). This policy change aims to adjust economic growth rewards by prioritizing ecological value in development assessments. Global evidence shows that effectively implementing green technologies can reduce costs of the low-carbon transition while creating benefits such as green jobs and promoting technical innovation (Dulal and Akbar, 2013). GIP primarily serves to direct industrial development by incorporating ecological principles into regulatory frameworks *via* instruments such as differentiated access standards, innovation subsidies, and incentives for low-carbon technology transformation (Kou et al., 2023), while also offering a cost-sharing mechanism and market expectation guidance for enterprises undergoing green transformation. The energy conservation and emission reduction policy is a key part of GIP, helping to shift the economy towards being more environmentally friendly by encouraging less resource use and pollution, while also promoting the development of clean technologies and green industries. The energy conservation and emission reduction policy depends on local governments to lead and cities to implement it, utilizing financial incentives to encourage investment. This strategy aims to accelerate innovation and economic changes to achieve emission reduction targets. Most current research looks at GIP, overall productivity, technical innovation and development (Harrison et al., 2017), and the green transformation of industries (Rogge and Reichardt, 2016), but it overlooks how GIP affects ULUEE.

This study analyzes 287 prefecture-level cities from 2007 to 2022 to clarify how GIP drives ULUEE, viewed through the lens of fiscal intervention. By constructing a difference-in-difference model, the study focuses on the transmission effect of GIP on ULUEE through green technology innovation and energy system optimization and subsequently assesses its eco-governance value. It is found that GIP makes a significant contribution to ULUEE, which remains valid following various robustness tests. Further analysis reveals that GIP improves the level of urban green technological innovation and thus enhances ULUEE. Heterogeneity analysis reveals that GIP has a greater effect on ULUEE in resource-declining cities, small and medium-sized cities, and cities in old industrial bases, which indicates that the release of the ecological value of GIP relies on a certain urban foundation, and this effect is greater in regions with high environmental concerns, confirming the "social consensus-policy effectiveness" multiplier. Additionally, this effect is more pronounced in cities with lower levels of science and technology as well as education, suggesting that GIP can help compensate for deficiencies in urban science and education to enhance ULUEE. This study improves our understanding of how GIP can positively impact the environment, shows how these policies can make urban land use more eco-efficient, and provides practical ideas for making cities greener and better for the environment.

This paper makes several significant contributions to the field, which are outlined as follows. First, this study combines GIP with the analysis of how land use can be more eco-efficient, filling a gap in research about how ecological changes happen in land resource management. The current literature predominantly examines the influence of macroeconomic factors, such as economic growth (Lambin and Meyfroidt, 2011) and technological advancement (Villoria, 2019), but there are relatively few studies on how GIP can improve ecological efficiency by changing the behavior of land use subjects. GIP can effectively promote the green transformation of industries through various policy instruments. The dedicated fund for green industry development, established by central and local governments, reduces the financial burden on enterprises. It prioritizes clean energy equipment production, recycling economy industrial parks, and low-carbon technology research and development (Khattak et al., 2022). This initiative promotes a collaborative management model of "central guidance—local synergy" to accelerate the ecological restoration of contaminated land through policy leverage. This effect enhances carbon sequestration per unit of industrial land and achieves synergy between ecological function restoration and resource utilization. Furthermore, GIP can stimulate market innovation through varied industrial orientation, thereby providing sustained impetus for enhancing ULUEE. This paper thoroughly explores why green industrial policy is important and how it helps improve ULUEE, explaining how it works and providing new ideas for research in this area.

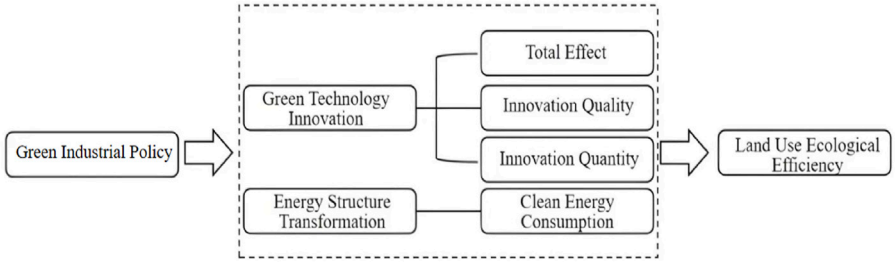


FIGURE 2
Diagram of theoretical mechanisms.

Second, this paper undertakes a more comprehensive analysis of the ecological benefits associated with GIP and examines the pivotal role of government in facilitating ecological transformation. This study elucidates the potential of GIP through the lens of ULUEE. The academic community generally pays less attention to the role of GIP in green transition and sustainable development. Furthermore, research on ecological efficiency predominantly focuses on green finance (Taghizadeh-Hesary and Yoshino, 2019), green credit (Xu et al., 2023) and green innovation, overlooking the critical role of GIP in enhancing ULUEE and its relevance to green transition. In addition, existing studies on GIP mostly focus on its environmental benefits, such as reducing carbon emissions and improving air quality (Feng et al., 2024), while a comprehensive evaluation of its economic benefits remains inadequate. This study breaks through the traditional thinking and constructs a dual-benefit evaluation system for "environment-economy", which reveals the internal mechanism of GIP affecting ULUEE through intermediary variables such as green technological innovation and clean energy substitution rate.

Third, this paper goes beyond the usual ways of classifying ecological transformation policy tools, such as financial support, subsidies for technological innovation (Howell, 2017), and administrative rules (Gupta et al., 2019), and for the first time looks closely at GIP as a separate tool. It also shows how GIP can create value. It further reveals the mechanism by which the value of GIP is released. Nevertheless, few studies have thoroughly discussed the capacity of GIP to facilitate green transformation and improve ecological efficiency enhancement by integrating the perspectives of land use and sustainable development. In the field of land use and urban planning, GIP can promote the innovation and development of low-carbon technologies, green buildings, clean energy, and other industries, thereby providing significant economic value in fostering sustainable industrial development and the efficient utilization of land resources.

The structure of this paper's research is outlined as Figure 2. The second section includes the theoretical analysis and hypothesis, explaining how GIP promotes and is put into practice, along with ULUEE. The third section delineates the research model design, sources of variables, and construction methodologies. The fourth section presents the findings of the empirical analysis, which includes correlation analysis, descriptive statistics, fundamental regression, and robustness testing. The fifth section provides an in-depth analysis, detailing the empirical impact of GIP on the mechanism of ULUEE. The sixth section concludes the research and offers policy recommendations.

2 Theoretical analysis and hypotheses

2.1 Green technology innovation

As urban growth increasingly faces substantial resource constraints and ecological sensitivities, the enhancement of ULUEE alongside the restoration of ecosystem carrying capacity have emerged as primary objectives within the framework of green development. In this context, green technology innovation is considered a crucial method for achieving synergy among resource conservation, pollution management, and ecological protection (Schiederig et al., 2012). GIP is a key factor in promoting green technology dissemination and institutional transformation. It influences the decision-making of enterprises and government through a triadic mechanism of industrial planning, financial incentives, and regulatory constraints (Zeng et al., 2025). Consequently, it integrates the principles of intensification and ecologization into land resource utilization, thereby systematically improving ULUEE (Yang and Umair, 2024). At the micro level, firms are key players in green technology research and development (Tang et al., 2020). GIP helps "mitigate uncertainty and guide the selection of technological pathways." The marketization of green technology, which requires significant initial investment and has long return cycles, can be obstructed by externalities, financial constraints, and technological uncertainty (Hu and Lin, 2022). GIP reduces institutional barriers to innovation by providing specialized subsidies, offering green credits and tax exemptions, enhancing returns on green R&D (Allan et al., 2021), and promoting resource allocation towards more efficient and lower-emission technologies. The core principle of green technology is to achieve simultaneous enhancements in environmental performance and economic advantages through the alteration of resource use and pollution emissions (Rennings, 2000). The advancement of green building technologies is a focused expression of this trend. GIP has conferred institutional advantages to green buildings regarding construction land indices, volumetric rate adjustments, and government procurement, among other factors. To achieve green certification and market recognition, firms often integrate green technologies during the design phase. This technological integration reduces energy and resource consumption throughout a building's life cycle while enhancing urban land's energy capacity and environmental impact, thereby significantly increasing

functional density and ecological sustainability per unit of land area (Hu et al., 2024). At the macro level, GIP exerts dual pressure of "incentive + constraint" on local governments *via* green building ratio assessments and environmental information disclosure (Tang et al., 2020), compelling them to favor green technologies during land approval and resource allocation processes. Numerous locations have established obligatory green building ratios in urban renewal and slum redevelopment initiatives, mandating that new projects attain a specific energy-efficiency rating or green star rating, which local governments utilize as a significant metric for evaluating policy implementation efficacy. This performance-driven system markedly improves the uniformity of local governments' actions in green development, enabling them to prioritize the promotion of green technology pathways in land allocation, planning regulation, and construction licenses. Within this institutional framework, market participants, including real estate developers and industrial park investors, have opted to incorporate green building design at the initial phase of their projects to get approval efficiency, financing benefits, and policy endorsement (Hu and Lin, 2022). In this process, green technology has transitioned from being an "added value" to a "necessity," greatly enhancing its technological significance in the land-use chain, hence facilitating the shift in land-use practices from traditional scale expansion to eco-efficiency.

GIP, through the strategic integration of traction and standard reconstruction, guides enterprises towards a sustainable technological trajectory while compelling local governments to enhance land-use decision-making through performance appraisal and information disclosure systems. This approach aims to extensively incorporate green technology in urban land development processes (Allan et al., 2021), thereby achieving the synergistic enhancement of land resource functions and the mitigation of ecological burdens. The extensive implementation of green technology alters the technological framework of land development and fosters the systematic improvement of the ecological value of land resources.

Therefore, we propose the following hypothesis.

H1: GIP fosters green technical innovation, thereby improving ULUEE.

2.2 Energy structure transformation

Alongside the advancement of green technology innovation, the optimization and modification of the energy structure serve as a crucial conduit for green industrial regulations to enhance the eco-efficiency of land utilization (Millot and Maïzi, 2021). The traditional energy framework is predominantly dominated by fossil fuels, with energy-intensive industries monopolizing land resources. This results in inefficient land utilization and significant ecological degradation, while perpetuating elevated energy intensity and pollution levels in land units over extended periods (Haberl et al., 2020). The implementation of GIP in the energy sector is altering the entrenched reliance on high carbon, high consumption, and high pollution practices. By fostering the adoption of new energy sources and promoting low carbon energy, it initiates the reconfiguration of land use and optimization of spatial structures, thereby achieving a systematic improvement in ULUEE. Firstly, in response to the common characteristics of low-efficiency land—such as significant development resistance and declining ecological value—the GIP has substantially reduced initial investment by establishing a dedicated fund for ecological restoration. Additionally, it has implemented a land use index exchange mechanism and provided rewards for infrastructure support. These measures collectively encourage market entities to prioritize the development of low-efficiency land resources. This development approach prevents the infringement on arable land while enhancing the ecological value of land functions through vegetation restoration, soil and water conservation, and other supportive initiatives. Secondly, within the framework of reconstructing the energy supply system, the policy encourages high energy-intensive industries to cluster around integration bases for wind, hydro, and storage. This is facilitated by a system that incorporates differential carbon tax pricing, green power certificate trading, and compensated utilization of energy rights. When enterprises encounter the dual challenges of extensive energy costs and low-carbon supply chain certification, they are more likely to select regions with significant green power availability and substantial ecological capacity for production bases. This approach disrupts the traditional industrial expansion along transportation routes and facilitates an industrial spatial reorganization supported by a multi-energy complementary system. The alteration in "land use preference" induced by the shift in energy structure has fundamentally reconfigured the spatial structure and ecological distribution pattern of urban land use (Wu et al., 2011). Furthermore, GIP expedites the relinquishment of land for surplus capacity in the steel, cement, and other sectors by instituting a trading market for capacity replacement indices and enforcing negative list management for the industry. Composite land use represents a significant form of ecological system innovation, driven by changes in the energy structure (Hansen and Coenen, 2015). The innovation of new energy scenarios, driven by the transformation of the energy structure, has further expanded the ecological functional boundaries of land use. Motivated by the green industry policy, integrated usage models such as "photovoltaic + agriculture," "wind energy + forestry," and "rooftop + power generation" have progressively emerged as a new paradigm with regulatory backing. These models not only facilitate the coexistence of energy production and ecological protection on the same parcel of land but also enhance both system resilience and environmental adaptability within these landscapes.

Consequently, GIP has catalyzed a transition in the energy structure from a "high-carbon centralized" model to a "low-carbon distributed" framework, while simultaneously reconstructing the utilization logic and ecological function system of the land. The logic of land use and the ecological function system have been restructured in this process. Land has evolved from only serving as a platform for energy production to functioning as a spatial nexus where energy systems, ecological networks, and industrial configurations intersect, hence augmenting its ecological efficiency through this integrative process. Based on these considerations, we propose the following hypotheses:

H2: GIP improves ULUEE by encouraging the alteration of the energy mix.

3 Methods

3.1 Models

3.1.1 Baseline regression model

This paper considers the pilot initiative of "energy-saving and emission reduction comprehensive demonstration city" as a quasi-natural experiment, utilizing the DID model to assess the net effect of the policy on eco-efficiency in land use. Since the Ministry of Finance and the National Development and Reform Commission (NDRC) selected a number of cities to carry out energy-saving and emission reduction pilot work in 2011, 2013 and 2014 respectively, we refer to the existing study (Wang et al., 2022) to develop a multi-period difference-in-difference model, the baseline model Equation 1 is established as follows:

$$LUE_{it} = \alpha_0 + \alpha_1 GIP_{it} + \alpha_i Col_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

Where i represents city and t represents year. LUE_{it} denotes the urban land use eco-efficiency of city i in year t; GIP_{it} denotes the dummy variable for demonstration city, when city i is selected as a pilot city in year t, this variable is set to 1, otherwise it is set to 0; Col_{it} is a series of control variables We focus on the coefficient α_1, if $\alpha_1 > 0$, it means that green industrial policy can enhance urban land use eco-efficiency; if $\alpha_1 < 0$, it means that green industrial policy reduces urban land use eco-efficiency. α_0 denotes the intercept, μ_i controls the urban fixed effects, ν_t controls the time fixed effects, and ε_{it} denotes the randomized disturbance term.

3.1.2 Mediating effects regression model

GIP is mediated by urban green technology innovation and energy structure transformation to improve urban land use eco-efficiency. This research designs a mediating effect model to ascertain if green technology innovation and energy structure transformation mediate the influence of green industrial strategy on land use eco-efficiency.

Referring to the approach of Baron and Kenny (1986), we employ a stepwise testing methodology to develop a mediating effect model. It subsequently constructs Equations 2, 3 based on Equation 1, as outlined below:

$$media_{it} = \gamma_0 + \gamma_1 GIP + \rho Col_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (2)$$

$$LUE_{it} = \beta_0 + \beta_1 media_{it} + \beta_2 GIP_{it} + \rho Col_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

Among them, LUE_{it} is the urban land use eco-efficiency of i city in the t period, $media_{it}$ is the proxy variable for green technology innovation or energy structure transformation of i city in the t period, and Col_{it} is the set of control variables. μ_i controls the urban fixes effects, ν_t controls the time fixes effects, ε_{it} represents the randomized disturbance term.

3.2 Variables

3.2.1 Explained variable

The ecological utilization of land must provide economic and social advantages while simultaneously minimizing environmental degradation and resource wastage, hence achieving eco-efficiency. Consequently, the ecological usage of urban land yields both "desired outputs" and "undesired outputs," the latter being represented by environmental contaminants, or negative externalities resulting from land use. The traditional DEA model does not account for non-desired outputs when assessing efficiency, which limits its ability to measure efficiency values in the presence of such outputs. To address this limitation, we incorporate slack variables into the objective function and treat non-desired outputs as part of the constraints based on the traditional DEA framework. Consequently, we employ the SBM-Undesirable model to evaluate the eco-efficiency of land use. Referring to the academic research, when there is a difference in the results under the assumptions of the two techniques, the results obtained based on VRS should be prioritized (Zheng et al., 1998). Therefore, the SBM-Undesirable model based on variable returns to scale (VRS) is adopted to measure ULUEE, and its basic principle is as follows: the land use system of each city is regarded as a decision-making unit (DMU), and it is assumed that there are n decision-making units, each of which consists of m input indexes x_{i0}, a desired output indexes y^e_{r0} and b non-desired output indexes y^n_{h0}. Defining matrix $X = (x_1, x_2, \ldots x_n) \in R^{m\times n}$, $Y^e = (y_1, y_2, \ldots y_n) \in R^{b\times n}$, $Y^n = (y_1, y_2, \ldots y_n) \in R^{b\times n}$, and X, $\mathrm{Y^e}$, $\mathrm{Y^n}$ are all greater than zero, the set of production possibilities can be defined as $\mathrm{p} = \{(\mathrm{x}, \mathrm{y^e}, \mathrm{y^n}) \mid \mathrm{x} \geq \mathrm{X\lambda}, \mathrm{y^e} \leq \mathrm{Y^e\lambda}, \mathrm{y^n} \geq \mathrm{Y^n\lambda}, \lambda \geq 0\}$, and then the efficiency of the green use of urban land (ρ^*) can be expressed as Equation 4:

$$\rho^* = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{D_i^-}{x_{i0}}}{1 + \frac{1}{a+b}\left(\sum_{r=1}^{a} \frac{D_r^e}{y_{r0}^e} + \sum_{h=1}^{b} \frac{D_h^n}{y_{h0}^n}\right)} \quad (4)$$

$$\mathrm{s, t, x_0 = X\lambda + D^-, y_0^e = Y^e\lambda - D^e, y_0^n = Y^n\lambda + D^n}$$

$$D^- \geq 0, D^e \geq 0, \mathrm{D^n} \geq 0, \lambda \geq 0$$

Where, ρ^* represents urban land use eco-efficiency, $0 < \rho^* < 1$, if $\rho^* = 1$, the decision-making unit is effective; $\rho^* < 1$ is the loss of decision-making unit's efficiency, and there is room for optimization and improvement of inputs and outputs; D^- denotes the redundancy of inputs, D^e denotes the insufficiency of desired outputs, and D^n denotes the redundancy of undesired outputs; and λ is the vector of weights. We construct the index system of urban land use eco-efficiency from two dimensions of factor input and output, and adopts the Super-SBM model with undesirable outputs. Table 1 illustrates the distinct connotation of each signal.

In terms of inputs, referring to the existing research (Jiang et al., 2021), land, capital and labor are selected as the necessary elements of land use. The land area serves as the foundation and medium for the development of urban "three living spaces," and alterations in urban construction land area can effectively indicate the reconfiguration and structural transformation of these spaces, thereby influencing the efficiency of urban land's green utilization. Capital and labor input are the main factors influencing regional economic efficiency and competitiveness, and the main industries in the city are the secondary and tertiary industries, so the number of employees in the secondary and tertiary industries in the city is a better measure of the input of the labor factor, and the amount of investment in fixed assets serves as an indicator of the capital factor.

In terms of outputs, the output unit is divided into desired outputs and non-desired outputs. Desired outputs encompass economic and social benefits, specifically the value added by secondary and tertiary

TABLE 1 Indicator system for urban land use eco-efficiency.

Index	Interpretation		Composition
Inputs	Land		Urban construction area/km^2
	Capital		Total investment in social fixed assets (in ten thousand CNY)
	Labor		Number of employees in secondary and tertiary industries (in ten thousand people)
Outputs	economic benefit	Desirable outputs	The added value of the second and third industries (in ten thousand CNY)
	social benefit		Total population of the city/million
	environmental benefit	Undesirable outputs	PM2.5 concentration
			carbon emissions

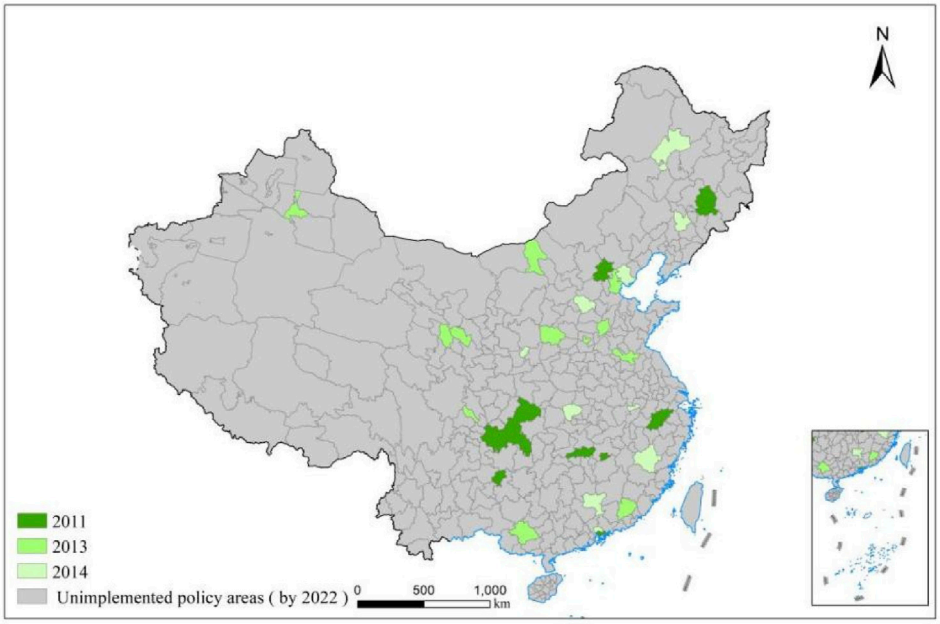


FIGURE 3
Spatial and temporal development of GIP in Chinese urban areas.

industries and the overall urban population; undesired outputs pertain to environmental impacts, including PM2.5 concentration and urban carbon emissions (Hu et al., 2022).

In terms of economic benefits, the value of urban land is primarily reflected in industrial and commercial activities (secondary industry: industry and construction; tertiary industry: services). Agriculture (primary industry) occupies a minimal share of urban land use and has a weak link to ecological efficiency. The added value from secondary and tertiary industries directly indicates the economic intensive utilization of urban land. Thus, we use this added value as our measure for economic benefits.

Regarding social benefits, the main function of urban land is to support human activities. Population size quantifies this support capacity and serves as a key indicator of "social benefits." Population growth drives built-up area expansion and significantly influences land use patterns. The total urban population effectively reflects how well land allocation meets social demands.

For environmental benefits, PM2.5 levels and carbon emissions represent negative externalities. PM2.5 indicates internal environmental quality, while carbon emissions highlight pressure on regional ecosystems. Together, these factors comprehensively capture the ecological costs associated with land development. Therefore, these variables are selected to represent environmental non-desired outputs.

3.2.2 Explanatory variable

The green industrial policy serves as the explanatory variable. Referring to the existing study (Hong et al., 2023), the dummy variable GIP is set based on the event that each city becomes an energy saving and emission reduction pilot city at different times, using the interaction term of the pilot city dummy variable with its construction start time dummy variable. Specifically, if city i is included in the pilot in year t, the city's GIP in year t and subsequent years is assigned the value of 1, and 0 otherwise. The details of GIP are shown in Figure 3.

TABLE 2 Definitions of key variables.

Variables	Definition (unit)		Symbol	Computed mode
Independent variable	Urban land use eco-efficiency		ULUEE	Calculated *via* SBM-Undesirable model
Dependent variable	Green industrial policy		GIP	If city *i* is included in the pilot in year *t*, assign a value of 1 to the city's GIP in year *t* and subsequent years, and 0 otherwise
Control variables	Degree of government intervention		DGI	General public budget expenditure/GDP
	The level of opening up		FDI	Actual utilization of foreign direct investment/regional GDP
	Industrial structure		IS	Secondary and tertiary GDP/Gross Regional Product
	Economic development level		EDL	ln (per capital gross regional product)
	Infrastructure level		INF	Urban road space *per capita*
Mechanistic variables	Green Technology Innovation	Green technology patent applications	TP	Number of green technology patent applications
		Green invention patent applications	IP	Number of patent applications for green inventions
		green utility model patent grants	UMP	Number of green utility model patent applications
	Energy structure	Clean energy consumption	CE	Total final energy consumption of wind, nuclear, hydro, natural gas, solar (million tons of coal)

3.2.3 Control variables

Referring to existing research (Zeng et al., 2022; Singh, 2023), the following variables are controlled: economic development level (EDL), measured by taking the natural logarithm of *per capita* GDP; industrial structure (IS), expressed as the ratio of the gross domestic product (GDP) of the secondary and tertiary industries to the GDP; and the infrastructure level (INF), measured by the *per capita* area of urban roads; in addition, in cities with a more dense distribution of foreign investment densely distributed cities, manufacturers have easier access to necessary capital and advanced technology and can improve land use efficiency more quickly; therefore, the impact of foreign direct investment also needs to be considered, and the degree of openness to the outside world (FDI) is measured in terms of the amount of actually utilized foreign direct investment as a share of GDP; finally, preferential policies, subsidies and incentives from the government can encourage agricultural producers to adopt a more economical, more environmentally friendly land use and promote sustainable land resource management (Chen X. et al., 2023). In this paper, the degree of government intervention (DGI) is expressed as the share of general public budget expenditure in GDP.

3.2.4 Mechanistic variables

The number of green patent applications reflects early investment in green innovation and indicates a city's green output. Substantive innovation, characterized by high-level technological advancements, drives technological progress, while strategic innovation merely complies with government policies and involves minor, low-level innovations (Li et al., 2025). Thus, we define "high-quality" invention patents as substantive innovation and utility model or design patents as strategic innovation based on China's patent law and existing research discussions (Hall and Harhoff, 2012). In this paper, mediating variables are constructed from two perspectives: innovation effect and energy structure transformation. The total number of green technology patent applications (TP), the total number of green invention patent applications (IP) and the green utility model patent grants (UMP) are selected as the proxy variables for the total green innovation effect, the quality of green innovation and the quantity of green innovation. The final energy consumption of wind power, nuclear power, hydropower, natural gas, and solar power (Yang et al., 2024) converted to the sum of standard coal is chosen to measure the city's clean energy consumption. The definitions of all variables are shown in Table 2.

3.3 Sample and descriptive statistics

Based on the availability and completeness of the data, this paper selects the panel data of 287 prefecture-level and above cities in China from 2007 to 2022 as the research sample. With the exception of the energy-saving and emission reduction pilot cities data from the National Development and Reform Commission's List of Comprehensive Demonstration Cities on Fiscal Policies for Energy Saving and Emission Reduction, as well as the PM2.5 concentration data from Columbia University's Center for Socio-Economic Data and Applications, all other indicators were sourced from the Statistical Yearbook of Urban Construction of China, the China Urban Statistical Yearbook, the China Statistical Yearbook, and the CSMAR database. Individual missing data were filled in using linear interpolation to obtain 4,592 sample data.

Table 3 presents the observed values, means, standard deviations, and maximum and minimum values for each

variable. The mean of ULUEE is 0.603, indicating that the ecological efficiency of the sample cities reaches only 60.3% of the theoretical optimal level, highlighting significant room for improvement. The standard deviation of 0.175 is relatively small, suggesting that efficiency values are concentrated among cities; however, there is considerable differentiation across them.

TABLE 3 Descriptive statistics.

Variable	(1)	(2)	(3)	(4)	(5)
	Obs	Mean	SD	Min	Max.
ULUEE	4,592	0.6030	0.1750	0.0774	1.0000
GIP	4,592	0.0642	0.2450	0.0000	1.0000
DGI	4,592	0.1920	0.1250	0.0426	2.3490
IS	4,592	0.8730	0.0823	0.5010	1.0590
FDI	4,576	0.0178	0.0200	−0.0180	0.3400
INF	4,512	17.2816	7.5795	4.2900	42.3691
EDL	4,592	10.5800	0.6970	4.5950	13.060
TP	4,592	0.0569	0.1870	0.0000	3.1960
IP	4,592	0.0279	0.1100	0.0000	2.3940
UMP	4,592	0.0291	0.0824	0.0000	1.0960
CE	4,464	1.2870	1.9550	0.0178	27.0400

4 Results

4.1 Baseline regression

Table 4 displays the findings from the baseline regression analysis examining the impact of GIP on ULUEE. Among them, column (1) does not include any control variables, and column (2)-column (6) gradually include control variables based on the consideration of two-way fixed effects of year and city. The regression coefficients of the core explanatory variables are always significantly positive, indicating that GIP significantly improves ULUEE.

4.2 Robustness check

4.2.1 Parallel trend test

Prior to evaluating the policy impact, it is essential to confirm that the sample adheres to the parallel trend assumption, meaning there is no statistical disparity between the ULUEE of the treatment group and the control group prior to the initiation of the pilot city building. Given that the development of the demonstration area is implemented in phases, this paper conducts a parallel trend test using the Event Study Approach (ESA) (Jacobson et al., 1993; Beck et al., 2010), and the model Equation 5 is set as follows:

$$ULUEE_{it} = \alpha + \sum_{k=-5}^{6} \beta_k D_{i,t_0+k} + \gamma X_{it} + \mu_t + \nu_i + \varepsilon_{it} \quad (5)$$

Where D_{i,t_0+k} denotes a dummy variable for the point in time before and after the policy in pilot city i. $k<0$ and $k>0$ denote year k before and after the policy, respectively. The coefficient is the variable on which the parallel trend test focuses, indicating the difference in *ULUEE* between the treatment and control groups before and after the implementation of the policy. If β_k is not significantly different from 0 during $k<0$, it indicates that the sample in this paper satisfies the parallel trend hypothesis; conversely, it indicates that the parallel trend hypothesis is not satisfied. The rest of the variable settings are consistent with the benchmark model. In addition, this paper excludes the year before policy implementation as the benchmark year to avoid multicollinearity.

The results of the parallel trend test are shown in Figure 4, with the horizontal axis indicating the years before and after GIP was implemented and the vertical axis indicating the dynamic effects of the policy. As can be seen from the figure, the regression coefficients before GIP were not significant, thus indicating that there was no significant difference between the experimental and control group cities during this period, and the hypothesis of parallel trends is valid. In addition, GIP did not have a significant impact on ULUEE in the year it was implemented, but the effect of GIP became apparent only after the second year, and the coefficient estimates showed a significant increase as the year went on and the policy continued to deepen. The above results show that the effect of the green industrial policy has a certain lag, and shows dynamic sustainability.

4.2.2 Placebo test

Although this paper strives to eliminate as many confounding factors influencing the results as possible and incorporates two-way urban fixed effects within the multi-period Difference-in-Differences (DID) model, it remains unable to completely mitigate the omission of certain unobservable city characteristic variables due to inherent objective constraints. For this reason, the influence of other unobservable factors on the selection of policy-influenced cities is further excluded through a placebo test (Cai et al., 2016), and a dummy group is constructed to conduct a repeated 500-times sampling regression, thus generating 500 different estimates of the policy effect, and the distribution of the estimated values is shown in Figure 5. The estimated coefficients of the placebo regression in the figure are distributed around 0 and mostly insignificant, and the coefficients are far away from the coefficient 0.028 in the benchmark regression, which is a small probability event in the placebo test, i.e., the regression results under the real DID setting are not by chance. Accordingly, it can be ruled out that the benchmark results in this paper are due to unobservable factors at the city and time level, and the placebo test passes.

4.2.3 Exclusion of relevant competing policies

During the sample period, there are several policies and regulations that are similar to the energy saving and emission reduction pilot policy, which may interfere with the regression results of this paper. In order to identify and solve these problems, this paper excludes the interference of contemporaneous policies such as the Carbon Emission Trading Pilot (CET), Low Carbon City Pilot (LCC), Green Finance Reform

TABLE 4 Baseline regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	ULUEE	ULUEE	ULUEE	ULUEE	ULUEE	ULUEE
GIP	0.034***	0.035***	0.034***	0.033***	0.031***	0.028***
	(3.97)	(4.03)	(4.02)	(3.88)	(3.65)	(3.27)
EDL		0.007	−0.000	0.005	0.028***	0.028***
		(1.01)	(−0.04)	(0.63)	(3.44)	(3.40)
DGI			−0.080***	−0.073***	−0.078***	−0.078***
			(−4.00)	(−3.68)	(−3.93)	(−3.93)
FDI				−0.556***	−0.547***	−0.548***
				(−5.81)	(−5.73)	(−5.74)
IS					−0.378***	−0.380***
					(−6.06)	(−6.03)
INF						−0.001***
						(−2.83)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4,592	4,592	4,592	4,576	4,576	4,496
R^2	0.787	0.787	0.787	0.790	0.792	0.793

Note: t-values in parentheses, ***, **, and * represent 1%, 5%, and 10% significance levels.

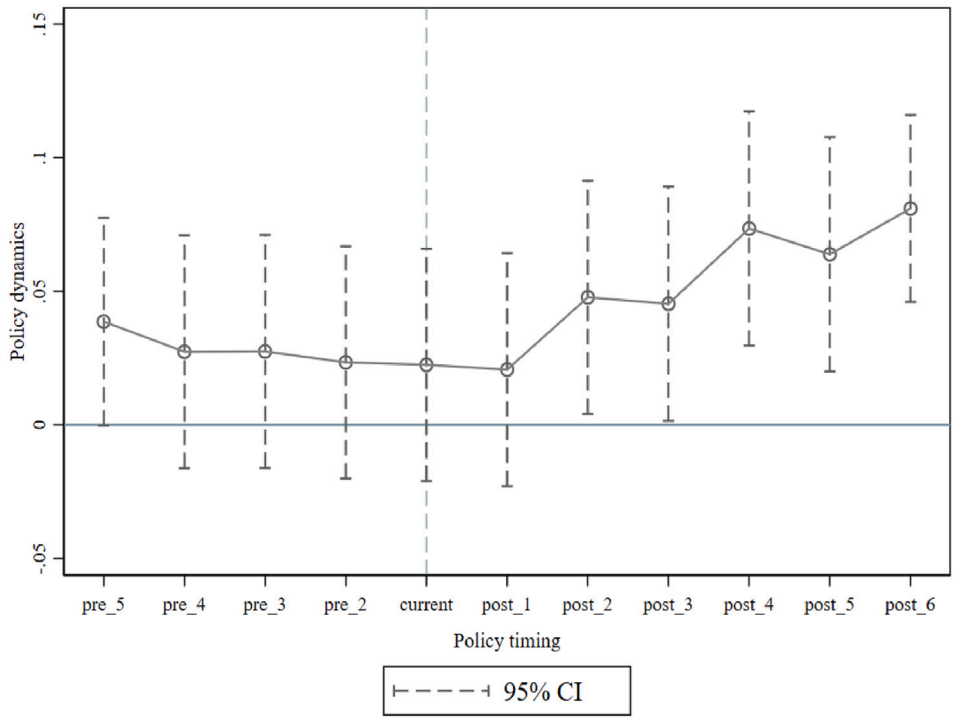


FIGURE 4
Parallel trend test.

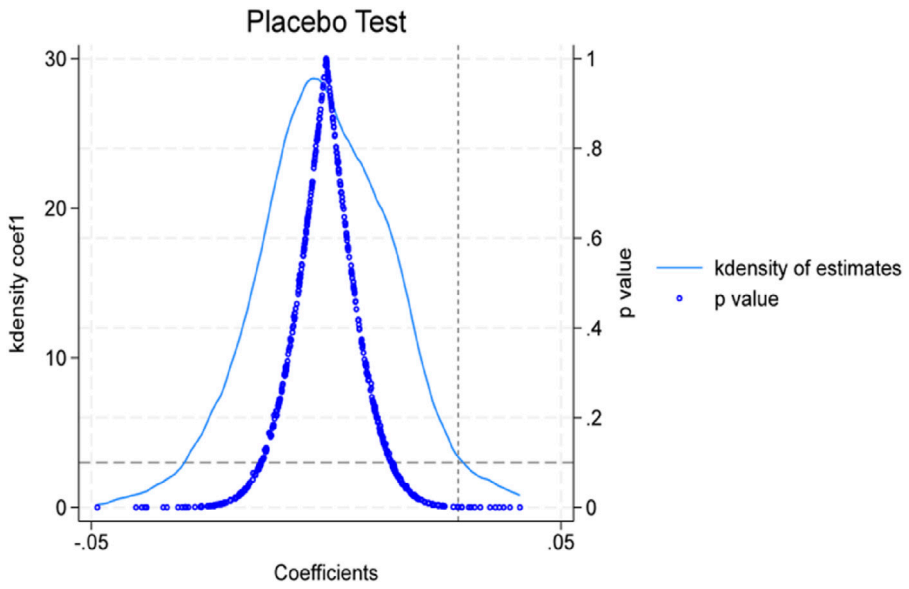


FIGURE 5
Placebo test.

and Innovation Pilot Area (GFRI), and Air Pollution Prevention and Control Action Plan (AKC). The specific reasons are as follows:

1. CET can facilitate the development of green industries by leveraging the cost implications of environmental pollution and the revenue generated from carbon market quotas. Consequently, this may positively influence the efficiency of land ecological utilization.
2. LCC contribute to enhancing the relationship between resources and the environment through institutional mechanisms designed for low-carbon development. This, in turn, provides a foundation for improving ULUEE.
3. AKC aims to mitigate air pollution in critical regions—primarily focusing on particulate matter (PM2.5)—through source reduction strategies. These efforts directly impact undesirable outputs related to land ecological utilization efficiency.
4. GFRI promotes the growth of green industries *via* innovative financial instruments and policies, potentially exerting an indirect effect on enhancing the efficiency of land ecological utilization.

In order to control the potential disturbance of GIP, this paper includes them in the model at the same time with GIP for regression test. The results in columns (1) (2) (3) (4) of Table 5 show that the impact of GIP on ULUEE is still significant at the 1% level, which further supports the robustness of the research results of this paper.

4.2.4 Lag period test

Considering that there may be a certain lag in the policy effect, and in order to weaken the influence of reverse causality, this paper re-runs the model test after treating the core explanatory variable one period lagged (L.GIP) (Wang and Ma, 2022), the estimation result is shown in column (5) in Table 5, and the coefficient of GIP is positive at the 1% significance level, which is in line with the results of the benchmark regression. The root cause of this lag stems from multiple time lags in policy transmission, system response, and behavioral adaptation. It takes time for policies to move from central deployment

TABLE 5 Lag period test and exclusion of relevant competing policies.

Variables	(1)	(2)	(3)	(4)	(5)
	ULUEE	ULUEE	ULUEE	ULUEE	ULUEE
GIP	0.026***	0.024***	0.031***	0.029***	
	(2.97)	(2.82)	(3.55)	(3.35)	
L. GIP					0.034***
					(3.91)
CET	0.017**				
	(2.24)				
LCC		0.031***			
		(6.21)			
AKC			−0.015***		
			(−3.19)		
GFRI				0.095***	
				(5.00)	
Controls	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	4,496	4,496	4,496	4,496	4,215
R^2	0.794	0.795	0.794	0.795	0.793

Note: t-values in parentheses, ***, **, and * represent 1%, 5%, and 10% significance levels.

TABLE 6 Mediation effect analysis: green technology innovation.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ULUEE	TP	ULUEE	IP	ULUEE	UMP	ULUEE
GIP	0.028***	0.094***	0.019**	0.053***	0.020**	0.041***	0.019**
	(3.270)	(8.443)	(2.172)	(7.867)	(2.336)	(8.247)	(2.195)
TP			0.100***				
			(8.496)				
IP					0.152***		
					(7.738)		
UMP							0.223***
							(8.523)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,496	4,496	4,496	4,496	4,496	4,496	4,496
R^2	0.793	0.702	0.797	0.691	0.796	0.688	0.797

Note: t-values in parentheses, ***, **, and * represent 1%, 5%, and 10% significance levels.

to local execution. Additionally, there is natural inertia in land ecological restoration and the replacement of high-carbon facilities. Enterprises' initial wait-and-see attitude towards policy stability (Bao and Cardoza, 2023) and local governments' need to balance short-term economic pressures further delay the realization of effects.

4.3 Mechanism testing

According to the policy synthesis and theoretical examination in the preceding study, GIP can improve the efficiency of ULUEE *via* green technology innovation and energy structure transformation. This paper classifies green technological innovation into three categories: the overall effect, the quality, and the quantity of green technological innovation. It employs the total number of green patent applications (GTP) to assess the overall effect, the number of green invention patent applications (GIP) to evaluate quality, and the number of green utility model patent applications (GUMP) to gauge quantity. To convey the results, the aforementioned indicators are multiplied by 0.0001 to modify the scale. As far as the energy structure transition is concerned, this paper refers to the measurement method of existing literature (Yang et al., 2024), and uses the sum of final energy consumption of wind power, nuclear power, hydropower, natural gas and solar energy (million tons of coal) as a proxy variable for clean energy consumption.

4.3.1 Green technology innovation

The results of the empirical tests are shown in Table 6. The regression results in columns (1), (2), (4) and (6) show that the coefficient estimates of GIP are all significantly positive at the 1% level, indicating that GIP promotes the level of green technological innovation in the city compared to other cities. Columns (3), (5) and (7) the effect of green technology innovation on ULUEE is significantly positive at the 1% level, which is consistent with the previous theoretical analysis. Green technology innovation presents a significant partial mediating effect between green industrial policy and urban land use eco-efficiency, and the hypothesis one holds.

4.3.2 Energy structure transformation

In order to verify the mediating path of green industrial policy affecting urban land use eco-efficiency through energy structure transformation, the impact of green industrial policy on urban land use eco-efficiency is studied using clean energy consumption as a mediating variable. The regression results are shown in Table 7, column (2) indicates that the green industrial policy can significantly enhance the clean energy consumption and activate the green and sustainable development of energy, and column (3) the role of energy structure transformation on urban land use eco-efficiency is significantly positive at the 1% level, that is, it promotes urban land use eco-efficiency in the pilot cities, and the hypothesis two holds.

4.4 Heterogeneity analysis

The preceding analysis and verification indicate that GIP has markedly enhanced ULUEE, with green technology innovation and energy structure transformation serving as intermediary factors. This paper further analyzes the disparities in urban characteristics (resource endowments, population size, industrial traits) and economic and environmental factors (environmental awareness, technological advancement, education level) influenced by GIP on ULUEE.

4.4.1 Heterogeneity of urban characteristics

Resource endowment heterogeneity test: The condition of regional resource endowment profoundly influences ULUEE, and

TABLE 7 Mediation effect analysis: energy structure transformation.

Variables	(1)	(2)	(3)
	ULUEE	CE	ULUEE
GIP	0.028***	0.806***	0.017*
	(3.270)	(10.525)	(1.927)
CE			0.016***
			(9.210)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	4,496	4,400	4,400
R^2	0.793	0.871	0.794

Note: t-values in parentheses, ***, **, and * represent 1%, 5%, and 10% significance levels.

the eco-efficiency of land usage in the majority of resource-dependent cities has not attained an optimal state. Concurrently, the quantity of resource-depleted cities is steadily rising, necessitating the enhancement of ULUEE and the advancement of green transformation in economic and social development. The "On the Issuance of the National Sustainable Development Plan for Resource-Based Cities (2013–2020)" categorizes resource-based cities into four types: growth, mature, decline, and regeneration. The analysis focuses solely on the variety of mature, declining, and regenerative cities, as the fiscal strategy for energy saving and carbon reduction does not encompass expanding urban areas. A mature city is one where resource development is stable, with resource-based industries as the mainstay, but it faces potential decline risks. A declining city has nearly exhausted resources, prominent historical legacy issues, a severely weakened economy, and struggles with transformation. A regenerative city has largely moved beyond resource dependence, with successor industries dominating and successful transformation achieved. The test of resource endowment heterogeneity is shown in Table 8. In the sample of declining cities, the coefficient of GIP is 0.143, which is significant at the 1% level. In the regenerative sample, the result in column (3) shows that the coefficient of GIP is 0.05, which is significant at the 5% level. That is, GIP enhances ULUEE in both declining and regenerating cities, and the enhancement effect on declining cities is stronger. The cause may be that declining cities possess a significant amount of traditional industrial land usage, resulting in pronounced inefficiencies in land utilization. GIP facilitates brownfield remediation and the establishment of green industrial parks *via* a dedicated fund to optimize the utilization of existing land resources. Mature cities are nearing land development saturation, and the lock-in effect of infrastructure and industry results in elevated transition costs and decreased marginal gains from policy implementation.

Heterogeneity test of city size: Considering that the difference in city size will bring about various impacts on resource allocation, industrial agglomeration and residents' lifestyles, which will make the impacts of GIP on ULUEE in cities of different sizes different. This paper analyzes the heterogeneity of the sample cities into large cities and small and medium-sized cities based on the Notice on Adjusting the Standard for the Division of City Scale issued by the State Council, taking the resident population of municipal districts of "1 million people" as the dividing line. The findings in column (4) of Table 8 indicate that the coefficient for the large-scale city sample is negative and not statistically significant, whereas the coefficient for the small and medium-sized city sample is significantly positive, demonstrating that GIP substantially enhances ULUEE in small and medium-sized cities. This phenomenon may be attributed to several factors. Firstly, the industrial landscape of large cities is predominantly characterized by service and high-tech sectors. Secondly, land use in these areas is highly intensive, with development intensity having reached a critical threshold. Consequently, the potential for further energy savings and emission reductions is limited due to marginal space constraints. Additionally, the complexity of land use structures complicates interest coordination among stakeholders. As a result, the effectiveness of policy measures remains minimal. While small and medium-sized cities have rough land use, GIP can eliminate backward production capacity and guide green industries to move in, directly enhancing ULUEE.

Heterogeneity test for industrial characteristics: Due to the high overlap between pollutant emissions and industrial agglomerations, many empirical studies have verified the positive correlation between industrial agglomeration and pollutant emissions in China (Chen et al., 2020). Old industrial bases refer to relatively complete and concentrated industrial areas formed in the planned economy relying on state investment and construction. With the advancement of reform and opening up, the economic development of the regions where these old industrial bases are located has begun to lag behind that of the eastern coastal regions. As a result, China has successively launched a number of programs and strategies to promote the adjustment and upgrading of old industrial bases. Old industrial base cities are characterized by heavy industry and a high degree of government leadership and support. The government tends to help the development of enterprises that lack viability, which leads to distortions in the endowment and production structure. In addition, old industrial base cities are usually less market-oriented than new industrial base cities, which leads to heterogeneity in green industrial policy policies between the two. This paper divides the old industrial bases according to the National Old Industrial Base Adjustment and Transformation Plan (2013–2022), and divides the sample into 94 old industrial base cities and 204 non-old industrial base cities. Then, the impact of green industrial policy on the eco-efficiency of land use in cities with different industrial structures is analyzed using split-sample regression.

The results of the heterogeneity analysis of industrial characteristics are shown in column (6) and column (7) of Table 8, which indicate that GIP shows a positive enhancement of urban land use eco-efficiency in old industrial base cities, while for non-old industrial base cities, energy conservation and emission reduction pilots do not have a significant positive effect on urban land use eco-efficiency. This suggests that compared with non-old industrial base cities, green industrial policy in old industrial base cities can enhance urban land use eco-efficiency more effectively. The possible reason for this is that old industrial base cities are highly dependent on policies and need external funds to promote transformation. The industrial structure of cities that are not part of

TABLE 8 Heterogeneity analysis: city-based characteristics.

Variables	Resource endowment			City size		Industrial characteristics	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mature	Declining	Regenerative	Large	Small or medium	Old industrial base	Non-old industrial base
GIP	0.039	0.143***	0.050**	−0.009	0.064***	0.060***	0.012
	(1.504)	(5.119)	(2.150)	(−0.843)	(4.810)	(4.506)	(1.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	960	368	240	1,584	2,912	1,456	3,040
R^2	0.759	0.756	0.919	0.797	0.763	0.775	0.806

Note: t-values in parentheses, ***, **, and * represent 1%, 5%, and 10% significance levels.

the old industrial base is characterized by greater flexibility, a higher proportion of emerging industries, and an increased degree of land use intensification. Furthermore, the effects of policy are more prominently manifested in driving technological innovation and optimizing the structure of land use.

4.4.2 Heterogeneity of the economic environment

Heterogeneity test for environmental concern: This paper measures the degree of regional environmental concern based on the frequency of environmental protection-related words in local government reports, grouped at their median, and the regression results are shown in Table 9. The impact coefficient is 0.022 in cities with high environmental protection concern, and 0.02 in cities with low environmental protection concern, but only column (1) is significant, indicating that green industrial policy has a more significant effect on the improvement of urban land use eco-efficiency in cities with greater environmental protection concern. This strongly supports the "social consensus - policy effectiveness" multiplier effect. In regions with high public attention, this effect is evident: a strong social consensus on environmental protection increases the constraints on local governments when implementing related policies. This rigidity stems from significant external pressure due to public participation and media oversight. The public monitors policy implementation through reporting, hearings, and advocacy, compelling the government to minimize symbolic enforcement and ensure compliance. The media plays a vital role by exposing issues, setting agendas, and shaping public opinion, which amplifies pressure into an unavoidable political cost that raises the risk of governmental failure in enforcing policies. Public participation provides localized supervision and feedback while media scrutiny generates widespread accountability. The synergy between these forces creates a continuous "pressure - response - escalation" dynamic. This externally driven environment of consensus-based pressure compels governments to implement policies more rigorously and transparently while optimizing enforcement processes. As a result, this significantly enhances the effectiveness of land use environmental protection policies and improves ecological efficiency overall.

Heterogeneity test for scientific and technological level: The primary objective of GIP is to enhance ULUEE through energy transformation, technological innovation, and other strategies. Regions with advanced technology demonstrate greater absorption capacity and higher innovation conversion efficiency, effectively translating policy guidance into productivity outcomes. According to the Environmental Kuznets Curve theory and endogenous growth theory, technological progress is essential for balancing economic growth with ecological protection. Investments in technology drive green innovations—such as clean energy solutions and circular economy technologies—thereby improving land utilization efficiency. The proportion of scientific and technological expenditure reflects local governments' commitment to development; it quantitatively indicates their policy intentions. A higher proportion signifies a stronger focus on promoting economic transformation through technology investments, aligning with the goals of green industrial policies. Considering the heterogeneity of cities' high-tech level, we grouped them at their median, and the regression results are shown in Column (3) and Column (4) of Table 9. The promotion effect of GIP on ULUEE in high-tech level areas is not significant, while the effect on low-tech level areas is positive at 1% statistical level, and the coefficient of the former is smaller than that of the latter, which suggests that GIP mainly affects ULUEE in low-tech level areas. The potential explanation for this phenomenon is that low-tech regions are characterized by a substantial presence of traditional industries that consume high levels of energy while exhibiting low efficiency. These areas typically have a limited initial energy-efficiency baseline. Consequently, the marginal benefits derived from green technology innovation in these regions are significantly greater than those observed in high-tech areas. This disparity ultimately results in a more pronounced enhancement of ULUEE.

Heterogeneity test for education level: Considering that the level of urban education is associated with the level of urban economic development and is related to public environmental awareness (Peng and Lin, 2009). In this paper, urban local government education expenditure is utilized as a measure of the level of urban education. The data is categorized into two groups based

TABLE 9 Heterogeneity analysis: economic environment.

	Environmental concern		Technology level		Educational level	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
GIP	0.022**	0.020	0.014	0.068***	0.016	0.028**
	(2.028)	(1.190)	(1.365)	(3.523)	(1.116)	(2.362)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,297	2,179	2,255	2,212	2,246	2,218
R^2	0.815	0.813	0.795	0.801	0.797	0.806

Note: t-values in parentheses, ***, **, and * represent 1%, 5%, and 10% significance levels.

on educational attainment: high education level and low education level, with the median serving as the dividing point. A regression analysis is conducted, and the results are presented in Table 9. According to the regression results, the coefficient in column (6) is significantly positive, while the coefficient in column (5) is not significant, indicating that GIP has a significant effect on the enhancement of ULUEE in the areas with low education level. The observed heterogeneity in the results may be attributed to the fact that regions with higher education levels have already reached their maximum potential for land use intensity. In contrast, regions with lower education levels tend to rely more on governmental administrative directives for policy implementation. Consequently, GIP can more effectively optimize land resource allocation in lower-education regions and enhance governmental regulatory efficiency in land use through mandates for energy conservation and emissions reduction, thereby significantly improving ULUEE.

5 Discussion

5.1 Conclusion

As the disparity between limited land resources and the expanding urban population during urbanization intensifies (Zhao et al., 2018), enhancing the eco-efficiency of urban land utilization has emerged as a critical concern for sustainable urbanization and development in China (Lu et al., 2018). This paper investigates GIP and its potential to enhance ULUEE through green technological innovation and transformation of the energy structure. It provides a theoretical foundation for addressing the dual challenges of efficiency and ecology in China's utilization of land resources. GIP fundamentally reorganizes the principles of land development through the "technology-energy-land" connection mechanism. Innovations in green technology diminish the environmental burden per unit of land, while new energy configurations enhance the spatial organization of land. This dual approach significantly enhances the ecological efficiency of urban land, substantiates the efficacy of green industrial policy in addressing the "ecology-development" dilemma, and offers empirical evidence for the synergistic advancement of China's new urbanization model and the "dual-carbon" objective. Moreover, the realization of ecological value through GIP is contingent upon a robust urban economic foundation. The essential conditions related to industry, scientific research and education, as well as environmental protection efforts enable these green industrial policies to operate more effectively, thereby enhancing ULUEE. This paper enhances the ecological significance of GIP and elucidates its mediating role in the sustainable use of land resources. However, it does not investigate the variability of policy implementation effects across diverse regional institutional contexts, nor does it systematically evaluate the long-term implications of the integration of integrating policy instruments on the multifunctionality of land use. Furthermore, the study has not examined the issue of local government alienation that may arise during policy implementation, including the possible hazards of "policy idling" or "data distortion," which require further exploration in future research.

5.2 Policy recommendations

Regionally Differentiated Land Regeneration and Green Industry Synergy Mechanism. Tailor industrial policies to regional disparities, focusing on support for declining industrial areas and old bases. Establish a coordinated framework for "land remediation and industrial green upgrading." Create a Central Land Ecological Regeneration Special Fund with specific purposes: Address abandoned mining sites and contaminated land; fund green low-carbon industrial parks on remediated land; provide subsidies for enterprises using nationally certified green technologies in equipment upgrades. Complementary incentives include: Phased income tax relief for projects on regenerated land; partial VAT rebates for companies implementing green renovations; introduction of low-interest loans for green

technology. Establish a long-term incentive mechanism by linking new development land quotas to core ecological indicators of regenerated land, such as carbon sequestration capacity and pollution reduction intensity, creating an "Investment-Remediation-Efficiency Gain-Incentive" closed loop.

Spatial-Energy-Technology System Optimization and Institutional Innovation. Enhance the integration of the "technology-energy-land" system by mandating the inclusion of distributed photovoltaic systems, energy storage facilities, and other clean energy infrastructure in comprehensive territorial spatial planning. Focus on utilizing underused industrial rooftops, abandoned mining sites, and similar areas for hybrid wind-solar-storage energy projects. Implement flexible land use duration systems for these composite projects. Establish provincial-level ecological performance evaluation standards with indicators such as vegetation coverage and carbon sequestration volume. Pilot stratified property rights registration for "above-ground - underground/subterranean - ecological space." In energy-intensive zones, enforce a "Clean Energy Quota and Development Intensity Linkage," requiring enterprises/parks to install clean energy systems or "PV + carbon sink forests" based on their land area. Entities with exceptional ecological performance may receive increases in floor area ratio (FAR). Designate low-carbon industry development corridors along major energy transmission routes to secure land supply for strategic industries like new energy vehicles and energy storage. Implement "conditional land transfers tied to green projects" to promote agglomeration.

Full-Cycle Policy Governance and Capacity Building System. Strengthen governmental accountability: Integrate the "Annual Land Ecological Efficiency Improvement Rate" into local sustainable development assessments. Use multi-source data verification ("satellite monitoring + on-site validation + enterprise reporting") for credibility. Impose penalties like reduced development quotas or adjusted fiscal transfers for non-compliant regions. Establish a National Land Ecological Efficiency Monitoring Platform to publish city rankings, subject to independent audits. Enforce strict fund oversight, banning cross-regional remediation and cosmetic restoration projects, with severe penalties for data falsification. Launch a "Green Transition Capacity Partnership Program," mobilizing national technical institutions to provide 3–5 years of assistance (covering ecological restoration and green industry planning) to declining industrial regions, funded centrally.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

YL: Conceptualization, Funding acquisition, Project administration, Resources, Software, Writing – original draft, Writing – review and editing. XX: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Supervision, Writing – original draft, Writing – review and editing. JC: Conceptualization, Data curation, Formal Analysis, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing. CH: Formal Analysis, Funding acquisition, Project administration, Resources, Visualization, Writing – original draft, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Wenqing Tao,
Zhongnan University of Economics and Law, China
Chao Jin,
Chongqing Technology and Business University, China
Qijia Zhang,
Nanjing Agricultural University, China

*CORRESPONDENCE
Ming Xu,
xmtgzy2025@163.com

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Can the ecological protection red line policy promote food security? -- based on the empirical analysis of land protection in China

Ming Xu[1,2]*

[1]School of National Security, Southwest University of Political Science and Law, Chongqing, China, [2]School of Economics, Southwest University of Political Science and Law, Chongqing, China

Introduction: China's food security is confronted with multiple pressures such as farmland degradation and ecological constraints. As a crucial factor influencing the ecological environment of food, strictly adhering to the ecological protection red line provides an important institutional guarantee for ensuring grain production capacity. In this context, studying the impact of ecological protection red line policy (ERP) on food security (FS) provides a new research direction for developing countries to safeguard national security and protect national food security.

Methods: This paper selects China as the object of quasi-natural experiment research, takes the panel data of 31 provinces from 2005 to 2023 as the research sample, measures the actual development level of China's food security by using the entropy method, explores the impact of the ecological protection red line policy on food security by using the different-in-differences model, and investigates the heterogeneity between the two by using the quantile model.

Results: This study demonstrates that the level of food security in China shows a fluctuating upward trend, confirming that the ecological protection red line policy has a significant promoting effect on food security and demonstrates obvious heterogeneous effects. In addition, land transfer (LT) and land reclamation (LR) have strengthened the promoting effect of the ecological protection red line policy, verifying the mediating role between the two.

Discussion: This study not only enriches the research on the relationship between ecological protection red line policy and food security from a theoretical perspective, but also empirically proves that the implementation of ecological protection red line policy is an important policy guideline for enhancing the ecological protection capacity of land and the sustainable capacity of food production. This research not only provides significant reference for improving the construction of China's food security risk governance system, but also offers valuable experience for achieving national ecological security and food security.

KEYWORDS

ecological protection red line policy, food security, land use change, sustainable agricultural development, ecological protection, national security

1 Introduction

Protecting food security is an important strategic goal in China. Ensuring food security foundations constitutes an integral component of China's economic advancement and a fundamental imperative for modernizing agriculture. As the lifeblood of grain production, China attaches great importance to strictly adhering to the ecological protection red line (Zhang et al., 2022b). The ecological protection red line refers to the areas with significant ecological functions or high sensitivity in the ecological space (Yue et al., 2024). It is not only an area that must be strictly protected by force, but also an important institutional arrangement to ensure that the ecological functions of these important areas do not decline, their areas do not decrease, and their natures do not change (Zhao et al., 2025). It can be said that the ecological red line, as an innovation in China's ecological and environmental protection system, is of great significance for optimizing the ecological security pattern and ensuring regional ecological security of the country. Protecting the ecological red line of cultivated land is the bottom line and lifeline of national land protection and ecological security (Zhang et al., 2022a). Thanks to China's firm adherence to the red line for arable land, the country's grain production has remained consistently stable at over sixty million kilograms, and the comprehensive grain production capacity has significantly increased. Therefore, doing a good job in the management of ecological conservation red lines is to enhance the supply level of regional ecological products and ecosystem services, reduce the interference of human activities, ensure that cultivated land resources are not threatened by the environment, and ensure that people can "eat enough and eat well" (Chen et al., 2024a). By increasing the quantity and quality of cultivated land, the risks to food production security can be effectively alleviated. Under the premise of ensuring that people's survival and health are not threatened by food supply, food security can be further achieved (Li and Song, 2022). Therefore, exploring how and to what extent the implementation of ERP affects FS is of great significance for the policy implementation effect, land protection and the improvement of the food security governance system.

According to the environmental data jointly released by Yale and Columbia University, China ranks relatively lower in global ecological and environmental performance indicators compared to developed countries. To some extent, this indicates that China's current protection of the ecological environment is far inferior to that of other developed countries (Ma, 2025). Therefore, how to alleviate ecological and environmental risks and problems remains a key project in our country. ERP is an important institutional innovation in China's deepening of the reform of the ecological civilization system and mechanism. It is not only the bottom line and lifeline for maintaining ecological security, ensuring ecological regulation functions, and providing a good living environment, but also a booster for realizing the FS strategy. However, food and energy security, as a global issue, functioning as a critical safeguard for public wellbeing, food safety (FS) simultaneously constitutes a foundational element essential for upholding China's national security strategy (Du et al., 2025). Therefore, how to make good use of environmental policies to prevent and defuse risks in grain production, processing and consumption, and how to make good use of cultivated land resources to increase grain output, are particularly important in maintaining FS. Fundamentally, the purpose of implementing ERP is to attach importance to the protection of cultivated land resources in the process of local governments pursuing economic growth and ensure that the land is not threatened by the environment (Liu et al., 2025). In reality, as local governments or agricultural business entities often tend to focus more on short-term land development gains and neglect the protection of permanent farmland, the risk of cultivated land loss has not been fundamentally controlled (Zhou et al., 2024). Therefore, safeguarding both arable land resources and crop production requires not only prioritizing the mitigation of farmland ecological pollution and preventing land degradation, but also fostering robust international trade collaboration to ensure the sustained quality of cultivated land and grain output. Against this backdrop, ERP as an important policy constraint for land ecological protection, has played a significant supporting role in ensuring ecological environment security, FS and national security.

From the existing research, ERP, as an important measure and tool for protecting the ecological environment of land in China, playing a pivotal role in mitigating environmental contamination and land resource degradation, ERP-related scholarly investigations are primarily concentrated within three key domains. Firstly, starting from the theory, by taking the aspects of land use, ecosystem services and ecological compensation policies as the research perspectives, the implementation effect of ERP is analyzed in a theoretical and critical way to evaluate the promoting effect of ERP on the ecological environment (Bai et al., 2016; Jiang et al., 2019; Guo et al., 2023). Secondly, based on empirical evidence, existing literature has respectively regarded ERP as policy evaluation and policy investigation, and adopted the DID model and logistic regression model respectively to explore that the implementation of ERP has had a substantive promoting effect on protecting biodiversity, policy satisfaction, land coverage area, and willingness to pay (Choi et al., 2022; Hu et al., 2022). Finally, starting from the impact effect, existing studies have mainly focused on exploring the promoting effect of ERP on ecological service functions, sustainable economic development and green innovation (Liu et al., 2021; Fu et al., 2023; Wang et al., 2024).

FS as an important topic of global concern, has played a significant role in ensuring people's living needs and promoting national economic development. Research on FS also focuses on the following three aspects. First, starting from the development process, existing literature has explored the evolution of the FS concept. The FS concept has undergone an in-depth transformation from the initial survival, to having enough food and clothing, and then to the current hygiene and nutrition, from having food to having good food quality (Chen and Kates, 1994; Maxwell, 1996; Poole et al., 2021). Secondly, from the measurement level, the measurement methods of FS in the existing literature mainly focus on two levels: the area of major food crops and the index system. Among them, the crop areas are mainly rice, wheat, corn and soybeans (Cui and Zhong, 2024). The indicator system covers aspects such as Food supply, Food access, Policy Security, and Economic Security (Zhao et al., 2023; Xu and Lu, 2025). Thirdly, starting from the influencing factors, existing studies have mainly evaluated the impact on FS from the aspects of environmental regulation, sustainable economic development, land use and ecological environment protection, providing important reference significance for protecting the

ecological environment and sustainable food development (Odoms-Young et al., 2024; Xu et al., 2025a).

While prior research offers insightful perspectives on ERP-FS linkages, empirical assessments specifically examining ERP's direct influence on FS remain limited. Constrained by external agricultural environmental and soil quality factors, effective ERP implementation necessitates region specific approaches to sustainably enhance grain production and supply systems (Gao et al., 2020). Moreover, both grain output and ecological outcomes carry equal weight in ERP policy evaluation, serving as fundamental criteria derived from its top-level design and empirical effectiveness. Although the existing research has achieved rich results, there are still the following limitations: On the one hand, although the existing studies have conducted multi-index analyses of FS, they have not focused on the entire grain industry chain and lack systematic analysis. On the other hand, existing studies have only focused on the impact of land on FS and have not investigated the direct assessment effect of ERP on FS. Overall, in this study, ERP has a certain promoting effect on FS. However, as a developing country, it is also necessary to consider how to give full play to the advantages of ERP while protecting land to better promote FS. Hence, assessing ERP's impact on FS is imperative: Does implementation substantively promote FS? Through which mechanisms does ERP affect FS? This paper aims to establish an assessment of the impact mechanism of ERP on FS through scientific policy evaluation methods, provide decision-making guidance for the government to promote land ecological security, and offer reference significance for other developing countries in land quality protection, land ecological protection, and environmental ecological security. The purpose of this study is to utilize land ecological protection policies to ensure grain production, promote the improvement of the land ecological governance system, guarantee China's FS, and achieve the dual benefits of agriculture and land ecological protection.

In summary, this study's key marginal contributions are manifested through: Firstly, a total of 589 samples from 31 provinces in China from 2005 to 2023 were selected as the analysis objects of this study. The actual development level of FS in China was scientifically and systematically measured by using the entropy method. Taking advantage of the DID model, the actual relationship between ERP and FS was discussed, and five robustness test methods were provided. Prove the rationality of the research. Secondly, this study fully took into account the actual situation of China's grain, explored the development status of FS in different regions and at different quantiles, provided a more accurate basis for formulating ERP in accordance with local conditions, and conducted an assessment using the quantile model. Thirdly, deeply explore the influence mechanism of ERP on FS, and analyze the mediating role of LT and LR in the promoting effect of EW on FS. This research enriches the related studies between ERP and FS. It not only provides ideas for developing countries to achieve sustainable land development and sustainable food development, but also offers significant reference for China's governance system for ensuring food security, ecological security, and improving the national security risk governance system.

The specific structure of this study is arranged as follows: First, in the introduction of this study, the theoretical significance, practical significance and literature review of researching ERP and FS are expounded. Secondly, in the Policy Background and Theoretical Framework of this study, the policy background of ERP is proposed, and three hypotheses about ERP promoting FS are presented at the theoretical level. Thirdly, the methods and data sources of this research were proposed. Fourth, this study explored the promoting effect and mechanism of ERP on FS through an empirical model. Fifth, it has put forward policy suggestions and future research directions for this study, providing reference significance for the development of developing countries.

2 Theoretical mechanism

2.1 Policy background

The concept of ERP first emerged in the "Opinions of The State Council on Strengthening Key Environmental Protection Work" in 2011, which stated that "ecological red lines should be demarcated in important ecological function areas, land and Marine ecological environment sensitive areas, fragile areas and other regions (Zhang and Wen, 2008)." In 2014, the Ministry of Environmental Protection of China issued the "Technical Guidelines for the Delineation of Ecological Function Baselines of the National Ecological Conservation Red Line (Trial)" (Shan et al., 2024). This guideline describes the ecological red line as: The ecological conservation red line is a strictly controlled boundary delineated in accordance with the law in key ecological function areas, ecologically sensitive areas and fragile areas, *etc.* It is not only the bottom line for national and regional ecological security, it also the first programmatic technical guidance document for the delineation of ecological conservation red lines in China. In November 2015, the Ministry of Ecology and Environment officially issued the "Notice on Carrying Out Pilot Work for the Control of Ecological Conservation Red Lines", exploring aspects such as environmental access, performance assessment, ecological compensation and supervision in ecological conservation red line areas (Zeng et al., 2024). This also indicates that the country will officially implement ERP in 2016. The policy evolution process of demarcating ecological red lines is shown in Figure 1 below.

2.2 Direct impact

From the perspective of land governance, the ecological protection red line demarcated by the Chinese government is essentially to ensure the bottom line of cultivated land resources and cultivated land quality and safety through policy regulation, in order to achieve the dual goals of stable grain production and stable ecosystem. Functioning as a pivotal territorial governance instrument, ERP enforces permanent prime farmland conservation while concurrently boosting cropland ecological resilience and food supply sustainability (Wang, 2022). From an implementation standpoint, the ERP system delivers essential safeguards against cultivated land non-grain utilization and secures grain production spatial capacity through integrated mechanisms for farmland preservation and ecological risk prevention. Firstly, ERP has an "anchoring effect" on the utilization of cultivated land resources (Lu et al., 2025c). The constraints of land ecological protection have prompted the intensive transformation of agricultural production methods, driving the concentration of water and soil resource elements towards the construction of high-standard farmland,

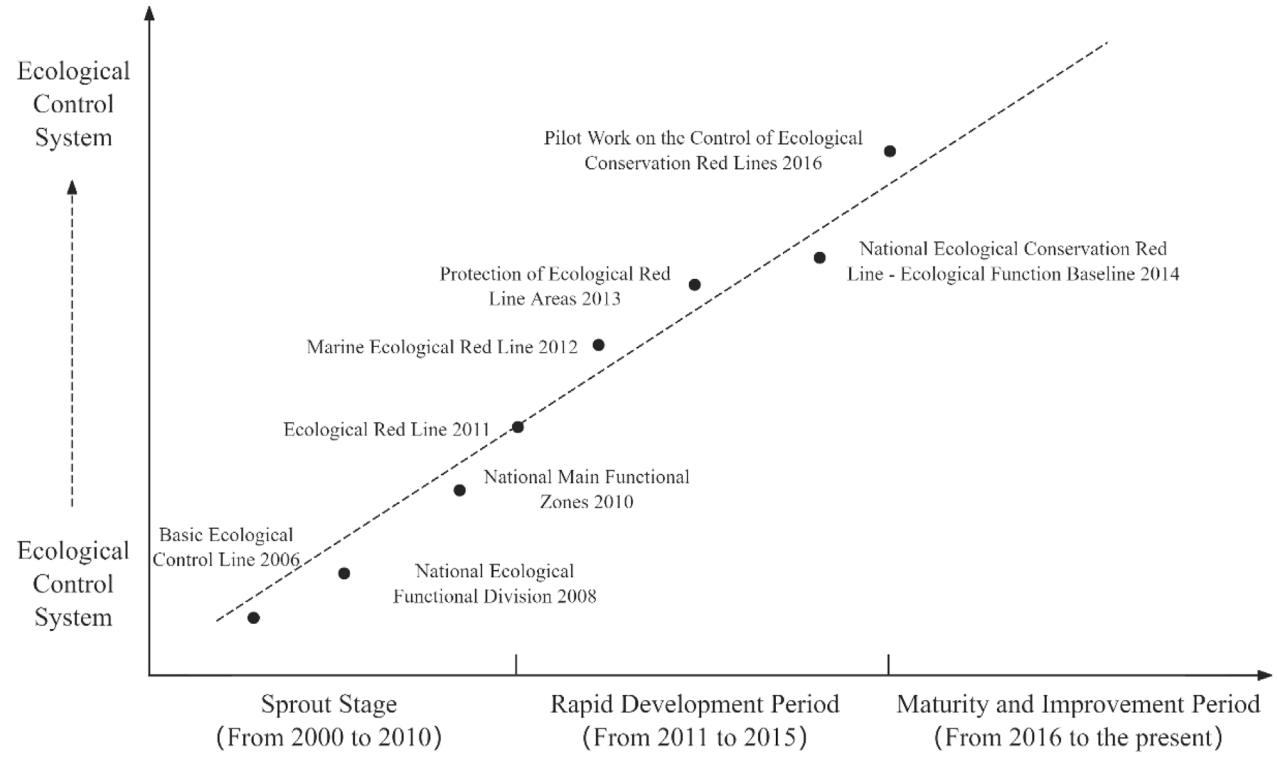


FIGURE 1
The policy evolution process of demarcating ecological red lines.

promoting the coordinated improvement of cultivated land quality and grain production capacity, and ensuring the fundamental FS and sustainable grain production capacity. Secondly, when ERP strengthens the ecological control of cultivated land, it may trigger a "competitive and cooperative effect", prompting the grain production industry to increase production capacity while attaching greater importance to the protection of cultivated land resources. Enterprise synergy accelerates cropland protection technology diffusion while optimizing land resource allocation through collective knowledge exchange. Further enhance the intensive utilization of cultivated land and the comprehensive grain production capacity. Finally, ERP exerts a "radiation effect" on grain enterprises. As the land ecological governance system transmits the policy constraints of farmland protection to grain enterprises, it strengthens the demonstration and promotion of farmland protection technologies by grain enterprises, promotes the learning effect among grain enterprises in various fields, and transforms the traditional extensive utilization model of farmland into a large-scale intensive operation model of farmland. While achieving sustainable development of food, we should also promote the modernization and high-quality development of agriculture.

Therefore, this paper proposes hypothesis H1 that ERP has a promoting effect on FS.

2.3 Indirect impact

In the process of farmland protection in our country, the problems of land fragmentation and decentralized land operation have led to the lack of agricultural scale benefits and resource allocation, thereby causing the emergence of inefficient utilization of traditional farmland (Zhang et al., 2023). With the implementation of ERP, cropland quality and utilization rates are substantially enhanced, while land transfer and reclamation processes accelerate significantly (Ran et al., 2024). Meanwhile, with the large-scale operation of land and the in-depth integration of contiguous cultivated land, farmers' enthusiasm for growing grain has been stimulated, the land reclamation rate has increased, the allocation of land factors and the application path of production technology have been reconstructed, and the comprehensive grain production capacity has been promoted (Xue et al., 2024; Shi and Liao, 2025). Firstly, land transfer can promote the reorganization of land elements. Grain business entities can obtain contiguous cultivated land resources through large-scale operations and optimize the spatial layout of grain crops by relying on the reclamation and improvement projects. Land transfer-reclamation collaboration curbs idle and inefficient cropland use, securing foundations for stable grain production. Secondly, land transfer and land reclamation can be combined with grain production factors to integrate the problem of reduced grain production caused by fragmented and extensive land in traditional grain production. By improving the ecological governance system, the risks of grain production and operation can be alleviated. This transformation not only breaks the contradiction between the supply of cultivated land resources and grain production, it has also effectively optimized the adaptation relationship between cultivated land and food crops, significantly improved the land utilization rate, and alleviated the contradiction of food supply. Finally, the improvement of land transfer and land

reclamation has alleviated the FS risk, broken the technical gap between land ecological protection under different conditions, and farmers can learn more about land ecological protection technologies through land transfer, directly improving the efficiency of grain planting and grain output, and indirectly increasing farmers' income from growing grain, making farmers more willing to grow grain. So as to achieve FS through the utilization of land ecological protection.

Therefore, this paper proposes the hypothesis that H2, LT and LR play a mediating role in the evaluation of FS by ERP.

2.4 Heterogeneity influence

As a developing country, China has significant differences in ecological protection levels, land quality and policy implementation among different provinces and cities (Wang et al., 2018; Lu et al., 2025b). In this case, it may lead to different promoting effects of ERP on FS in different regions and at different FS levels. First, in economically backward areas, the guarantee efficiency of ERP for FS is actually more obvious. This phenomenon stems from the coordinated integration of "ecological bottom line constraints" and "precise land protection". Despite the relatively backward economy, there is a high focus on the goal of land ecological protection. By ensuring the large-scale operation of cultivated land and avoiding the loss of cultivated land resources. This will further alleviate the problems of land ecological degradation and food risks. Secondly, in economically developed regions and economically average regions, the economic and technological levels are relatively higher compared to less developed regions, and the agricultural infrastructure construction is relatively complete. However, due to the relatively small area of cultivated land in economically developed regions, the promoting effect of ERP is not obvious. While economically average regions, as major grain-producing areas, focus on grain production and supply. Instead, it led to the ERP having a reverse effect during the implementation process. Thirdly, across varying FS levels, higher-security regions prioritize cropland protection red lines and intensify focus on land ecological integrity. Therefore, the promoting effect of ERP is stronger. Although the ecological protection level in low-level areas is relatively poor, it will generate a "learning effect", and the promoting effect of ERP will be slightly lower than that in high-level areas.

Therefore, this paper proposes hypothesis H3 that ERP has a heterogeneous effect on FS.

3 Methods

3.1 Identification strategy

Based on the above theory, ERP was issued in November 2015 to implement ERP, and the official standardized implementation time point across the country was from 2016 to the present. Moreover, the promotion of ERP has shown typical characteristics of gradual and regional implementation. This indicates that the impact of ERP implementation on FS at different time points will present different evaluation results. Meanwhile, as a quasi-natural experiment, ERP, when using the DID model, not only has the advantage of rich sample heterogeneity but also can effectively assess how the implementation of ERP actually affects FS. In view of this, this paper will select the DID model to explore the promoting effect of Chinese ERP on FS.

3.2 Measurement model setting

3.2.1 Benchmark regression model

Based on the above analysis, in order to better study the situation of land ecological protection, we take the ecological protection red line policy implemented by China in 2016 as the research object. Meanwhile, due to the certain differences in agricultural and grain development among various regions in our country. Therefore, this study employs the DID model, partitioning the ecological protection red line policy into experimental and control groups. The formula is as follows:

$$FS_{it} = \alpha + \beta ERP_i \times I_t^{post} + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In Model (1), FS_{it} is the explained variable, representing food security, and ERP_i is the core explanatory variable, representing the ecological protection red line policy; I_t^{post} is a dummy variable for the time point of policy implementation; X is the set of control variables. i and t represent the ith province and the tth period respectively. α is the constant term. The estimated parameter β is the net effect. μ_i represents the regional fixed effect, λ_t represents the year fixed effect, and ε_{it} represents the random disturbance term.

3.2.2 Parallel trend test and dynamic effect test models

Furthermore, the validity and rationality of the estimation using the DID model mainly lie in whether the assumption of parallel trends is met. That is, if there is no policy shock to food security, the time trends of the treatment group and the control group of the ecological protection red line should be consistent. Therefore, a series of dummy variables need to be included in the standard regression to further track whether the food security of each province (municipality, autonomous region) has the same changing trend when the ecological protection red line policy has not been implemented, and the following model is constructed:

$$FS_{it} = \alpha + \sum_{t=2005}^{2023} \beta_t \left(ERP_i \times year_t\right) + \delta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Parallel trend refers to the situation where the food security levels of the experimental group and the control group show the same trend before the implementation of the policy. That is, if the ecological protection red line policy is moved forward, no significant policy effect will be identified. Therefore, in this paper, the leading and trailing variables of the policy year are set as $year_t$, and the countermeasure effect is selected as β_t. If $\beta_t\,(2005 < year \leq 2016)$ is not significant or the joint is not significant at this stage, it can indicate that the hypothesis of the parallel trend test is satisfied, and during the $\beta_t\,(2016 < year < 2023)$ time period, it will represent its dynamic effect.

3.3 Variable selection

3.3.1 Explained variable

Food Security (FS), in terms of both connotation and extension, the core of China's FS is people-oriented, ensuring that people's

TABLE 1 System of indicators of the level of food security.

Target level	Level 1 indicators	Secondary indicators	Tertiary indicators (units)	Weights	Quality
FS	Food supply security	Volatility of total food production	(Total food production in the current year - average of total food production in the last 5 years)/total food production in the current year (%)	0.002	-
		Land mobility	Cultivated land per capita (mu/person)	0.057	+
		Grain reserves	Total grain production (tons)	0.068	+
		Resilience of crops to disasters	Area affected by crops/area sown with crops (%)	0.004	-
		Food supply stability	Grain purchases (tons)	0.136	+
		Food Circulation	Grain sales (tons)	0.123	+
	Food production security	Stability of food production	Grain sown area (millions of hectares)	0.063	+
		Level of financial support for agriculture	Grain sown area/total sown area (%)	0.019	+
		Agricultural innovativeness	Total power of cropland machinery (10,000 kW)	0.067	+
		Level of human capital	Qualified food workers (persons)	0.135	+
		Agricultural productivity	Gross agricultural output/primary sector employment (yuan/person)	0.049	+
		Infrastructure development	Number of agricultural water conservancy facilities constructed (units)	0.097	+
	Food access security	Rural Engel coefficient	Rural food consumption expenditure/total consumption expenditure (%)	0.009	-
		Food price volatility	(Current year food price index - previous year food price index)/current year food price index (%)	0.001	-
		Food share	Total food production/resident population (tons/person)	0.053	+
		Road density	Length of transport routes (rail, road, waterway)/urban area (km/sq km)	0.070	+
	Sustainable food security	Pesticide application rate	Pesticide application per unit of food sown area/crop sown area (%)	0.006	-
		Fertilizer application rate	Fertilizer application per unit of food sown area/crop sown area (%)	0.004	-
		Agricultural film use	Agricultural film uses per unit of food sown area/crop sown area (%)	0.004	-
		Quality assurance	Effective irrigated area/crop sown area (%)	0.034	+

diverse preferences for food are met at any time level. Furthermore, given China's huge population size, FS is confronted with multiple threats both at home and abroad. Therefore, in this paper, FS is expressed as a general term for comprehensive food security formed by the input of various endowment factors. The specific indicator system is shown in Table 1.

(1) Regarding the measurement system, drawing on the existing research basis (Lee et al., 2024; Xu et al., 2025c), it is proposed to select corresponding indicators from four dimensions: food supply security, food production security, food acquisition security, and sustainable food security. Compared with the existing research (He et al., 2025), it can start from the entire food industry chain. Present and measure the possible security risks in the grain industry scientifically and reasonably.
(2) Regarding the measurement method, to avoid possible analytical biases, the entropy value method is selected for measurement. The advantages of the entropy method over principal component analysis and factor analysis lie in its ability to comprehensively consider the degree of variation of indices in various indicators, providing more precise weight empowerment, having a simpler calculation process, making the comprehensive evaluation results more scientific, fair and reasonable compared to other weighting methods, and having the advantages of being unaffected by the preferences of evaluators compared to subjective weighting methods

3.3.2 Core explanatory variables

The ecological protection red line policy (ERP), in this paper, the interaction term of the dummy variable at the policy time point is selected as the core explanatory variable of this paper (Wang and Yang, 2025). In addition, since China began to steadily promote ERP in 2016, it has continuously emphasized the quality of the land environment and ensured the efficient utilization of land resources (Wang and Yang, 2025). As a result, the land within the scale red line in our country has shown a certain growth trend. Therefore, in order to scientifically and reasonably explore the situation of land

protection in China, we choose ERP as the research object for protecting the ecological environment of land, and take the implementation node of the ecological protection red line time as the starting point of the research, with 2016 as the base year, to characterize ERP. Among them, I_t^{post} is a dummy variable at the time point of policy implementation. And when t < 2016, $I_t^{post} = 0$, while when t is greater than or equal to 2016, $I_t^{post} = 1$.

3.3.3 Control variables

Considering that there are many factors affecting FS, this paper refers to the existing research (Lu et al., 2025a; Xu et al., 2025b) and will set the following control variables: Urbanization rate (URB), which is represented by the proportion of urban population to the permanent resident population in each province in this paper. Government fiscal intervention (FE) is measured by the proportion of provincial government fiscal expenditure to the GDP of each province. The degree of agricultural technology (ATD) is measured by the total power of *per capita* agricultural machinery; Industrial structure (IS), the proportion of the added value of the primary industry in each province to the GDP of that province is selected to represent the industrial structure. The degree of economic development (LNGDP) was measured by selecting the total *per capita* GDP of each province. To further ensure the comparability of the estimation results and reduce the interference of variable dimensions, the total *per capita* GDP was logarithmic processed.

3.3.4 Mediating variables

(1) Land transfer (LT), as a key path for the marketization of land and the structure of scale operation to release the allocation of factors, can not only enhance the efficiency of integrating fragmented land and matching grain business entities, but also provide fundamental assistance for improving grain production. Referring to the existing research (Fei et al., 2021), the ratio of the transferred area of household contracted cultivated land to the total area of household contracted managed cultivated land was selected to represent land transfer.

(2) Land reclamation (LR), the large-scale and contiguous reclamation and the integration of restoration technologies, as the core paths to improve land quality, can not only optimize the synergy among cultivated land elements, but also enhance the synergy between land and grain production. Referring to the existing research (Dong et al., 2025), the ratio of the sown area of crops to the total area of cultivated land was selected to represent the land reclamation index.

3.4 Data sources and descriptive statistics

This paper investigates ERP and FS within the Chinese context. To reflect the availability and operability of relevant indicators, the original data related to FS comes from the "China Grain and Strategic Reserves Yearbook" and the development work reports of each province, and the data of control variables are from the "China Statistical Yearbook" and the "China Rural Statistical Yearbook". Considering that the data of each indicator may be missing in different years, in order to obtain as complete the data resources as possible and reflect the latest situation of ERP and Chinese FS, this study set the sample time range from 2005 to 2023, and selected 31 provinces as the sample regions. Nevertheless, data gaps persist for several provinces. This study employs linear interpolation and exponential smoothing to impute these missing values. The statistical analysis results of the symbols and representativeness of each variable are shown in Table 2 as follows.

3.5 Spatio-temporal evolution trend

To better present the spatio-temporal variation trend of FS in China, based on the existing data samples of this study, we have drawn a spatio-temporal evolution trend graph. Figure 2 specifically depicts the variation trend of FS in China from 2005 to 2023. It can be clearly seen that FS shows a fluctuating upward trend. This indicates that from 2005 to 2023, under the joint influence of policy support, technological innovation and the concept of sustainable agriculture, China not only effectively responded to multiple risks and challenges, consolidated the foundation of food security, but also laid a solid foundation for ensuring long-term food supply security. Furthermore, with the strengthening of the strategic position of national food security, the popularization and application of precision agriculture technologies and disaster prevention and mitigation measures, as well as the continuous release of policy dividends such as high-standard farmland construction and producer subsidies, agricultural production entities are investing more in ensuring stable output and improving quality and safety. Meanwhile, with the continuous increase in investment in agricultural science and technology, the wide application of precision agriculture technology and efficient resource utilization models, as well as the implementation of ecological compensation policies and farmland protection systems, agricultural producers have gradually shifted to more intensive and sustainable production methods, ultimately driving FS to show an overall upward development trend despite fluctuations during this period.

4 Result

4.1 Benchmark regression results

To verify the direct effect of ERP on FS, this study conducted an empirical evaluation using Formula 1, and the results are shown in Table 3. Among them, column (1) shows the direct regression results of ERP and food security under fixed effects, column (2) shows the regression results under the addition of control variables and fixed effects, and column (3) shows the regression results using Bootstrap sampling for 1,000 times. From the regression results in column (1) of the above table, it can be found that the policy dummy variable is positively significant at the 1% level without adding control variables, indicating that the implementation of ERP has significantly improved the level of FS. After adding five control variables such as urbanization rate, government financial support, industrial structure, agricultural technology and high-quality economic development on the basis of column (1), the estimated coefficients of the policy dummy variables in columns (2) and (3)

TABLE 2 Descriptive statistics of variables.

Variable description	Code	N	Average	Standard deviation	Min	Max
Food security	FS	589	0.174	0.077	0.049	0.517
Ecological protection red line policy	ERP	589	0.421	0.494	0	1
Urbanization	URB	589	0.559	0.146	0.207	0.895
Government financial support	FE	589	0.266	0.191	0.091	1.353
Industrial structure	IS	589	0.105	0.0565	0.0020	0.327
Agricultural technology	AT	589	0.299	0.192	0.064	1.196
Economic development	GDP	589	10.570	0.685	8.559	12.207
Land transfer	LT	589	0.251	0.188	0.001	0.958
Land reclamation	LR	589	1.277	0.417	0.494	2.395

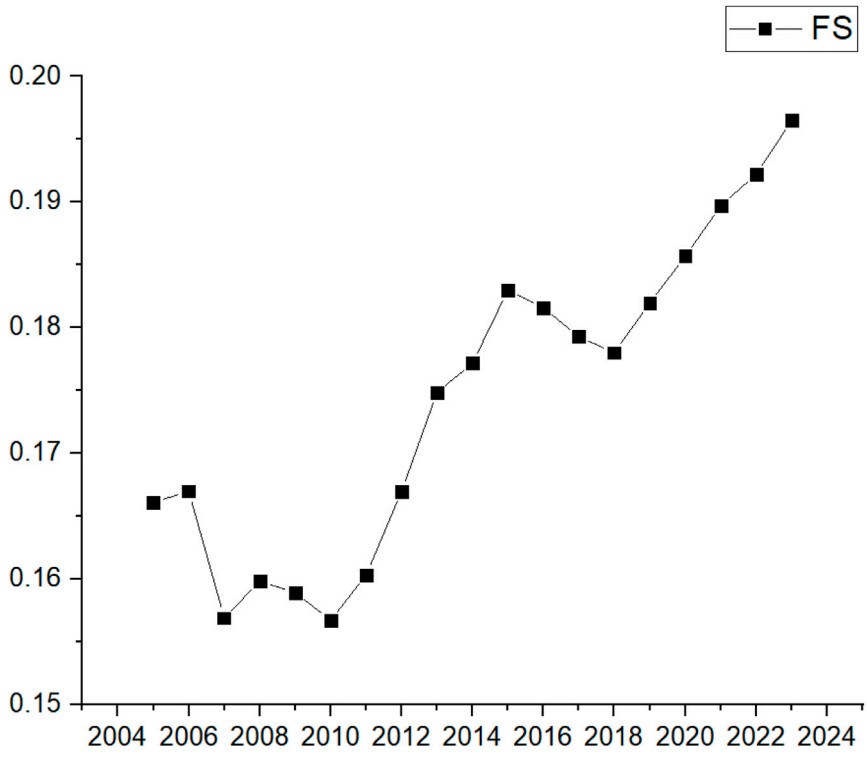


FIGURE 2
Spatiotemporal evolution trend of FS.

did not change much, and the significance was slightly lower. This indicates that the implementation effect of ERP is not only in line with the original intention of national policy-making, it also indicates that ERP plays an important role in ensuring the national FS, and Hypothesis H1 has been verified. Furthermore, by controlling variables, it can be found that government financial support and agricultural technology have significantly enhanced the level of food security. This proves that the government's support for agriculture can drive the development of the grain industry and simultaneously promote the improvement of the level of FS. Meanwhile, the improvement of agricultural technology levels promotes the production efficiency of the grain industry and can also drive the protection of land resources. This also implies that: First of all, ERP cannot do without the financial support of the government, including promoting rural economic development, popularizing rural finance, and increasing farmers' income, *etc.* It can effectively improve the utilization efficiency, production efficiency and transfer efficiency of farmland, help improve the planting efficiency and product quality of grain, and further reduce the risks of grain production and supply. Secondly, ERP has promoted the development and application of advanced agricultural technologies, including smart agriculture,

TABLE 3 Direct effect.

Variable	(1)	(2)	(3)
ERP	0.193*** (0.019)	0.195*** (0.069)	0.195** (0.082)
URB		−0.099 (0.173)	−0.099 (0.193)
FE		0.249*** (0.079)	0.249*** (0.091)
IS		−0.264 (0.230)	−0.264 (0.451)
AT		0.095** (0.046)	0.095* (0.052)
LNGDP		0.009 (0.050)	0.009 (0.053)
Year	Control	Control	Control
Region	Control	Control	Control
Cons	−1.903*** (0.013)	−2.007*** (0.461)	−2.620*** (0.538)
R^2	0.494	0.513	0.974
N	589	589	589

Note: The values in parentheses are robust standard errors; *, **, and *** respectively indicate significance at the levels of 10%, 5%, and 1%. The following tables are the same.

TABLE 4 Time Placebo test.

Variable	(1)	(2)	(3)	(4)
	Policy node = 2006	Policy node = 2007	Policy node = 2008	Policy node = 2009
ERP	0.195 (0.156)	0.195 (0.156)	0.195 (0.156)	0.195 (0.156)
Control variables	Control	Control	Control	Control
Year	Control	Control	Control	Control
Region	Control	Control	Control	Control
Cons	−2.007* (1.007)	−2.007* (1.007)	−2.007* (1.007)	−2.007* (1.007)
R^2	0.513	0.5130	0.513	0.513
N	589	589	589	589

water-saving irrigation, and pest and disease early warning systems, enhancing the security resilience of the grain industry and thereby preventing food security risks from the source of grain planting. Finally, the implementation of ERP fundamentally promotes the transformation of grain production. The ecological protection and improvement of land mean the diversification of planting, enhancing the stability and diversity of the grain production system and ensuring the supply and sustainability of grain. This means that the fact of ERP plays an important foundational role in the development of modern agriculture. It not only helps to achieve the strategic goal of China's FS, but also contributes to improving the national security governance system and protecting the ecological environment of the land.

Summarizing the above empirical assessment results, this study took various provinces in China as the research objects and, in combination with the actual situation in China, found that ERP can indeed effectively promote the improvement of FS levels in China. This result is highly consistent with the reality that China is a major agricultural country and attaches great importance to the protection of cultivated land. Similarly, as the world's largest developing country, China's abundant arable land resources are an important foundation for ensuring the stability of grain production. The proposal and implementation of ERP can guarantee the quantity and quality of arable land to the greatest extent, ensuring that China can prevent and defuse potential grain crises. This not only provides important experience for improving China's food security risk early warning system and food security risk governance system, but also serves as a benchmark for other developing countries around the world.

4.2 Parallel trend test

To ensure the validity and authenticity of the ERP assessment of FS, further tests should be conducted on the experimental group and the control group to ensure that they have the same trend before the policy implementation. Therefore, in order to further avoid the possible deviation of the estimation results caused by interfering factors, this paper will use Formula 2 to conduct parallel trend tests six years before the policy implementation and eight years after the policy implementation. The specific results are shown in Figure 3 below. According to the policy effect estimation trajectory diagram,

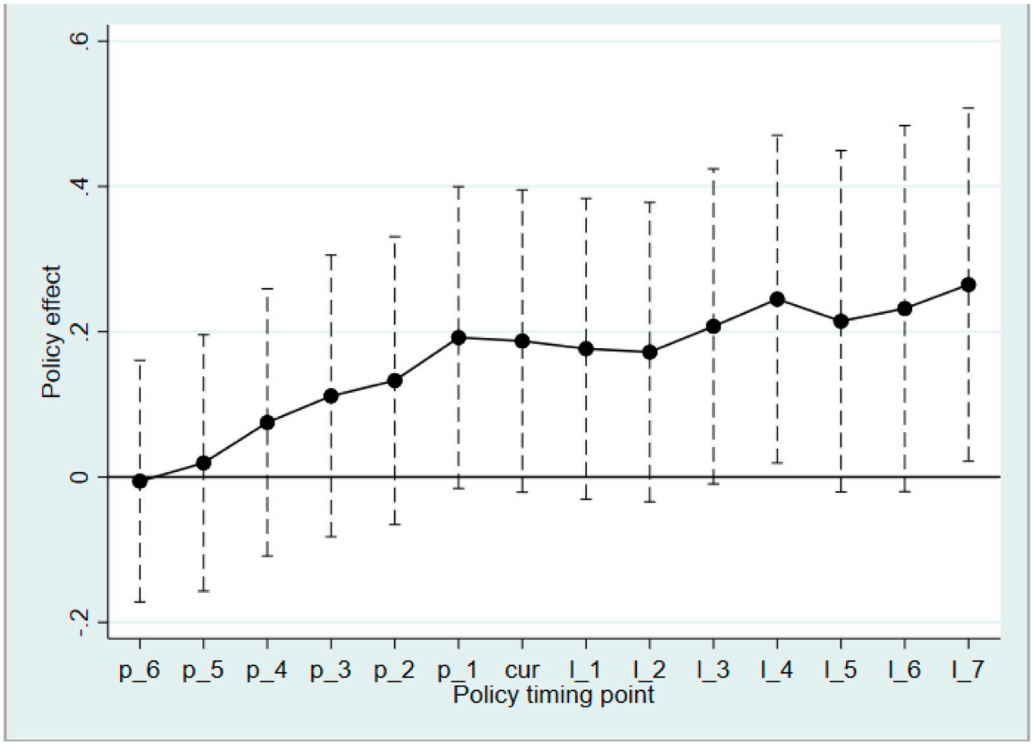


FIGURE 3
Parallel trend test.

it can be intuitively seen that the estimation results are not significant during the pre-implementation period of the policy. Moreover, as time goes by, after reaching the policy implementation point, the ERP estimation parameters begin to be significant, and the policy effect gradually increases over time, indicating that the policy effect of ERP before implementation is not significant. There is no difference in the actual situation of FS between the experimental group and the control group. This is due to the lag of agricultural production and the fact that land quality is affected by the environment, resulting in poor cultivated land resources and quality. However, after the implementation of ERP, it has promoted the protection of land quality and the increase of the scale of the land red line, effectively enhancing food security. Therefore, to meet the hypothetical requirements of the parallel trend test, it is reasonable and reliable to use the DID model to explore the policy effect of ERP on FS.

4.3 Robustness test

4.3.1 Time placebo test

Although the characteristic variables of a large number of provinces have been controlled in the quasi-natural experiments in this paper, there is still a possibility that some unobserved provincial characteristic factors may affect the evaluation results of ERP. The time placebo test can solve the fundamental problem of confounding effects in the time dimension in policy evaluation by constructing a counterfactual framework. Its advantage lies in the ability to eliminate the interference of time trends, identify expected effects and test the sensitivity of model Settings. It is the gold standard for verifying the robustness of causal inference conclusions (Margo, 1999). This paper randomly selects 2006, 2007, 2008 and 2009 before the policy implementation as the policy time points for placebo tests. The results are shown in columns (1) and (2) of Table 4. From the policy node from 2006 to 2009, the ERP coefficients were all negative and not significant, which can indicate that ERP did not have a policy effect before 2016. The robustness of the benchmark regression findings has been partially validated.

4.3.2 Lag method and tail narrowing method

Given that agricultural production and agricultural economic benefits inherently have a lag, in order to further enhance the reliability and robustness of this study. Firstly, this paper selects to conduct a re-regression of the lag period of the explained variable FS. Taking the lag period of the explained variable as the evaluation object can not only effectively alleviate the endogeneity problem and solve the reverse causality problem, it is proved that the evaluation result of ERP for FS is not caused by the contingency of model setting (Bellemare et al., 2017). The specific results are shown in Column (1) of Table 5. It can be seen that ERP remains positive and is significant at the 5% level. This further proves that ERP can effectively promote the improvement of FS level both in the current period and in the future, thereby verifying the robustness of the benchmark regression results. Secondly, in this paper, the control variable is lagged by one period for regression again. The core value of the control variable lagging by one period lies in using the time sequence to cut off the reverse causal path from FS to the control

TABLE 5 Tests by the lag method and the tail narrowing method.

Variable	(1)	(2)	(3)	(4)
ERP	0.147** (0.069)	0.270*** (0.067)	0.218*** (0.067)	0.294*** (0.080)
Control variables	Control	Control	Control	Control
Year	Control	Control	Control	Control
Region	Control	Control	Control	Control
Cons	−2.130*** (0.488)	−1.601*** (0.458)	−1.771*** (0.445)	−1.306*** (0.499)
R^2	0.482	0.538	0.510	0.515
N	558	558	579	513

variable, thereby alleviating the possible endogeneity problem of the control variable. The sensitivity of the benchmark results to the endogeneity problem of the control variables can be evaluated (Wilkins, 2018). It can be seen from column (2) of Table 5 that the coefficient of ERP for FS remains positive and is significant at the 1% level, once again proving the robustness of the benchmark regression. Thirdly, this paper chooses to process FS by the tailing method, mainly to evaluate the sensitivity of the benchmark empirical results to extreme values and outliers (Wang et al., 2023). It can be seen from column (3) of Table 5 that ERP is still significantly positive at the 1% level, proving that the promoting effect of ERP on FS remains valid after eliminating or weakening the influence of extreme values, once again demonstrating the robustness of the results and not being affected by a few extreme observations. Fourthly, to eliminate the interference of administrative privileges and the inclination of central financial resources, this paper selects to re-evaluate the promoting effect of ERP by excluding the samples of the four municipalities directly under the Central Government in China (Zhao and Xi, 2022). The results can be seen from column (4) of Table 5 that the promoting effect of ERP on FS is still significant below 1%, once again proving the robustness of this paper.

4.4 Heterogeneity test

To clarify the impact of ERP on FS at a higher level, this study conducted re-regression among different geography and different quantiles respectively to explore the heterogeneous effects of ERP on FS. This not only enriches the understanding of the effect of ERP, but also provides a more refined perspective for developing countries on land protection and food protection.

4.4.1 Geographical regional heterogeneity

Although land ecological protection is an important foundation for ensuring food production and supply, as China is a major grain importer and exporter and a developing country, there are obvious differences in land protection, food production resources and economic development among different geographical regions. Therefore, the mechanism of ERP's effect on FS may show significant geographical heterogeneity. For this purpose, this study chose to divide the samples from the Chinese region into three regions: the eastern, central, and western regions, and then conducted regression respectively. The results in columns (1)–(3) of Table 6 show that ERP in the eastern region has a promoting effect on FS, but not significantly. The reason is that in the developed eastern regions, the ecological red line areas usually overlap with high-quality cultivated land resources, resulting in the pressure of "non-grainization" of cultivated land resources after they are included in ecological protection areas. Meanwhile, although ERP emphasizes the protection of the quantity of cultivated land, it pays insufficient attention to the improvement of quality and the synergy of ecological functions. Although it shows a promoting effect in the eastern region, it is not significant. It is worth noting that ERP in the central region shows a significant inhibitory effect on FS. This is mainly because the ecological red lines in the central region are mostly demarcated in ecologically sensitive areas such as rivers, lakes, wetlands, and the periphery of forests, which restricts the utilization of high-quality land and cultivated land resources. This reflects that some local governments in this region, in order to meet ecological targets, have included gentle slopes and forest edges that could have been cultivated in the red lines. Furthermore, the functional positioning of the central region as a major grain-producing area and the ecological compensation standard being much lower than the income from growing grain make it face more constraints in the process of balancing the protection of high-quality cultivated land resources and FS. However, in the western region, ERP shows a significant promoting effect on FS, and the influence coefficient is significantly positive at the 1% level. This is mainly due to the fact that the region has promoted the terraced development of cultivated land resources under the impetus of ERP, which has to some extent alleviated the problem of cultivated land erosion. Moreover, the western region has combined the protective forest project with the construction of ecological red lines for cultivated land to further prevent natural disasters and effectively ensure grain production. In addition, with the implementation of ERP, the ecological pollution of grain has been alleviated, farmers' enthusiasm for growing grain has been stimulated, and FS has been further guaranteed.

4.4.2 Quantile heterogeneity

This study captured the structural differences of the FS conditional distribution by selecting the quantiles of different conditional distributions, revealed the heterogeneous influence of ERP on FS, especially focusing on extreme values, thereby capturing the potential nonlinear relationships among variables (Lodder and Hieftje, 1988). For this purpose, this study selected

TABLE 6 Geographical regional heterogeneity.

Variable	(1)	(2)	(3)
	Eastern region	Central region	Western region
ERP	0.100 (0.131)	−0.875*** (0.313)	0.843** (0.164)
Control variables	Control	Control	Control
Year	Control	Control	Control
Region	Control	Control	Control
Cons	−2.822*** (0.963)	−4.437*** (1.463)	−0.787 (0.679)
R^2	0.626	0.526	0.510
N	589	589	589

TABLE 7 Quantile heterogeneity.

Variable	(1) P10	(2) P30	(3) P50	(4) P70
ERP	0.052* (0.031)	0.065** (0.025)	0.049** (0.023)	0.069** (0.030)
Control variables	Control	Control	Control	Control
Year	Control	Control	Control	Control
Region	Control	Control	Control	Control
Cons	−4.123*** (0.408)	−3.514*** (0.574)	−4.015*** (0.698)	−4.423*** (0.552)
R^2	0.879	0.859	0.849	0.839
N	589	589	589	589

four quantiles of 10%, 30%, 50%, and 70% to explore the dynamic characteristics of the effect of ERP on FS under different levels of land protection. The results in Table 7 show that there is a significant distribution heterogeneity in the impact of ERP on FS: At the 70% quantile, it can be seen that the promoting effect of ERP is the most prominent, and its coefficient is significantly positive at the 5% level. As the quantile decreases, the promoting effect gradually weakens. The promoting effect rebounds at the 30% quantile and is significantly positive at the 10% level at the lowest 10% quantile, proving Hypothesis H3.

This nonlinear variation result can indicate that the protection effect of ERP on cultivated land resources is closely related to the FS level between regions. In areas with a higher FS level, the agricultural ecological foundation is better and the quality of cultivated land resources is higher. ERP is more likely to optimize the grain production mode through the technology spillover effect. For example, the combination of green agricultural technology and land consolidation can rapidly improve land quality and enhance land output capacity. This also indicates that the promoting effect of ERP on FS mainly lies in the following aspects: On the one hand, it is necessary to give full play to the advantages of land protection in areas with a higher FS level. On the other hand, different regions should implement different differentiation strategies. For example, in lower-level regions, environmental supervision and technical support should be strengthened even more to maximize the promoting effect of ERP.

TABLE 8 Indirect effect.

Variable	(1) LT	(2) LR
ERP	0.671*** (0.058)	0.399*** (0.112)
Control variables	Control	Control
Year	Control	Control
Region	Control	Control
Cons	0.872** (0.384)	4.764*** (0.745)
R^2	0.804	0.479
N	589	589

4.5 Mediation effect analysis

4.5.1 Land transfer

The results in column (1) of Table 8 show that LT has a significant mediating effect in the influence of ERP on FS. By strengthening the rigid constraints of agricultural land space, ERP not only directly ensures the stability of the total amount of cultivated land resources, but also reshapes the long-term guarantee mechanism for enhancing grain production capacity through the synergistic effect of LT's policy regulation and market mechanisms. Firstly, ERP has restructured the balance between the protection of cultivated land and the development and construction of rural land by solidifying permanent basic farmland, promoting the

transformation of the traditional land use situation where only expansion is emphasized but quality is not to green ecological land. In addition, standardizing the access regulations and use control of land transfer can promote the concentration of fragmented farmland into new types of agricultural business entities, systematically break through the capacity bottleneck of small-scale operations, deeply integrate the red line guarantee of farmland with the input of modern agricultural factors, enhance the sustainable capacity of land, and consolidate the foundation of FS.

Secondly, ERP has strengthened the scale agglomeration effect of farmland quality protection and improved the collaborative mechanism for enhancing grain production capacity. At present, the standardized operation of land transfer promotes the formation of large-scale grain operation entities, thereby affecting the application demand of modern agricultural production technology and effectively increasing agricultural science and technology investment and the upgrading of professional services. Meanwhile, with the support of the intelligent supervision system for cultivated land, through dynamic monitoring and precise regulation of data such as cultivated land quality and crop growth, sustainable land development is achieved, further ensuring stable and increased grain production.

Finally, ERP has deepened the reform of farmland protection and governance, and established a regulatory framework that combines land rights protection with responsibility constraints. ERP has further accelerated the process of standardizing land transfer, forming a collaborative system for cultivated land management and protection led by provincial governments in China and implemented by new types of grain business entities. In addition, the demonstration subjects of large-scale land transfer should be included in the certification system for cultivated land protection. Through standardized transfer contracts, the quality constraints of cultivated land should be integrated into the entire process of grain production. Local governments should dynamically implement differentiated protection and compensation policies based on the health indicators of cultivated land, further strengthening the foundation of FS resilience.

4.5.2 Land reclamation

The results in column (2) of Table 8 show that LR has a significant mediating effect on the impact of ERP on FS, and it is also significant at the 1% statistical level. Through the consolidation of fragmented land and the development of reserve resources, ERP not only directly strengthens the total guarantee of cultivated land resources, but also promotes the sustainable improvement of grain production capacity by relying on the synergy effect of integrated reclamation technologies and internal policy drive. Firstly, ERP has restructured the pattern of territorial space development and protection, broken the predicament of low efficiency and waste in traditional cultivated land utilization, and promoted the transformation of the cultivated land resource system towards a green and ecological direction. Meanwhile, the development of land reserve resources and the regeneration of wasteland have enhanced the intensity of engineering reclamation, further improved the technical division of labor in bioremediation, optimized the path of land consolidation, and promoted the sustainable operation of grain production from marginal farmland development to high-quality farmland, reducing the risks of overdraft and ecological disturbance caused by farmland utilization.

Secondly, ERP has strengthened the synergy and diffusion effect of cultivated land restoration technologies and enhanced the large-scale economic attributes of cultivated land resources. Through the ERP-driven demand for reclamation, the systematic application of soil reconstruction and ecological land technologies has been achieved, promoting the transformation of the main skills of land consolidation towards engineering remediation and biological governance. In addition, the policy constraints of ERP integrate sustainable farming techniques throughout the entire reclamation process, enabling the new cultivated land to simultaneously achieve farmland restoration and ecological risk prevention and control at the stage of capacity formation, and further reducing the environmental threats in the process of grain production and operation.

Finally, the collaborative evolution of ERP and reclamation projects has achieved a model of intelligent land governance. The main body of land consolidation has systematically upgraded the land use model by applying digital restoration algorithms to the land. During this process, not only has the precise prevention and control of environmental and ecological risks of cultivated land been formed, but also the protection of land resources has been achieved by building a monitoring and early warning platform for cultivated land quality and non-point source pollution. In addition, the department of food and natural environment resources has deeply resolved the structural contradiction of land ecological degradation by strengthening the intelligent supervision of farmland protection regulations, laying a technical foundation for the construction of a land protection and FS governance system, and providing significant assistance for ensuring food production and supply.

4.6 Discussion

This study explored the role and influence of ERP on FS. The conclusion proved that the implementation and enforcement of ERP in China would effectively promote FS, verified hypothesis H1 of this paper, and was consistent with the conclusions of existing research results (Lü et al., 2013). This proves that cultivated land resources, as the lifeblood of grain production, are an important cornerstone for consolidating national security. To better safeguard national food security, it is necessary to protect the ecological red line of land and ensure the quantity and quality of cultivated land. LT and LR have demonstrated a significant promoting effect in the facilitation of FS by ERP, which proves that the development of LT and LR can promote the implementation of ERP and have a clear leading role in maintaining China's food security and improving the food security risk early warning system. Hypothesis H2 of this paper was verified and maintained consistency with the conclusions of existing research results (Chen et al., 2024b; Xu et al., 2025a). It can be said that China and other developing countries should attach importance to the development of LT and LR, give full play to their advantageous role in protecting the national FS, and further promote the construction of the national food security governance system. Furthermore, this study confirmed that ERP has significant differences on FS in different regions of China, especially in the western regions where the promoting effect of ERP is particularly obvious, while this is not the case in other regions. The hypothesis H3 of this paper was verified, which is the same as the previous research results (Xu et al., 2018). In fact, due to the unbalanced

development among different regions in China, especially the significant differences in policy implementation caused by the varying economic levels of different regions, there is obvious heterogeneity in the implementation effect of ERP. For other developing countries around the world, they can draw on their own situations and those of different development regions in China.

5 Conclusions and policy recommendations

5.1 Conclusion

In this study, we constructed a measurement system of ERP and FS, explained the promoting effect of ERP on FS from a theoretical perspective, and explored the mechanism by which ERP affects FS. Furthermore, the panel data of 31 provinces in China from 2005 to 2023 were selected as the empirical evidence for this paper. Three models, namely, the DID model, the quantile model and the mediation model, were respectively utilized to investigate the influence effect, influence mechanism and heterogeneity between ERP and FS from a multi-dimensional perspective. The main findings are as follows:

Firstly, the results of the regression through the benchmark DID model indicate that the direct impact of ERP on FS shows a significant promoting effect, and no significant change was found in this result after adding various control variables. Furthermore, we verified the equilibrium trend test and found through the time placebo test, variable lag test and tailing test that the promoting effect of ERP on FS did not change significantly. This conclusion emphasizes that the state should strengthen the implementation and application of ERP to promote FS.

Secondly, the heterogeneity regression results show that ERP has a significant promoting effect on FS in the western region of China, but it shows no significant effect in the eastern region, and it shows an inhibitory effect in the eastern region. Furthermore, studies show that in areas with a higher FS, the promoting effect of ERP is more prominent. This result indicates that in regions with a higher FS, the advantage of ERP in promoting FS is more obvious. It further explains that in regions with a higher FS, the implementation of ERP should be prioritized to more effectively achieve the strategic core goal of the country to protect FS.

Thirdly, the results of the mediating effect indicate that LT and LR have significant mediating effects in the assessment of the impact of ERP on FS. Among them, the increase in the index of land transfer and land reclamation is conducive to providing assistance for land factors and technological factors in food production, supply and sustainability, and offers important support for improving FS. This conclusion provides a specific direction for the Chinese government's financial input in land and grain, and also offers practical experience for developing countries.

5.2 Policy recommendations

Firstly, strictly adhere to the ecological protection red line and build a guarantee system for the resilience of cultivated land. The core constraint of red line control is the core guarantee for releasing the governance efficiency of land space and consolidating the foundation of food security. The natural resources department should coordinate the spatial pattern of farmland protection and ecological restoration, optimize the coordinated layout of permanent basic farmland and land ecology, and accelerate the formation of a three-dimensional guarantee system consisting of grain production capacity reserve bases, intelligent land monitoring networks, and farmland quality cultivation mechanisms. Concurrently, state and local authorities should coordinate cultivated land development by: establishing standardized health certification systems, implementing land grading protocols, refining protection compensation mechanisms, and boosting grain production efficiency. Concurrently prioritize targeted fiscal investments in land improvement and grain production, advance cultivated land restoration technologies, and synchronously enhance ecological conservation capacity with agricultural productivity.

Secondly, deepen the coordination of red line control and restoration technologies, and strengthen the quality of cultivated land and grain production. The innovation of land ecological governance systems and the integration of land ecological restoration technologies are the core driving forces for enhancing the sustainable productivity of cultivated land. It is suggested that the government and environmental protection departments accelerate the research and development of smart ecological land technologies and promote the integration of soil reconstruction and bioremediation technologies. Further improve the land allocation mechanism, enhance the efficiency of grain production, and provide institutional guarantees for enhancing the resilience of the cultivated land system. In addition, by deeply integrating land ecological control with the empowerment of farmland restoration technologies, we can promote breakthroughs in the ecological red line policy between enhancing grain production capacity and maintaining the resilience of grain production, accelerate the extension of the farmland restoration industrial chain, and fully implement the strategic response of promoting production capacity through restoration and ensuring food security through control.

Thirdly, we will strengthen the support system for ecological red line control and improve the long-term mechanism for farmland protection and quality enhancement. Strictly adhering to the ecological protection red line serves as a fundamental institutional constraint for ensuring food security. On the one hand, the government should accelerate the improvement of the collaborative supervision mechanism for ecological red lines, be self-sufficient in the national food security strategy and the national security strategy, deepen the development strategy for agricultural, ecological and natural resource security, ensure that permanent basic farmland and high-standard farmland are not encroachment upon or damaged, and enhance the resilience of food production. On the other hand, efforts should be accelerated to establish a compensation mechanism for ecological protection of cultivated land within the red line area, improve the mechanism for balanced ecological protection of cultivated land, set up core systems for incentives to improve the quality of cultivated land and for the prevention and control of pollution risks in grain production, and improve the early warning system for food security risks. We will fully implement the shared responsibility of the Party and government for food security, enhance the government's capacity to safeguard food security, establish a comprehensive assessment responsibility mechanism that links the ecological value of cultivated land with the effectiveness of food security guarantees, and take local governments and the Ministry of Agriculture as the main responsible parties to curb

the reduction of the ecological red line area of cultivated land and ensure national food security.

5.3 Research deficiencies and prospects

Future research can be conducted through: First, a deeper exploration of the data dimensions of ERP and FS. Although this study uses provincial panel data to demonstrate the macro impact of ERP on ERP, the transmission mechanism at the micro level still requires more in-depth research. For instance, by using data from city panels, county panels, and the enterprise level, and in combination with the specific implementation of policies, it can deeply demonstrate the role path of ERP in land protection and FS. The second is to strengthen the research on the dynamic coupling between the ERP implementation environment and land factors and FS. Further demonstrate the long-term mechanism and spatio-temporal heterogeneity characteristics of ERP for FS, providing more precise theoretical support for improving the land protection and FS governance system.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

MX: Project administration, Software, Methodology, Data curation, Investigation, Writing – original draft, Visualization, Resources, Conceptualization, Validation, Funding acquisition, Writing – review and editing, Supervision, Formal Analysis.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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EDITED BY
Chengqi Wang,
University of Nottingham, United Kingdom

REVIEWED BY
Yazhu Wang,
Chinese Academy of Sciences (CAS), China
Qingmin Zeng,
China West Normal University, China

*CORRESPONDENCE
Woon-Seek Lee,
iewslee@pknu.ac.kr

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Impact of land resource misallocation on carbon emission efficiency: empirical evidence from 274 cities in China

Zhongqi Wen, Woon-Seek Lee* and Sheen Woo

Graduate School of Management of Technology, Pukyong National University, Busan, Republic of Korea

Introduction: With the acceleration of urbanization and the implementation of the "dual carbon" goals, the impact of Land Resource Misallocation (LRM) on Urban Carbon Emission Efficiency (UCEE) has attracted increasing attention.

Methods: Based on panel data from 274 Chinese cities during the period 2010–2022, we constructed a LRM index and employed a two-way fixed-effects model to empirically analyze the relationship between LRM and UCEE.

Results: The results revealed that LRM significantly hindered the improvement of carbon emissions efficiency in cities. The mechanism analysis indicates that this negative effect is primarily transmitted through the obstruction of Industrial Structure Upgrading (ISU) and Green Technological Innovation (GTI). Further, regional heterogeneity tests showed that the suppressive effect was more pronounced in the central and western regions, small- and medium-sized cities, and non-resource-based cities.

Discussion: In terms of policy implications, deepening market-oriented reforms of the land system, optimizing land use structures, reducing administrative intervention in land allocation, and simultaneously promoting industrial upgrading and GTI to enhance UCEE are recommended.

KEYWORDS

land resource misallocation, urban carbon emission efficiency, industrial structure upgrading, green technological innovation, panel data analysis

1 Introduction

Global warming poses an unprecedented challenge to sustainable development, and the urgency to reduce greenhouse gas (GHG) emissions never increased. Rapid urbanization and industrialization, especially in developing economies, significantly intensified energy consumption and carbon emissions (Abbasi et al., 2020). Although cities occupy only a small proportion of the Earth's surface, their energy use contributes approximately 70% of global CO_2 emissions (Luqman et al., 2023). Therefore, improving Urban Carbon Emission Efficiency (UCEE) (i.e., achieving greater economic and social output while reducing carbon emissions) has become a key strategy for addressing climate change and maintaining economic growth. Enhancing urban carbon emission efficiency is crucial not only for achieving global climate goals such as those outlined in the Paris Agreement but also for promoting sustainable urban development (Fan and Xu, 2025). This is particularly relevant for China, which, despite significant progress in deploying renewable energy in recent years, has also become one of the largest carbon emitters globally (Raihan and Bari, 2024; Wang

et al., 2024). China pledged to reach peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (Zhang et al., 2023; Zhang H. et al., 2024). Achieving this transformation requires a fundamental decoupling of economic growth from carbon emissions, which, in turn, requires significant improvements in carbon efficiency across all sectors of the urban economy. Carbon emission efficiency generally reflects the effectiveness with which an economy or city generates output or achieves development goals per unit of carbon emissions (Chen et al., 2025). Quantitatively, carbon emission efficiency is often expressed as the ratio of economic output (or other benefit indicators) to carbon emissions or inversely as the carbon intensity of economic activities (Li et al., 2024). A higher UCEE implies that a city produces more GDP, services, or social welfare per ton of CO_2 emitted, indicating a higher degree of sustainable, low-carbon development. Therefore, enhancing the urban carbon emission efficiency is critical for achieving emission reductions while sustaining socioeconomic progress (Zhang Y. et al., 2024).

Numerous studies explored the determinants of UCEE. Technological innovation and energy structure are frequently identified as key drivers. For instance, clean energy and advanced technologies can significantly enhance efficiency by reducing carbon emissions per unit of energy use or output (Miao et al., 2024). Similarly, industrial structure plays an important role: cities dominated by high-tech industries and services typically exhibit better carbon efficiency than those centered on heavy industry because of the lower emissions of the tertiary sector (Zhang H. et al., 2024). Robust environmental policies and regulations can also improve the UCEE by promoting energy conservation and emission control. Recent analyses of Chinese cities show that stricter environmental regulations and lower energy intensity (energy use per unit GDP) are significantly associated with higher carbon efficiency, emphasizing the importance of governance and green investment (Zhang H. et al., 2024). Summarily, existing literature suggests that technological, structural, and policy-related factors jointly contribute to improvements in UCEE.

However, one critical factor was overlooked in the discussion on urban carbon efficiency, namely, the role of urban land use and allocation. The spatial distribution of land across different uses and cities may also substantially affect carbon emissions (Wen et al., 2025). Urban form and land use patterns fundamentally shape energy demand and emissions. For example, unplanned urban sprawl often leads to increased vehicle use and higher *per capita* emissions, while compact, well-planned cities enable more efficient infrastructure and lower carbon footprints (Abbasi et al., 2020). Studies emphasize that optimizing urban spatial structures (e.g., promoting polycentric layouts and higher density) can enhance carbon efficiency by reducing travel distances and conserving land resources (Fan and Xu, 2025). These findings suggest that urban planning and land management are crucial for achieving emission reduction goals. Furthermore, in many emerging economies, land is not fully allocated through market forces, although it is heavily influenced by government policies and institutional arrangements (Wen et al., 2025). This often results in Land Resource Misallocation (LRM), in which the distribution of land across industrial, commercial, and residential uses deviates from economically efficient or environmentally optimal patterns. China is a typical case in which land ownership is shared between the state and collectives, giving governments the dominant authority over land allocation. Land use has become a critical policy instrument for stimulating economic growth. Under the "land-for-development" strategy, local governments tend to allocate large portions of urban land to industrial uses at artificially low prices to attract manufacturing investment and boost GDP (Han and Huang, 2022). While this approach has fueled rapid industrialization, it has also led to inefficient urban layouts such as oversized and underutilized industrial parks. This reflects an imbalance in land use and a misallocation of land resources away from potentially more efficient or higher-value applications (Han and Huang, 2022). For example, land misallocation results in higher emissions and lower efficiency. Using data from Chinese cities, Han and Huang (2022) found that land misallocation, especially overallocation to industrial land, significantly increases urban carbon emissions. Their analysis suggests that this effect operates through multiple channels: land misallocation hampers industrial upgrading, inhibits technological innovation, and undermines the benefits of economic agglomeration, thereby locking cities into inefficient, high-carbon development paths (Han and Huang, 2022). Similarly, Zhou et al. (2022) directly confirmed the adverse effects of land resource misallocation on urban carbon emission efficiency. They reported that cities with higher degrees of misallocation tend to have significantly lower carbon efficiency, implying that poor land allocation results in higher total emissions and lower economic output per unit of carbon (Zhou et al., 2022).

Although the academic community has gradually begun to explore the relationship between LRM and UCEE, this field is still in its infancy, with several important knowledge gaps yet to be addressed. For example, whether land misallocation is a significant determinant of urban carbon emission efficiency has not been fully examined or empirically validated in the existing literature (Gao and He, 2024). Furthermore, the underlying mechanisms through which land misallocation affects carbon efficiency are poorly understood. Much of the empirical literature focuses on either the direct impact of the industrial structure on emissions or treats the industrial structure as a mediating variable for other factors (Gao and He, 2024; Cheng Y. et al., 2025; Xue et al., 2025), neglecting its potential role as a transmission mechanism linking land misallocation and urban carbon efficiency. While some studies explored the relationship between land misallocation and green technological innovation (Xu et al., 2025), a lack of research still exists on the mediating pathway of "Land Resource Misallocation–Green Technological Innovation–Urban Carbon Emission Efficiency," which overlooks the crucial role that green innovation may play in this linkage (Nan et al., 2022).

Therefore, we examined the impact of LRM on UCEE, identified whether misallocation is a key determinant, and uncovered its transmission mechanism. Using panel data from 274 prefecture-level cities in China between 2010 and 2022, we constructed a two-way fixed-effects model to empirically assess the relationship between LRM and carbon emission efficiency. The results show that land misallocation significantly inhibits improvements in carbon emissions efficiency, and robustness checks confirm the validity of the baseline findings. These empirical results

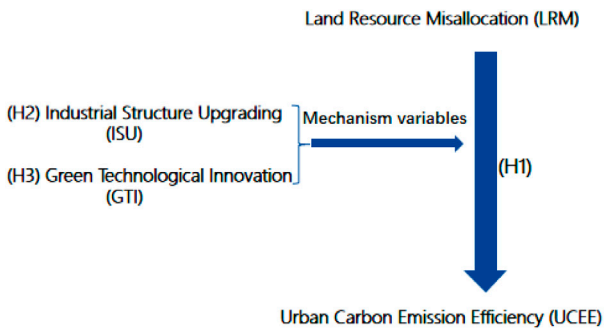


FIGURE 1
Conceptual framework.

contribute to the literature by addressing a previously overlooked dimension in environmental economics—highlighting LRM as a significant factor influencing UCEE. The mechanism analysis reveals that LRM impedes carbon efficiency, primarily by suppressing Green Technological Innovation (GTI) and hindering Industrial Structure Upgrading (ISU). The identification of these two mediating variables confirms that ISU and GTI play pivotal roles in the transmission mechanism through which land misallocation affects UCEE. This finding not only enriches the theoretical framework of the mechanism but also addresses a significant gap in the existing literature. Heterogeneity analysis further showed that this inhibitory effect was more pronounced in the central and western regions, small- and medium-sized cities, and non-resource-based cities. We verified the robustness of our findings by replacing the core explanatory variable with the ratio of land transfer revenue to urban construction land area. Additionally, we address endogeneity concerns using the interaction term between the average urban terrain slope and the annual economic growth target of the city as an instrumental variable, and the conclusions remain robust. The use of this instrumental variable strengthens the validity of causal identification in assessing the effect of LRM on UCEE, thus contributing to the methodological literature by addressing endogeneity concerns that have been largely overlooked in prior studies. These findings confirm the rigorous identification of LRM as an important determinant of urban carbon emissions efficiency.

The remainder of this paper is organized as follows. Section 2 develops the theoretical framework and research hypotheses; Section 3 describes the data, variables, and empirical model; Section 4 presents and discusses the empirical results; Section 5 concludes with key findings, policy implications, and future research directions; and Section 6 provides a brief summary.

2 Theoretical framework and hypotheses

To illustrate the hypothesized relationships between LRM and UCEE, this study constructs a conceptual framework, as shown in Figure 1. Specifically, H1 tests the direct effect of LRM on UCEE, while H2 and H3 explore the mediating roles of ISU and GTI, respectively.

2.1 Direct impact of land resource misallocation on urban carbon emission efficiency

LRM refers to the inefficient allocation of land across industrial sectors and functional uses, often stemming from government intervention deviating from market-oriented mechanisms (Zhou et al., 2023). In China, such distortions are reflected not only in the quantity or spatial distribution of land supply but also deeply embedded in land pricing structures and property rights systems (Huang et al., 2025). A prominent manifestation of this phenomenon is that local governments, driven by short-term fiscal revenue and economic growth targets, allocate land at artificially low prices to high-energy-consuming industries (An, 2024; Chen and Yuan, 2025), effectively reducing land use costs for carbon-intensive sectors (Gao et al., 2022). This practice distorts urban spatial development patterns, constrains the emergence of low-carbon industries, and undermines the competitiveness of green and innovative enterprises in the land market, thereby limiting their expansion and contribution to carbon reduction (Jiang et al., 2022; Wu et al., 2023). Such an institutional bias exacerbates the feedback loop between resource misallocation, industrial path dependence, and carbon lock-in, locking cities into a high-emission growth trajectory (Cheng Y. et al., 2025). Furthermore, existing literature suggests that the concentration of land allocation in low-productivity sectors also leads to structural inefficiencies, reflected in declines in total factor productivity (TFP). This misallocation reinforces traditional high-pollution industrial structures, further entrenching rigid emission patterns and reducing the overall carbon emission efficiency (Gao and He, 2024). For instance, Zhou et al. (2022), based on panel data from Chinese cities, found that higher degrees of land misallocation were associated with poorer urban carbon performance. Summarily, we argue that LRM has become a significant structural barrier to improving the efficiency of urban carbon emissions. Hence, we propose the following hypotheses:

H1. LRM hinders improvements in UCEE.

2.2 Mechanism of industrial structure upgrading

In the context of carbon neutrality, the optimization and upgrading of industrial structures are widely recognized as key pathways for improving the efficiency of urban carbon emissions. The core lies in transforming urban economies from traditional high-carbon, resource-intensive industries toward green, low-carbon, and high-value-added emerging sectors (Zhou et al., 2022), ultimately targeting the development of industries characterized by elevated value capture, advanced technological embeddedness, and eco-efficient production paradigms (Ran et al., 2023). This transformation not only helps reduce carbon intensity and improve energy structure but also enhances green productivity at the urban level through technological advancement (Chen and Yuan, 2025). However, as a typical institutional distortion, land–resource misallocation may serve as a suppressive mechanism during this transition. The misallocation compresses the accessibility of land for high-tech industries and

modern services, hampers spatial agglomeration and capital-deepening of green industries, and thus weakens the advancement of industrial upgrading (Xie et al., 2022; Cheng G. et al., 2025). Furthermore, resource dependence impedes the advancement and upgrading of industrial structure (Wang et al., 2019). The suboptimal allocation of land factors may reinforce existing high-carbon industrial structures through "path dependence," resulting in a "lock-in effect" preventing the transition to more advanced industrial forms and undermines carbon efficiency (Cheng G. et al., 2025). Therefore, we argue that LRM may suppress improvements in UCEE by obstructing ISU. Accordingly, we propose the following hypothesis:

H2. LRM inhibits the improvement of UCEE by impeding ISU.

2.3 Mediating mechanism of green technological innovation

Under the guidance of the "dual carbon" goals, GTI is widely regarded as a critical lever to enhance UCEE. Its essence lies in decoupling economic growth from carbon emissions by improving resource utilization efficiency and environmental performance through technological progress and institutional innovation (Deng et al., 2019; Nan et al., 2022). The Green Technological Innovation encompasses not only clean production, energy-saving technologies, and renewable energy, but also green transformation in institutions, management, and business models, forming the core of urban green development capacity that aligns with the long-term sustainability paradigm (Li and Liao, 2020). As land is an essential input for green innovation, its allocation directly influences the formation of the green technological capacity of a city. The existence of LRM may hinder the GTI, thereby weakening UCEE. An imbalanced allocation of industrial land increases the carbon intensity per unit of economic output and limits the potential for large-scale adoption of clean technologies (Chu et al., 2019). For example, when land is preferentially allocated to polluting and energy-intensive industries, green firms face higher land costs, weaker infrastructure support, and insufficient innovation network connections, ultimately suppressing investments in green R&D and the diffusion of sustainable technologies (Du and Li, 2021). Contrarily, green industries and service sectors depend on high-quality land and a supportive ecological environment; however, under a distorted land allocation regime, such sectors are often marginalized in urban space, weakening the capacity for sustainable development of the city (Cheng G. et al., 2025). Based on this logic, we propose the following hypothesis.

H3. LRM inhibits the improvement of UCEE by hindering the development of GTI.

3 Methodology

3.1 Sample selection and data sources

We used panel data from 274 prefecture-level cities in China over a 13-year period from 2010 to 2022, comprising 3,562 observations, to investigate the relationship between LRM and carbon emissions efficiency, as well as its underlying mechanisms. Observations with missing values (city-year pairs) were excluded to ensure consistency in the alignment of all variables, and 3,004 valid observations were ultimately retained for the benchmark regression. All data were analyzed using the Stata software. To address heteroscedasticity, robust standard errors were used in all regressions. To mitigate the influence of outliers, all continuous variables are winsorized at the top and bottom 1%.

The data for each indicator were sourced as follows: LRM data were obtained from the *China Urban Construction Statistical Yearbook* and carbon emission efficiency data were derived from the CEADS database. Data on ISU, population density, human capital, financial development level, foreign direct investment, and per-capita fiscal expenditure were collected from statistical yearbooks, bulletins, and statistical bureaus at various government levels in China. GTI data are obtained from the CNRDS database. The environmental regulation intensity was compiled from government work reports published on official government websites.

3.2 Variable measurement

3.2.1 Explanatory variable

LRM serves as the central explanatory variable within this empirical framework. Land resource allocation refers to the distribution of land across industries (Cheng G. et al., 2025). Under the vertically integrated governance system and current land policy framework of China, land is publicly owned and the government holds substantial discretion over its allocation. In pursuit of economic benefits, local governments tend to supply large quantities of industrial land, while restricting the provision of land for commercial and residential purposes, leading to the excessive expansion of industrial land. This phenomenon was defined here as the land resource misallocation (Zhang Y. et al., 2024). Accordingly, we measured LRM using the proportion of industrial land within the total urban construction land. This ratio reflects the extent to which land allocation is biased toward secondary industries, capturing the potential influence of government-led land resource distribution on carbon emission efficiency.

LRM was calculated using the following Equation 1:

$$LRM = \frac{Industrial\ Land\ Area}{Total\ Construction\ Land\ Area} \times 100 \quad (1)$$

3.2.2 Dependent variable

The dependent variable is UCEE. We adopt a super-efficiency Slack-Based Measure (SBM) model incorporating undesirable outputs (CO_2 emissions) to measure UCEE. This method was first proposed by Tone (2001), and we followed the approach of Zhou et al. (2022) by simultaneously considering both input and output indicators with indicator selection based on data availability. Compared with traditional models for measuring UCEE, the proposed model offers several advantages. First, it directly incorporates undesirable outputs (i.e., CO_2 emissions), thereby avoiding efficiency distortion caused by data transformation in

conventional approaches. Second, it relaxes the upper bound of efficiency scores, allowing differentiation among highly efficient cities. Third, by adopting a non-radial optimization framework and a directional distance function, it accurately identifies the improvement potential of individual input and output factors. These features make the model a robust and suitable tool for assessing UCEE. The specific indicators used to calculate the UCEE were as follows:

(1) Input variables include the following factors.
   i) Capital input, represented by the annual stock of fixed assets in the city (unit: ten thousand yuan).
   ii) Labor input, measured by the number of employed persons in the city (unit: ten thousand persons)
   iii) Energy input, represented by the total energy consumption in the city (unit: ten thousand tons of standard coal).
(2) Desirable output variable: Real GDP of the city (unit: ten thousand yuan).
(3) Undesirable output variable: Urban CO_2 emissions (unit: 10,000 tons), which are estimated based on the consumption of major energy types and their corresponding emission factors, including coal, oil, natural gas, and electricity.

The corresponding model is as follows:

$$Min\,\varphi = \frac{1 + \frac{1}{m}\sum_{k=1}^{m}\frac{\delta_k^-}{x_{ko}}}{1 + \frac{1}{n+s}\left(h_1\sum_{r=1}^{n}\frac{\delta_r^+}{y_{ro}} + h_2\sum_{q=1}^{s}\frac{\delta_q^b}{b_{qo}}\right)} \quad (2)$$

In Equation 2 above, the variables δk^-, δr^+, and δqb are referred to as *slack variables*. δk^-, δr^+, and δqb represent the slack in the *k*-th type of capital input, the shortfall in the *r*-th desirable output, and the surplus in the *q*-th undesirable output, respectively. While φ denotes the carbon emission efficiency score of the decision-making unit (DMU o). Correspondingly, xko, yro, and bqo denote the inputs of the *k*-th capital, *r*-th desirable output, and *q*-th undesirable output for decision-making unit *o* (DMU *o*). The objective of the model is to minimize input redundancies and excessive undesirable outputs while maintaining the current level of desirable outputs, thereby improving the carbon emission efficiency.

The computational methods for these slack variables are expressed in Equations 3–5:

$$\delta_k^{-} = x_{ko} - \sum_i \lambda_i x_{ki} \quad (3)$$

$$\delta_r^{+} = \sum_i \lambda_i y_{ri} - y_{ro} \quad (4)$$

$$\delta_q^{b} = b_{qo} - \sum_i \lambda_i b_{qi} \quad (5)$$

The weighted linear combinations in Equations 3–5 are defined as follows: $\sum_i\lambda_i x_{ki}$ represents the minimum required input of factor k, based on a weighted combination of peer DMU. $\sum_i\lambda_i y_{ri}$ indicates the maximum achievable level of desirable output r, under current technology. $\sum_i\lambda_i b_{qi}$ denotes the lowest attainable level of undesirable output q, considering environmental constraints. Here, λ_i is the weight assigned to each DMU in constructing the reference (efficient) frontier.

Based on the super-efficiency SBM model, 3,562 observations of UCEE were calculated using Equation 2. The efficiency values range from 0.020 to 1.110, with a mean of 0.332, indicating an overall low level of carbon efficiency. This finding suggests that significant room for improvement exists in the synergy between carbon reduction and economic growth in Chinese cities. Although a few cities exhibited UCEE values approaching 1, indicating relatively balanced development, most cities fell into the low-efficiency range, reflecting their continued reliance on traditional high-emission, low-output development models.

3.2.3 Mechanism variables

We introduced two mechanism variables: ISU and GTI.

To measure the level of industrial structure upgrading, we follow the method by Murakami (2015), employing a structural indicator widely used in related research, namely, the level of service-oriented industrial transformation, referred to in this study as ISU. Specifically, this indicator is measured as the ratio of the added value of the tertiary sector to that of the secondary sector. This reflects the shift in economic activity from traditional manufacturing to high-value-added and low-carbon modern services (Zhou et al., 2023). A higher ratio indicates a greater share of the service sector in the national economy, representing a higher level of industrial structural upgrade.

The second variable is GTI. Following the method of Wu et al. (2022), we use the number of obtained green patents as a proxy. This metric is widely accepted in environmental economics. Prior to the regression analysis, we apply a log transformation to the count of green patents after adding one (Liu et al., 2021). This transformation helps smooth the skewness of distribution and enhances the comparability of green innovation levels across cities.

3.2.4 Control variables

UCEE is affected by several factors. Referring to existing literature (Zhou et al., 2023; An, 2024; Shao et al., 2024; Huang et al., 2025), we control for the following variables: (1) Population Density (PD), measured by the number of permanent residents per unit of land area (unit: persons/km^2); (2) Financial Development (FD), calculated as the ratio of the sum of year-end loan and deposit balances of financial institutions to the GDP of the city in the same year; (3) Human Capital (HC), measured by the share of permanent residents holding an associate degree or higher (unit: %); (4) Foreign Direct Investment (FDI), measured as the share of actual utilized foreign direct investment in the annual GDP of the city (unit: %); (5) Per Capita Fiscal Expenditure (PCFE), based on the general public budget expenditure *per capita*, where population is defined as the number of permanent residents (unit: yuan/person); (6) Environmental Regulation Intensity (ERI), represented by the proportion of environment-related terms in the annual work report of the local government.

3.3 Empirical model

Following the methodology of Ma et al. (2025), we constructed a two-way fixed effects model in a benchmark regression to capture the inhibitory effect of LRM on carbon emissions efficiency across cities and over time, thereby testing Hypothesis 1.

TABLE 1 Descriptive statistics.

Variables	N	Min	Max	Mean	SD	p25	p50	p75
UCEE	3,004	0.150	0.834	0.326	0.115	0.252	0.302	0.374
LRM	3,004	2.091	37.710	18.640	8.191	12.270	19.000	24.330
PD	3,004	23.220	2,614.000	471.700	427.900	191.400	358.200	620.500
FD	3,004	0.987	6.559	2.459	1.122	1.670	2.154	2.906
HC	3,004	0.113	9.607	1.863	1.993	0.642	1.169	2.093
FDI	3,004	0.007	7.677	1.769	1.730	0.395	1.277	2.528
PCFE	3,004	2,643.000	21,706.000	8,819.000	3,849.000	5,960.000	8,292.000	11,009.000
ERI	3,004	0.479	1.905	0.949	0.271	0.759	0.908	1.086

Note: UCEE, urban carbon emission efficiency; LRM, land resource misallocation; PD, population density; FD, financial development; HC, human capital; FDI, foreign direct investment; PCFE, per capita fiscal expenditure; ERI, environmental regulation intensity.

TABLE 2 Correlation test.

Variables	UCEE	LRM	PD	FD	HC	FDI	PCFE	ERI
UCEE	1							
LRM	−0.029	1						
PD	0.001	0.194***	1					
FD	−0.038**	−0.072***	0.201***	1				
HC	0.007	0.003	0.261***	0.589***	1			
FDI	0.030	0.141***	0.295***	0.043**	0.260***	1		
PCFE	0.002	−0.019	0.063***	0.395***	0.275***	0.017	1	
ERI	0.010	−0.071***	−0.115***	0.060***	0.044**	−0.097***	0.133***	1

Note: Pearson correlation coefficients are reported. ***p < 0.01, **p < 0.05, *p < 0.1.

Baseline regression model:

$$UCEE_{ct} = \alpha_c + \alpha_t + \alpha_0 + \beta_1 LRM_{ct} + \gamma X_{ct} + \varepsilon_{ct} \quad (6)$$

In the model, c, t, α_c and α_t, α_0, ε_{ct}, $UCEE_{ct}$, and γX_{ct} denote the city, year, capture city and year fixed effects, constant term, error term, carbon emission efficiency, and a vector of control variables, respectively.

4 Empirical results and analyses

4.1 Descriptive statistics

To better understand the characteristics of the research sample and obtain an overview of the panel data, we conducted a descriptive statistical analysis of the main variables. The analysis was performed using the Stata software, and the results are presented in Table 1.

The dependent variable, UCEE, has a mean value of 0.150, a median of 0.302, and a standard deviation of 0.115, indicating a certain degree of variation in carbon efficiency, which provides a sound foundation for further empirical investigation. The independent variable, LRM, shows a mean of 18.64 and a median of 19.00, suggesting that the overall level of the variable is concentrated around 19. Additionally, the descriptive statistics of the other variables indicated that all variables fell within a reasonable range, confirming the appropriateness of the sample selection in this study.

4.2 Correlation analysis

Table 2 presents the results of correlation analyses. At the preliminary level, LRM appeared to be negatively correlated with UCEE, although the relationship was not statistically significant, indicating the need for further investigation. Additionally, most p-values in the correlation test were <0.01, suggesting that the variables exhibited strong correlations at the 1% significance level.

4.3 Multicollinearity test

Multicollinearity refers to a strong correlation among the explanatory variables in a regression analysis, which may result in unstable coefficient estimates and reduced statistical significance. The Variance Inflation Factor (VIF) test is commonly used to detect multicollinearity. Here, we applied the VIF test to examine the multicollinearity among the explanatory variables. As shown in Table 3, all the VIF values were below the critical threshold of

TABLE 3 VIF test.

Variables	VIF	1/VIF
LRM	1.060	0.941
PD	1.200	0.831
FD	1.740	0.573
HC	1.700	0.588
FDI	1.190	0.844
PCFE	1.210	0.829
ERI	1.040	0.958

TABLE 4 Baseline regression.

Variables	(1)	(2)
	UCEE	UCEE
LRM	−0.001***	−0.001***
	(-3.11)	(-2.96)
PD		0.000
		(1.53)
FD		−0.005
		(-1.45)
HC		0.010***
		(2.77)
FDI		−0.001
		(-0.77)
PCFE		−0.000
		(-0.55)
ERI		0.002
		(0.30)
Constant	0.347***	0.322***
	(50.04)	(11.71)
Observations	3,004	3,004
R-squared	0.585	0.587
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

10, indicating that multicollinearity was not a concern. Therefore, multicollinearity does not threaten the validity of the empirical results.

4.4 Baseline regression analysis

The baseline regression employed a two-way fixed effects model and adopted a stepwise regression approach. The results of Equation 6 are presented in Table 4. In the first step, the control variables were excluded. The estimation results show that the coefficient of the variable LRM (β_1) is negative and statistically significant at the 1% level. In the second step, after including the control variables, the coefficient of LRM (β_1) remains significantly negative at the 1% level (coefficient = -0.001, $p < 0.01$). Therefore, Hypothesis 1 is supported, confirming that LRM significantly reduces UCEE.

4.5 Robustness and endogeneity tests

4.5.1 Alternative measurement of independent variables

To ensure the robustness of the empirical findings, we replace the core independent variable with an alternative measure: the ratio of land concession revenue to urban construction land area. Land concession revenue data were compiled from the National Bureau of Statistics of China, the *China Land and Resources Yearbook*, and official disclosures from local governments. The results in Column (1) of Table 5 show that the coefficient remains significantly negative at the 1% level. This confirmed the reliability of the core conclusions.

4.5.2 Robustness test: excluding the impact of COVID-19

To further verify robustness, we excluded observations from 2020 to 2021, which were significantly affected by the COVID-19 pandemic. The regression results reported in column (2) of Table 5 indicate that the core findings remain stable and are not influenced by major external shocks, thereby reinforcing the robustness of the study.

4.5.3 Endogeneity test: Instrumental variable approach

To address potential endogeneity issues arising from omitted variables or measurement errors, we employed the two-stage least squares (2SLS) method with an instrumental variable (IV). We constructed IV as the interaction term between the average terrain slope of a city and its economic growth target for the corresponding year. The terrain slope data were sourced from the *Gridded Dataset of Terrain Relief Degree in China*, and the economic growth target was obtained from local government work reports. The theoretical rationale is as follows: terrain conditions affect the amount of developable land, while the economic growth target reflects the preference of the local government for land development intensity. Their interaction captures the pressure a city faces in achieving its economic goals under specific topographic constraints, which in turn affects its land allocation behavior. Therefore, this interaction term is theoretically correlated with land-resource misallocation. Simultaneously, it does not directly influence carbon emission efficiency but only affects it indirectly through the land allocation mechanism. Given that the main effects of both terrain slope and economic growth targets are controlled, the exogeneity assumption of the instrument is also satisfied. This variable was calculated by multiplying the average slope (in degrees) with the economic growth target of the by the city (in percentages) and scaling the product by a factor of 100.

Table 6 presents the estimation results. Column (1) reports the first-stage regression, in which the coefficient of the instrumental

TABLE 5 Robustness tests.

Variables	Alternative independent variable	Excluding the impact of COVID-19
	(1)	(2)
	UCEE	UCEE
LCR	−0.001***	
	(-3.64)	
LRM		−0.001***
		(-2.92)
PD	0.000*	0.000
	(1.67)	(1.17)
FD	−0.005	−0.005
	(-1.55)	(-1.40)
HC	0.011***	0.008*
	(2.86)	(1.83)
FDI	−0.001	−0.001
	(-0.55)	(-0.56)
PCFE	−0.000	−0.000
	(-0.50)	(-0.19)
ERI	0.002	0.002
	(0.28)	(0.29)
Constant	0.299***	0.324***
	(11.36)	(10.27)
Observations	3,000	2,597
R-squared	0.586	0.606
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses. LCR, land concession revenue.

variable is 0.091 and is significantly positive at the 5% level ($p < 0.05$), confirming its relevance in explaining LRM. In Column (2), after incorporating the instrumental variable, the second-stage regression results show that the coefficient of LRM remains negative (−0.020) and significant at the 10% level ($p < 0.1$), indicating that the core conclusion remains robust after accounting for endogeneity.

4.6 Mechanism analysis

Given the potential over-identification issues associated with the traditional three-step approach to causal mechanism identification, we adopt a revised two-step empirical strategy inspired by Zhou et al. (2023) and Qing et al. (2024). This approach was designed to empirically test the mechanism by which LRM affects UCEE. The first step involved empirically testing the effect of LRM on the two mediating variables of ISU and GTI. In the second step, rather than conducting an additional regression analysis, we rely on existing authoritative literature and logical inferences to verify the established correlations between the mediating variables and carbon emissions efficiency. This allowed us to infer the mediating role of ISU and GTI in the relationship between LRM and UCEE.

The corresponding models are presented in Equations 7, 8:

$$ISU_{ct} = \alpha_c + \alpha_t + \alpha_0 + \beta_1 LRM_{ct} + \gamma X_{ct} + \varepsilon_{ct} \quad (7)$$

$$GTI_{ct} = \alpha_c + \alpha_t + \alpha_0 + \beta_1 LRM_{ct} + \gamma X_{ct} + \varepsilon_{ct} \quad (8)$$

Table 7 presents the results. Column (1) shows that the coefficient of LRM on ISU is negative and statistically significant at the 5% level (coefficient = −0.002, $p < 0.05$), indicating that LRM inhibits ISU. Column (2) shows that the coefficient of LRM on GTI is also negative and significant at the 5% level (coefficient = −0.005, $p < 0.05$), suggesting that LRM impedes the development of GTI.

Regarding the correlation between ISU, GTI, and UCEE, experts and scholars provided substantial evidence. Studies showed that the advancement and upgrading of industrial structures can, to a certain extent, suppress carbon emissions in neighboring regions and significantly improve urban carbon emission efficiency (Deng et al., 2023; Cheng Y. et al., 2025). Miao et al. (2017) and Liao et al. (2024) empirically validated the relationship between Green Technological Innovation and urban carbon emission efficiency. Their findings indicate that green innovation plays a key role in promoting low-carbon transformation and has a significantly positive impact on improving UCEE, a view widely acknowledged in academic circles.

Summarily, LRM impedes ISU, thereby suppressing improvements in UCEE; similarly, it hinders the advancement of GTI, which in turn limits the enhancement of UCEE. These two causal pathways are well substantiated, thus confirming hypotheses 2, 3.

4.7 Heterogeneity analysis

4.7.1 Geographic heterogeneity of cities

To further examine the spatial differences in the impact of LRM on UCEE, we followed the approach of Zhou et al. (2022) and conducted regional regressions based on the eastern, central, and western regions of China. The regression results are presented in Table 8.

These findings indicate significant regional heterogeneity in the impact of LRM on carbon emission efficiency. Specifically, in the Central and Western regions, the coefficients of the land misallocation variables were negative and statistically significant at the 5% and 10% levels, respectively. This suggests that LRM significantly suppresses improvements in UCEE in these regions. Contrastingly, the coefficient in the eastern region is statistically insignificant, which may be attributed to the more developed institutional environment of the region and higher factor allocation efficiency, thus partially offsetting the negative effects of land misallocation.

This result aligns with that of the known regional differences in terms of administrative governance capacity, land market

TABLE 6 Endogeneity test: 2SLS.

Variables	First stage	Second stage
	(1)	(2)
	LRM	UCEE
IV	0.091**	
	(0.04)	
LRM		−0.020*
		(0.01)
PD	−0.003**	−0.000
	(0.00)	(0.00)
FD	0.413**	0.002
	(0.17)	(0.01)
HC	−0.187	0.006
	(0.17)	(0.01)
FDI	−0.206**	−0.005*
	(0.08)	(0.00)
PCFE	0.000	−0.000
	(0.00)	(0.00)
ERI	0.550	0.013
	(0.36)	(0.01)
Observations	2,987	2,987
R2		−0.83
F	5.03	1.54
CD Wald F	6.33	
SW S stat.	9.27	

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses. IV: the interaction term between the average terrain slope of a city and its economic growth target for the corresponding year.

development, and industrial maturity. Cities in the central and western regions are more reliant on administratively driven land allocation and industrial expansion for their economic development, making them more vulnerable to inefficient land use. Such distortions in land allocation hinder ISU and weaken the green innovation ecosystem, ultimately exerting a negative impact on carbon emission efficiency.

Therefore, policies aimed at improving UCEE should fully consider the regional disparities. Particularly, greater emphasis should be placed on strengthening land market institutions and optimizing land use structures in Central and Western China to mitigate the environmental externalities resulting from resource misallocation.

4.7.2 Heterogeneity by city size

To further investigate whether the impact of LRM on UCEE varies by city population size, we conducted group regressions based on city size, following the classification criteria proposed by An (2024). According to the *Notice of the State Council on Adjusting the Standards for City Size Classification* (Guo Fa (2014) No. 51), cities with a permanent urban population of one million or more are categorized as large cities, whereas those with fewer than one million residents are classified as small- and medium-sized cities. Table 9 presents the estimation results for the two groups.

The results revealed significant heterogeneity based on city size. Specifically, in small and medium-sized cities, the coefficient of the Mismatch variable was significantly negative at the 5% level, indicating that LRM significantly suppressed improvements in carbon emission efficiency. Contrastingly, the effect is statistically insignificant in large cities, suggesting that the impact is weaker or negligible in these contexts.

This difference may stem from the disparities in governance capacity, industrial maturity, and institutional flexibility between large and small cities. Large cities generally possess more efficient land markets, better regulatory frameworks, and stronger technological infrastructures, enabling them to absorb or offset the distortions caused by land misallocation. Comparatively, small- and medium-sized cities are more constrained by administrative land allocation mechanisms and are more susceptible to the inefficiencies of distorted land use patterns, which in turn limits their ability to pursue low-carbon transformation.

These findings highlighted the need for different policy interventions. Large cities should focus on optimizing existing mechanisms to enhance carbon efficiency, whereas small- and medium-sized cities urgently need to address structural distortions in land allocation to unlock their potential to improve carbon emission performance.

4.7.3 Heterogeneity by resource endowment type

To examine whether the impact of LRM on UCEE differs between resource-based and non-resource-based cities, we followed the classification method of Zhang Y. et al. (2024). Based on the *National Plan for the Sustainable Development of Resource-Based Cities (2003–2020)*, the sample cities were divided into two subgroups, resource-based and non-resource-based cities, and separate regressions were conducted. According to official documents, resource-based cities refer to those that have long relied on the extraction and primary processing of natural resources such as coal, petroleum, and non-ferrous metals as their primary economic foundation. Table 10 presents the regression results for both city types.

The regression results reveal that the resource endowment type leads to significant heterogeneity in the effect of LRM on UCEE. Specifically, in non-resource-based cities, the coefficient of LRM variable was significantly negative at the 5% level (−0.001, $t = -2.38$), indicating that LRM significantly hindered improvements in UCEE. Contrastingly, in resource-based cities, the coefficient is not statistically significant (−0.001, $t = -1.43$), suggesting that in cities with strong resource dependence, LRM may not be a primary constraint on UCEE enhancement.

This discrepancy may be attributed to entrenched industrial structures and relatively rigid land-use policies in resource-based cities. In these cities, economic operations are often heavily influenced by state-led investment priorities and legacy infrastructure. Even if land allocation becomes more efficient, its effect may be offset by the dominance of resource-intensive, high-

TABLE 7 Mechanism test.

Variables	(1)	(2)
	ISU	GTI
LRM	−0.002**	−0.005**
	(-2.58)	(-2.32)
PD	0.000	0.000***
	(0.29)	(4.16)
FD	0.157***	−0.090***
	(9.29)	(-5.23)
HC	0.036***	0.021
	(3.01)	(1.34)
FDI	0.001	0.026***
	(0.11)	(3.62)
PCFE	−0.000	0.000*
	(-0.40)	(1.65)
ERI	0.003	−0.086***
	(0.19)	(-2.75)
Constant	0.597***	4.603***
	(8.24)	(41.77)
Observations	3,004	3,004
R-squared	0.885	0.960
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses. ISU, industrial structure upgrading; GTI, green technological innovation.

emissions industries. Comparatively, non-resource-based cities typically possess more diversified industrial structures and greater institutional flexibility, making them more responsive to land allocation distortions.

These findings emphasize the importance of designing differentiated policy frameworks. For non-resource-based cities, correcting LRM is the key to improving UCEE. However, for resource-based cities, more fundamental structural reforms, such as industrial transformation or the implementation of environmental compensation mechanisms, may be required to achieve sustainable low-carbon transition goals.

5 Discussion

5.1 Key findings

Based on panel data from Chinese cities, we constructed a two-way fixed effects model to systematically assess the impact of LRM on UCEE. Furthermore, it empirically examines two mediating mechanisms, ISU and GTI, through which misallocation exerts indirect effects. The main findings were as follows:

First, LRM significantly hinders the improvement of UCEE, confirming that such institutional distortions lead to higher carbon emissions per unit output. This finding is consistent with that of Zhou et al. (2022), who showed that a higher degree of misallocation between industrial and commercial land is correlated with lower carbon efficiency. Similarly, Cheng Y. et al. (2025) quantitatively estimated that a 1% increase in the land misallocation index results in an average increase of 0.502% in urban carbon emissions. This implies that the oversupply of low-cost industrial land by the local governments aimed at rapid development promotes the expansion of energy-intensive industries, reduces energy efficiency, and substantially suppresses carbon emission efficiency (Han and Huang, 2022). Generally, the recent studies overwhelmingly confirms the significant negative effect of LRM on carbon efficiency. However, not all studies reached consistent conclusions. For instance, Chen and Yuan (2025) argued that the negative effect of land misallocation on carbon efficiency is significantly weakened in regions where land marketization reforms progressed. This finding suggests that in economically advanced regions with sound market mechanisms, the inhibitory effect of land misallocation is relatively weak. Therefore, differences in regional development stages and policy environments explain the variations in empirical results across studies.

Second, the mechanism analysis indicates that LRM reduces carbon emission efficiency by obstructing the transition of the industrial structure from high-carbon to low-carbon sectors, thereby inhibiting industrial upgrading. Numerous studies support the notion that barriers to industrial transformation are a critical transmission channel through which land misallocation affects carbon efficiency (Zhou et al., 2022; Cheng Y. et al., 2025). Zhou et al. (2022) explicitly stated that land misallocation delays industrial upgrading, increases the proportion of highly polluting and energy-intensive industries, and suppresses carbon efficiency improvements. Cheng Y. et al. (2025) further demonstrated through a mediation analysis that approximately 16.3% of the total effect of land misallocation is transmitted via changes in industrial structure. This provides additional evidence that land misallocation indirectly hinders the shift from high-carbon to low-carbon industries, thus lowering the CEs. However, Cheng Y. et al. (2025) also highlighted that industrial upgrading accounts for only a small part of the total effect, suggesting the existence of other influential mechanisms beyond the scope of structural transformation.

Third, our study shows that LRM suppresses GTI, further weakening UCEE. Several scholars argue that the distorted allocation of land factors restricts the concentration and input of green innovation, thereby indirectly reducing carbon efficiency (Han and Huang, 2022). Han and Huang (2022) provided empirical evidence that land misallocation significantly inhibits green innovation activities and weakens economic agglomeration, leading to increased emissions. Xu et al. (2025) find that land misallocation has a direct and significant negative impact on urban green innovation capacity, operating through structural, scale, and spatial agglomeration. Similarly, Chen and Yuan (2025) showed that misallocated land leads to insufficient investment in green R&D and delays in technological advancement, thus reducing the driving force for emission reduction. However, other studies offer different perspectives. Zhou et al. (2023), through mechanism analysis, empirically

TABLE 8 Heterogeneity by geographic location.

Variables	(1)	(2)	(3)
	Eastern	Central	Western
LRM	0.000	−0.002**	−0.001*
	(0.04)	(-2.58)	(-1.95)
PD	0.000***	−0.000	0.000
	(2.64)	(-0.21)	(0.51)
FD	0.004	−0.007	−0.021**
	(0.84)	(-1.06)	(-2.02)
HC	−0.003	0.009	0.024***
	(-0.50)	(1.61)	(2.96)
FDI	0.002	−0.007**	0.000
	(0.88)	(-1.98)	(0.10)
PCFE	−0.000	0.000	−0.000
	(-0.74)	(0.61)	(-0.97)
ERI	0.024**	−0.011	0.000
	(2.02)	(-1.05)	(0.02)
Constant	0.241***	0.388***	0.350***
	(5.29)	(8.79)	(7.36)
Observations	1,116	1,163	725
R-squared	0.637	0.537	0.619
City FE	YES	YES	YES
Year FE	YES	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

TABLE 9 Heterogeneity by city size.

Variables	(1)	(2)
	Large cities	Small and medium cities
LRM	−0.001	−0.001**
	(-0.98)	(-2.47)
PD	0.000	0.000**
	(0.94)	(2.36)
FD	0.009	−0.010**
	(1.45)	(-2.41)
HC	−0.003	0.021***
	(-0.53)	(4.10)
FDI	0.003	−0.004*
	(0.98)	(-1.80)
PCFE	0.000	−0.000
	(0.05)	(-0.92)
ERI	−0.005	0.006
	(-0.37)	(0.76)
Constant	0.285***	0.314***
	(4.24)	(11.43)
Observations	846	2,158
R-squared	0.504	0.616
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

identify economic agglomeration, industrial structure, and urbanization as joint mediators of the impact of land misallocation on energy efficiency, without highlighting green innovation as a channel. This may be due to the differences in the measurements of energy efficiency versus carbon efficiency. Overall, the majority of the literature supports the pathway of "land misallocation → inhibited green innovation → reduced carbon efficiency," though a few studies show divergent conclusions due to differences in research focus or the selection of control variables. This highlights the importance of considering multiple research perspectives and carefully selecting appropriate covariates.

Fourth, regarding heterogeneity, existing studies generally agree that land resource misallocation affects urban carbon emission efficiency, and also emphasize its heterogeneous effects based on city location (An, 2024), population size (Gao et al., 2023), and resource endowment (Zhou et al., 2022), which are consistent with those of the heterogeneity dimensions examined here. Our findings show that the inhibitory effect of land misallocation on carbon efficiency is significant only in the central and western regions (An, 2024), small and medium-sized cities (Gao et al., 2023), and non-resource-based cities (Zhou et al., 2022), aligning with that of most scholarly conclusions. However, Zhou et al. (2022) report that the effect is also significant in resource-based cities, which they attribute to the lagged effects of land policies—i.e., the land misallocation in the earlier period may affect current carbon efficiency. This does not contradict our findings as the lag effect may explain short-term inconsistencies in resource-based cities, whereas our analysis focused on the average effect over time.

5.2 Research contributions

This study contributes to the literature in both theoretical and methodological dimensions.

From a theoretical perspective, first, it supplements the institutional explanation of land-resource allocation from an environmental economics perspective. It explicitly highlights that land misallocation is not merely an issue of allocation efficiency but also one with far-reaching environmental consequences. Second, it constructs a dual-mechanism mediation framework of "Land Resource Misallocation–Industrial Structure Upgrading/Green Technological Innovation–Urban Carbon Emission Efficiency," addressing the limitations of earlier studies regarding the identification of transmission pathways (Gao and He, 2024; Cheng Y. et al., 2025).

TABLE 10 Heterogeneity by resource endowment type.

Variables	(1)	(2)
	Resource-based cities	Non-resource-based cities
LRM	−0.001	−0.001**
	(-1.43)	(-2.38)
PD	0.000	0.000*
	(0.09)	(1.86)
FD	−0.001	−0.007*
	(-0.14)	(-1.68)
HC	0.003	0.013***
	(0.60)	(2.66)
FDI	−0.003	−0.001
	(-0.89)	(-0.41)
PCFE	0.000	−0.000
	(1.45)	(-1.39)
ERI	−0.009	0.009
	(-0.97)	(0.99)
Constant	0.336***	0.305***
	(9.41)	(7.57)
Observations	1,207	1,797
R-squared	0.655	0.532
City FE	YES	YES
Year FE	YES	YES

Note: ***p < 0.01, **p < 0.05, *p < 0.1; robust t-statistics in parentheses.

From a methodological perspective, by introducing the interaction between the average terrain slope and the annual economic growth target of a city as an instrumental variable, we enhance the credibility of causal inferences regarding LRM and enrich methodological applications in environmental economics to tackle endogeneity problems.

5.3 Policy recommendations

From a policy perspective, our findings offer the following recommendations for promoting green development and optimizing land systems in China.

(1) Accelerate market-oriented reforms in land resource allocation, and break away from the administratively driven logic of land supply—especially by avoiding the preferential allocation of low-cost land to high-emission industries, to curb misallocation at its source.
(2) Strengthen land policy support for green enterprises, high-tech industries, and modern service sectors. The structure of land supply should be optimized to guide the upgrading of urban industrial layouts and facilitate low-carbon transformation.
(3) Use land allocation reform as a strategic entry point to promote a coordinated system of "green technology–institutional innovation–carbon governance". Leverage the synergy between industrial and technological policies to enhance innovation chains and strengthen emission reduction pathways.
(4) Implement differentiated land and industrial policies across various types of cities, with particular attention paid to non-resource-based and small-to medium-sized cities where land misallocation has constrained green development. The adaptability and inclusiveness of land allocation systems should be improved to support low-carbon governance.

5.4 Research limitations and future research directions

This study has some limitations.

First, although a comprehensive panel dataset was constructed and a two-way fixed-effects model was employed to explore the linear impact of LRM on UCEE, the spatial dependence and regional spillover effects of land misallocation were not fully addressed. Future research could incorporate spatial econometric models or multiscale geographically weighted regression (MGWR) models and update the dataset with post-2023 observations to further investigate the spatial transmission mechanisms and nonlinear characteristics of the influence of land misallocation on carbon efficiency across cities.

Second, in terms of mechanism analysis, future studies may consider introducing structural equation modeling (SEM) to enhance causal inference in mediating effect analysis. Furthermore, as current measurement indicators rely largely on static city-level data, future work could integrate remote sensing imagery, enterprise-level carbon emission records, and natural language processing (NLP) techniques to depict land-use behavior, green innovation activity, and policy enforcement intensity more dynamically and precisely at the micro level.

Third, given the diverse development stages and functional roles of Chinese cities, subsequent research could incorporate heterogeneity in urbanization levels and examine the distinct characteristics of tourism-oriented cities. Such efforts would provide more scientific and theoretical support and empirical evidence for achieving coordinated regional emission reduction and the modernization of land resource governance capacity.

6 Conclusion

Conclusively, we utilized panel data from 274 Chinese cities spanning the period from 2010 to 2022. A super-efficiency SBM model incorporating undesirable outputs was employed to measure UCEE, and empirical tests were conducted using panel regression

models with both city and time fixed effects. The results confirmed that LRM significantly undermines the efficiency of urban carbon emissions. Distorted land-use patterns and entrenchment of carbon-intensive industrial structures hinder cities from decoupling carbon emissions from economic growth. These findings emphasize the critical urgency of advancing land market reforms and implementing integrated spatial planning to enhance UCEE and steer cities toward a green and low-carbon transformation. Furthermore, it is essential to further refine land governance strategies tailored to different types of cities and evaluate their long-term impacts on carbon emissions efficiency.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZW: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Writing – original draft, Writing – review and editing. W-SL: Project administration, Resources, Supervision, Writing – original draft, Writing – review and editing. SW: Investigation, Validation, Visualization, Writing – review and editing.

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Pengzhen Liu,
Jinan University, China
Xue Lei,
Shanghai University, China
Yang Xu,
Xinjiang University, China
Xiaokai Li,
North China University of Water Conservancy and Electric Power, China

*CORRESPONDENCE
Ting Lei,
b2023140200165@stu.swupl.edu.cn

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Maintain ecological security: analyzing the impact of the digital economy on green and low-carbon land utilization

Ting Lei*

School of National Security, Southwest University of Political Science and Law, Chongqing, China

Introduction: Ecological security is an important part of the overall national security outlook. Maintaining ecological security is a fundamental, overall and strategic requirement related to the long-term stability of the country, the sustainable development of the nation and the happiness and well-being of the people. As the fundamental carrier for human survival and development, the utilization mode, intensity and spatial pattern of land directly determine the health, stability and service functions of the ecosystem, and further affect the ecological security of the region and even the world. At present, China's land resources are confronted with multiple challenges such as ecological and environmental constraints. As a key engine for achieving sustainable utilization of land resources, the digital economy provides a systematic solution for the green and low-carbon use of land. The green and low-carbon utilization of land is an important part of maintaining ecological security. This article explores the promoting effect of the digital economy (DE) on the green and low-carbon utilization of land (GUE). The digital economy is an important way to achieve the carbon reduction targets of land and maintain ecological security.

Method: This paper selects panel data from 31 provinces in China from 2011 to 2023 as research samples, and respectively uses the fixed effects model and the quantile model to explore the promoting and heterogeneous effects of the digital economy (DE) on the green and low-carbon utilization of land (GUE). Furthermore, the mediation model is employed to explore the mediating role of entrepreneurial activity and Internet penetration rate in the digital economy and the green and low-carbon utilization of land, aiming to investigate whether the mediating variables can play a promoting role in maintaining ecological security.

Result: First, the direct impact of the digital economy and the green and low-carbon utilization of land has shown a significant promoting effect. Second, the entrepreneurial activity level and the Internet penetration rate play a significant mediating role in the assessment of the impact of the digital economy on the green and low-carbon utilization of land. Thirdly, the digital economy has a significant promoting effect on the green and low-carbon utilization of land in the eastern and western regions of China, but it shows no significant effect in the central region.

Discussion: This article not only enriches the theoretical research on the green and low-carbon utilization of land by the digital economy, but also provides corresponding empirical evidence. To provide more precise theoretical support for improving the land governance system and achieving ecological and environmental security. Government departments should enhance policy

coordination and institutional allocation for the digital economy, combine the diffusion of green and low-carbon technologies with ecological compensation mechanisms, optimize the allocation efficiency of land factors and green and low-carbon technologies, promote the green and low-carbon transformation and upgrading of land, and while facilitating the realization of land carbon reduction targets, achieve the coordinated evolution of ecological protection and sustainable utilization of land resources. Only by deeply integrating "digitalization" into "greening" can ecological security be achieved under the premise of ensuring the green and low-carbon utilization of land resources, providing a solid foundation for building a moderately prosperous society and creating a modern model of harmonious coexistence between humans and nature.

KEYWORDS

digital economy, green and low-carbon utilization of land, entrepreneurial activity, internet coverage, national security

1 Introduction

In recent years, the global warming trend has continued to intensify, and extreme climate events have occurred frequently, posing a severe challenge to ecological security and sustainable development. Carbon emission reduction has become the core path to alleviate the climate crisis. Land use, as a key area of carbon emissions, generates nearly a quarter of the global greenhouse gas emissions (Tian et al., 2021). In China, along with the rapid process of urbanization and industrialization, the problem of carbon emissions caused by land development and utilization has become increasingly prominent. There is an urgent need to reconstruct the land use model through technological innovation to balance the goals of economic development and ecological protection. Against this backdrop, China explicitly put forward the strategic goal of "peaking carbon emissions before 2030 and achieving carbon neutrality before 2060" at the 75th session of the United Nations General Assembly, in order to improve agricultural ecological protection, safeguard the ecological red line of land, and ensure the green and high-quality development of agriculture (Ou et al., 2025). Meanwhile, enhancing the green and low-carbon utilization of land, as the core carrier for the optimal allocation of territorial space that integrates the control of ecological protection red lines, the development of carbon sink resources and intelligent monitoring technologies, has become a key approach to achieving the "dual carbon" goals and an important yardstick for measuring the level of regional ecological civilization construction.

Global ecological and environmental performance data warn us that enhancing ecological protection efficiency is an urgent matter, as it directly concerns national ecological security. Against this backdrop, China has prioritized mitigating ecological risks, and as a core natural resource, the way land is utilized profoundly affects the health and resilience of ecosystems. The traditional extensive land use model, especially the excessive development and pollution in the agricultural sector, not only threatens the quality of cultivated land but also becomes an important source of carbon emissions, exacerbating ecological risks (Jiang et al., 2022). The digital economy, with its powerful capabilities in data acquisition, analysis, integration and intelligent decision-making, provides a revolutionary tool for resolving the contradiction between land protection and development and achieving low-carbon, efficient and sustainable land utilization, becoming a key support point for maintaining ecological security: it can precisely monitor and warn, and build a "digital fence" for ecological protection red lines. It can optimize resource allocation and decision-making, and drive the low-carbon utilization of land. It can enhance the quality and resilience of cultivated land and jointly ensure ecological security (Li et al., 2023). It can promote transparency and synergy, strengthen policy implementation and international cooperation. Maintaining ecological security requires a fundamental transformation of land use patterns, moving towards a low-carbon, intensive and sustainable direction (Shi and Liao, 2025). The digital economy is not merely a tool replacement; rather, it has reshaped the paradigm of low-carbon land use by deeply integrating into the entire land management chain, from red line protection, process monitoring to decision-making optimization and quality improvement (Xu, 2025). By combining the rigid constraints of environmental policies with intelligent management, it effectively balances the local development impulse with the long-term ecological protection demands, providing a technological solution for resolving the contradiction between "short-term benefits and permanent protection." Therefore, vigorously developing and deepening the application of digital technology in the land sector is a modern strategic choice for building a more stable ecological security barrier and achieving harmonious coexistence between humans and nature. Empowering the low-carbon utilization of land with digital technology is a key path to strengthening the ecological security defense line.

In conclusion, the marginal contribution of this paper lies in the following: First, it provides theoretical and empirical evidence for the impact of the digital economy and the green and low-carbon utilization of land, offering reference value for developing countries in promoting the green and low-carbon utilization of land through the digital economy. Secondly, by combining the fixed-effect model selected in this paper, the empirical test of the differentiated emission reduction effects among the eastern, central, and western regions not only provides an important basis for precise regional governance but also offers a more accurate perspective for maintaining national ecological security. Thirdly, identify the dual mediating role of entrepreneurial activity and Internet coverage, clarify the direct path of how the digital economy can curb land carbon emissions through entrepreneurial activity and Internet coverage, and provide reference and implementation paths for

achieving low-carbon land utilization in the country. Fourth, this article provides corresponding policy suggestions for government departments, offering policy-level assistance for protecting ecological security and national security in the future.

2 Literature review

The digital economy, with digital knowledge and information as key production factors, modern information networks as important carriers, and information and communication bases as efficiency, is a new economic form that enhances efficiency. As the core engine of the new round of technological revolution and industrial transformation, it provides a brand-new paradigm for the low-carbon transformation of land through data element drive (Shi et al., 2025), technology penetration and reconstruction, and system collaborative optimization (Xu et al., 2025b; Raihan and Mainul Bari, 2024). Regarding the mechanism exploration of low-carbon land utilization, the existing research mainly analyzes the core mechanism system at the theoretical level. The first is to define the connotation of low-carbon land utilization. Scholars have summarized the connotation of low-carbon land use as "maximizing land economic and ecological benefits through the lowest carbon emission intensity" (Song et al., 2021; Wang et al., 2022). The second is to analyze the current predicament. Including multi-purpose land use conflicts (Usman and Makhdum, 2021; Zhang and Liu, 2022), Cost Constraints of Digital Technology Application (Huang et al., 2023; Jan et al., 2023; Zhang et al., 2024). Third, explore emission reduction paths, such as building a "monitoring" system empowered by digital technology (Zysman and Nitzberg, 2020; Wang et al., 2023a), Planning (Chen et al., 2023; Li et al., 2024), and evaluating the "Closed-loop Management System." The digital economy reshapes the logic of low-carbon land use from multiple dimensions, such as spatial compression, efficiency innovation, and circular catalysis. Essentially, it revolutionizes production methods through data, driving land use to shift from scale expansion to quality enhancement, and thereby achieving low-carbon land use and maintaining ecological security.

Regarding the impact on the GUL, existing research mainly focuses on the comprehensive benefits of the DE for the GUL. On the one hand, there is a supportive view, emphasizing that the DE promotes the low-carbon transformation of land through three paths: the first is the optimization of intelligent management and control. It is pointed out that the Internet of Things and big data can achieve dynamic monitoring of land resources (Yu Q. et al., 2023), precisely regulate high-carbon emission links such as agricultural fertilization (Wang et al., 2023b) and industrial energy consumption (Yao et al., 2022), and reduce the carbon emission intensity per unit of land. The second is the virtual substitution effect. It is proposed that measures such as e-commerce platform economy should be adopted to reduce the demand for warehousing land and compress physical space, and to curb the carbon footprint caused by land development (Karwacka et al., 2020; Zhou et al., 2020). The third is green technological innovation. Emphasize the acceleration of the application of digital technology in photovoltaic agriculture and carbon capture technology, and enhance the carbon sink capacity of the land. These studies suggest that the DE provides a technical paradigm for intensive land use under the "dual carbon" goals. On the other hand, there is a critical perspective. The research points out potential risks. First, the expansion of digital infrastructure may intensify the contradiction between "land and energy," highlighting the sharp increase in data center land occupation and the rise in regional energy consumption demand, partially offsetting the benefits of emission reduction (Huo et al., 2024). Second, it points out that algorithm-driven land allocation may trigger a "digital divide," such as less developed regions being forced to take over high-carbon industries due to technological deficiencies, leading to regional transfer of land carbon emissions (Shen et al., 2022; Liu et al., 2024; Huang et al., 2025). Furthermore, against the backdrop of the unbalanced development of the DE, there are significant differences in the coverage rate of digital infrastructure and the digital capabilities of various regions, resulting in the phased heterogeneity of the GUL (Shen et al., 2022; Bernini and Galli, 2024; Tang, 2024).

3 Theoretical mechanism

3.1 Direct effect

The DE reshapes the carbon emission pattern of land use through a path driven by data elements, technological infiltration and reconstruction, and system collaborative optimization. As an important catalyst for China's high-quality economic development, the digital economy has given rise to technological advancements and green innovations, which are crucial measures for achieving green and high-quality agricultural development. Making good use of the advantages of the digital economy is an important link in promoting the green and low-carbon utilization of land. First, the effect of intelligent monitoring and precise control. Digital technologies such as remote sensing, monitoring, and Internet of Things sensors can obtain real-time data on land resource utilization intensity and ecological environment. Through big data analysis, high-carbon emission links such as excessive fertilization and mechanical tillage energy consumption can be accurately identified, and the planting structure, irrigation scheduling, and energy distribution can be dynamically optimized. Promote the GUL per unit (Korherr and Kanbach, 2023; Razzaq et al., 2023). Second, the full-chain low-carbon decision support effect. Relying on artificial intelligence and blockchain technology, a land carbon footprint traceability platform is constructed to achieve full life cycle carbon emission control from land production planning to circulation and consumption. Relying on big data and intelligent algorithms to match land suitability assessment with the layout of low-carbon crops, the blockchain traceability system incentivizes the premium of green certified agricultural products and promotes the transformation of land to a low-energy consumption and high-carbon sink model (Jin et al., 2022). Third, the substitution effect of virtual space on physical resources. Widely apply digital platform economies such as agricultural product e-commerce and remote agricultural services to reduce the logistics and warehousing demands of traditional production and sales links, and lower the expansion of transportation land and related carbon emissions. Meanwhile, green and low-carbon digital technologies are utilized to simulate land development plans, thereby avoiding extensive land use planning with high carbon emissions and suppressing the

generation of land carbon emissions from the source (Chuai et al., 2024).

Based on this, this paper proposes: Hypothesis 1 (H1): The DE can significantly promote GUL.

3.2 Indirect effect

Entrepreneurship and the Internet, as crucial factors in the development of the DE, have always been regarded as important supports for achieving technological innovation and improvement, and also as an important part of alleviating the land environment. With the continuous improvement of the entrepreneurship level and digital infrastructure level in our country, the efficiency of land use has been greatly enhanced. By optimizing the density and spatial layout of land factor input, the entrepreneurship level and digital infrastructure level have significantly reduced the generation of land carbon emissions and effectively promoted GUL. Furthermore, the level of green and low-carbon land utilization is often constrained by the application of green and low-carbon land technologies and cannot do without the support of specialized land talents and cutting-edge digital technologies. Therefore, in terms of entrepreneurial activity, the increase in entrepreneurial activity has promoted the cultivation of specialized land talents. The cultivation of specialized land talents can facilitate the introduction of green technologies, ensure the green development of land, enhance the level of green and low-carbon land utilization, curb land ecological environment pollution, and thereby drive the green and low-carbon development of land. From the perspective of the popularity of the Internet, the improvement of digital infrastructure has further promoted the research and development of digital low-carbon technologies, enabling farmers to better achieve lower carbon emissions in land use. While promoting the green development of land, it can also ensure the efficiency of land input and output (Lu et al., 2020; Yu S. et al., 2023). This can not only promote the composite development of agricultural land and the improvement of the level of green land utilization, but also increase investment in smart land through the DE and expand the coverage of low-carbon detection facilities for digital land, thereby achieving a transformation from land transfer to green and low-carbon land utilization. This marks that entrepreneurship and the development of the Internet have entered a new stage of green land development.

Based on this, this paper proposes: Hypothesis 2 (H2): The DE can significantly promote the level of green and low-carbon land utilization through entrepreneurial activity and Internet coverage.

3.3 Heterogeneity effect

Due to the significant differences in the level of digital infrastructure, industrial structure characteristics, and policy implementation capabilities among different regions in China, as well as the varying degrees of emphasis placed by local governments on digital technology empowering GUL, the level of DE in promoting GUL will also show significant variations in different regions. On the one hand, in economically developed regions, the level of digitalization is relatively high. Local governments pay more attention to the coordination between digital governance and the territorial space planning system, achieving in-depth synergy between land development and land carbon reduction. A well-developed digital infrastructure provides a technical foundation for the management of smart farmland and the construction of low-carbon industrial parks, significantly enhancing the efficiency of intensive land use (Almalki et al., 2023; Jan et al., 2023). On the other hand, relatively economically backward regions will generate a "learning effect." However, due to the weak digital infrastructure restricting technological penetration, the development of clean energy and the protection of ecological land mainly rely on exogenous policies such as fiscal subsidies for driving, and the endogenous impetus for low-carbon land utilization is relatively insufficient. This further leads to a deficiency in the promoting effect in economically backward regions or the inability to demonstrate a significant promoting effect in the short term (Liu et al., 2023; Jin and Zhong, 2024).

Based on the above regional differentiation characteristics, this paper proposes: Hypothesis 3 (H3): The DE has a significant heterogeneous effect on GUL.

4 Data and methods

4.1 Model settings

4.1.1 Benchmark model

Based on the above analysis, the following fixed-effect model is constructed to verify the impact of the DE on the low-carbon use of land. Due to the inherent characteristics of each province that do not change over time (such as geographical conditions, historical agricultural structure, and policy traditions), these factors simultaneously affect the process of the DE and the low-carbon use of land. Fixed-effect models can eliminate individual fixed effects (such as provincial dummy variables) through within-transformation, avoiding estimation biases caused by omitted variables. The formula is as follows:

$$GUL_{i,t} = \alpha + \beta_1 DE_{i,t} + \beta_2 X_{i,t} + \mu_i + \varepsilon_{i,t} \quad (1)$$

In Model (1), GUL is the explained variable, representing the low-carbon utilization of land, and DE is the core explained variable, representing the digital economy; X is the set of control variables, and respectively represent the i province, the t period, μ_i represent the fixed effect, and $\varepsilon_{i,t}$ represent the random disturbance term.

4.1.2 Mechanism model

Furthermore, to further examine the possible mediating effect of the digital economy in promoting the green and low-carbon utilization of land, we further incorporate entrepreneurial activity and the level of Internet coverage into the benchmark model (1), extending to model (2):

$$Z_{i,t} = \alpha + \beta_1 DE_{i,t} + \beta_2 X_{i,t} + \mu_i + \varepsilon_{i,t} \quad (2)$$

TABLE 1 Index system for low-carbon land utilization.

Criterion layer	Layer of elements	Indicator layer	Weights
Economic push	Social development	Proportion of urban population to total population at the end of the year/%	0.03
		Per capita disposable income of urban residents/(ten thousand yuan/person)	0.09
	Economic growth	GDP growth rate (over previous year)/%	0.02
	Industrial transformation	Ratio of tertiary to secondary industries/%	0.13
	Scale expansion	New urban construction land area/km^2 in this year compared with the previous year	0.01
Energy consumption	Resource consumption	Residential water consumption per unit of construction land/(ten thousand t/km^2)	0.01
		Quantity of urban construction land consumed per unit of GDP/(km^2/100 million yuan)	0.01
	Energy consumption	Electricity consumption per unit of GDP/(kW·h/100 million yuan)	0.02
	Environmental pollution	Total urban carbon emissions per unit of construction land/(ten thousand t/km^2)	0.03
Low-carbon governance	Green and low-carbon capital investment	Science and technology expenditure per unit of construction land/(ten thousand yuan/km^2)	0.19
	Green and low-carbon labor investment	Annual amount of R&D per unit of construction land/(person-year/km^2)	0.15
	Green and low-carbon governance efforts	Investment in environmental pollution control per unit of construction land/(ten thousand yuan/km^2)	0.18
	Ecological, green and low-carbon guarantee	Urban *per capita* park green area/(m^2/person)	0.13
	Green and low-carbon space development	Green coverage rate of built-up area/%	0.01

TABLE 2 Control variables.

Variables	Code	Definition
urbanization rate	URB	The proportion of the urban population to the permanent resident population in each province
government intervention	FE	The proportion of provincial government fiscal expenditure in the GDP of each province
foreign direct investment	FDI	The proportion of foreign direct investment actually utilized by each province of its GDP
industrial structure	IS	The proportion of the added value of the primary industry in each province to its GDP

In Model (2), $Z_{i,t}$ is the mediating variables of this paper, namely entrepreneurial activity and Internet coverage level, $X_{i,t}$ represent a series of control variables.

4.2 Explanatory variables

4.2.1 Digital economy (DE)

This paper refers to the existing literature (Xu et al., 2025c), and selects the Digital Inclusive Finance index jointly compiled by the Digital Finance Research Institute of Peking University and Ant Financial for representation. The Digital Inclusive Finance Index is formed based on the massive real transaction data of users. Through the reasonable and scientific selection of 33 sub-indices, A relatively authoritative measurement of the development status of digital inclusive finance can also effectively demonstrate the development level of China's DE. And in order to better evaluate the benefits of the DE, we further carried out logarithmic processing.

4.3 Explained variable

4.3.1 Green and low-carbon utilization of land (GUL)

GUL, as the core carrier for the optimal allocation of territorial space, is a key yardstick for measuring the level of ecological civilization construction. The goal is to integrate the advantages of ecological protection red line control, carbon sink resource development, and intelligent monitoring technologies, and inject a continuous low-carbon driving force into regional high-quality development (Eweade et al., 2024). This paper refers to the existing research (Shi and Liao, 2025) and constructs an indicator system

TABLE 3 Descriptive statistics of variables.

Variables	N	Average	Standard deviation	Minimum	Maximum
DE	403	252.40	109.44	16.22	496.88
GUL	403	0.26	0.09	0.13	0.62
URB	403	0.60	0.13	0.23	0.90
FE	403	0.29	0.21	0.10	1.44
FDI	403	14.50	76.07	0.77	984.97
IS	403	0.10	0.05	0.00	0.26
EA	403	1,173.44	1,031	12.80	4,979.70
ICR	403	0.31	0.41	0.10	3.33

including three levels: "economic promotion, energy consumption, and low-carbon governance." These indicators together constitute a comprehensive indicator system for measuring GUL. Unlike most studies, this research particularly conducts an overall assessment of economy, energy, and governance, which not only helps to improve the agricultural industrial environment, but also provides a development direction for achieving sustainable development of the agricultural industry, promoting green agricultural development, and protecting ecological security. The specific measurement indicators for GUL are shown in Table 1.

4.4 Control variables

Considering that there are many factors affecting China's DE and GUL, this paper refers to existing studies (Xu and Lu, 2025a; Wang Y. et al., 2023). On this basis, this paper selects four control variables: urbanization rate, government intervention, foreign direct investment, and industrial structure. In fact, the selection of control variables can effectively avoid errors brought about by research. The four control variables chosen in this paper have a strong correlation with the core explanatory variables and the explained variables of this paper. From the perspectives of urbanization, government, investment, and industry, it can well prove the connection between the digital economy and the green and low-carbon utilization of land. The evaluation after adding control variables can effectively verify the relationship between DE and GUL. The specific results are shown in Table 2.

4.5 Mechanism variables

1. Entrepreneurial activity (EA), as a key engine for resetting the factors of land production and utilization, not only enhances the synergy efficiency between human capital and green and low-carbon technology capital, but also drives a systematic leap in GUL. Referring to the existing research (Tan et al., 2025), the proportion of individual and private employment in the total number of people in each province was used for measurement.
2. Internet coverage rate (ICR): As the core infrastructure for bridging the digital divide, the Internet coverage rate not only significantly lowers the threshold for technology acquisition but also reconstructs the elastic system of agricultural factor substitution. Referring to the existing research (Guan et al., 2023), the number of Internet accesses in each province was used and logarithmic processing was conducted.

4.6 Data sources and descriptive statistics

This paper is based on the current conditions of China's DE and GUL. To reflect the availability and operability of relevant indicators, the original data of relevant variables are from "China Statistical Yearbook," "China Rural Statistical Yearbook," "China Environmental Statistical Yearbook," "China Land Statistical Yearbook," and the Institute of DE of Peking University. Given that the data of various indicators may be missing in different years, in order to obtain as complete a data resources as possible and reflect the latest trends of the DE and GUL, the time range of the sample data in this paper is set from 2011 to 2023. As for the selection of sample regions, due to the limited data from Hong Kong, Macao, and Taiwan regions of China. Therefore, the remaining 31 provinces (autonomous regions) were selected as the objects for analysis and evaluation. The missing parts are filled in by using the linear interpolation method and the exponential smoothing method. The symbols of each variable and the statistical analysis results of their representativeness are shown in Table 3 as follows.

5 Model results

5.1 Empirical strategies and results

This paper first selects the above Formula 1 to evaluate the relationship between DE and GUL, conducts regression analysis using the fixed effects model, and performs regression analysis by adding control variables and by adding control variables. Firstly, the regression results without introducing control variables are examined. The results are shown in column (1) of Table 4. The study finds that without adding control variables, the regression coefficient of the DE is significantly positive at the 1% significance level. It is proven that the DE has a significant promoting effect on GUL. To further improve the accuracy and reliability of the research, in this paper, different control variables are added successively from

TABLE 4 Direct effect.

Variables	(1)	(2)	(3)	(4)	(5)
DE	0.04*** (15.34)	0.03*** (6.07)	0.03*** (5.85)	0.03*** (5.98)	0.03*** (5.71)
URBAN		0.17** (2.17)	0.19** (2.43)	0.14 (1.55)	0.08 (0.89)
FE			0.09 (1.46)	0.08 (1.41)	0.08 (1.43)
FDI				0.01 (1.63)	0.01*** (1.76)
IS					−0.62* (−2.87)
Fixed effects	Control	Control	Control	Control	Control
Cons	0.02 (1.04)	−0.03 (−1.09)	−0.06* (−1.79)	−0.04 (−1.13)	0.06 (1.19)
R^2	0.39	0.40	0.40	0.40	0.42
N	403	403	403	403	403

Note: T-statistics in parentheses; *, **, and *** indicate significance at the level of 10%, 5% and 1%, respectively, and the following tables are the same.

TABLE 5 Endogeneity test and robustness test.

Variables	(1)	(2)	(3)
DE	0.02*** (3.07)	0.03*** (4.74)	0.02*** (4.92)
Control variables	Control	Control	Control
Fixed effects	Control	Control	Control
Cons	0.01 (0.09)	0.13** (2.41)	0.02 (0.68)
N	372	372	403

(2) to (5) for re-regression, in order to capture more accurately the indirect influence of these potential influencing factors on the regression results. The results show that the coefficient of the DE remains positive and is still significant at the 1% significance level. This not only verifies that the improvement of China's DE development level has an important promoting effect on GUL. It is worth noting that the coefficient size of the DE does not change significantly with the introduction of control variables. This can further indicate that the research results of this paper have high robustness and further prove Hypothesis H1.

5.2 Endogeneity test and robustness test

The previous text has demonstrated that the DE has a significant promoting effect on GUL. To better prove the robustness of the baseline regression results, this paper will adopt the following four methods for verification. Furthermore, to avoid the endogeneity problems that may occur in regression, this paper will first conduct endogeneity tests. The specific methods are as follows:

First, the instrumental variable method. Considering that the traditional fixed effect assessment model may have estimation bias and endogeneity problems, this paper selects the lagging period of the DE as the instrumental variable of this paper (Zhu et al., 2022). The specific test results are shown in column (1) of Table 5. Among them, the value of the LM statistic is 351.792 and is significant at the 1% level, which indicates that there is no obvious weak instrumental variable problem in the benchmark regression of this paper. Furthermore, the coefficient value of the Wald F statistic is 6,371.549, which is far greater than the critical value of the 10% significance level. This rejects the null hypothesis that the selected instrumental variable is unidentifiable, proving that the selection of the instrumental variable is scientific and reasonable. At the same time, it also demonstrates that the benchmark regression in this paper will not be affected by endogeneity. Second, the control variable lags behind by one stage. Referring to the existing research methods (Xu et al., 2025d), choosing the one-period lag method of the control variable in the robustness test can not only reduce the endogeneity problem in the estimation of the benchmark model, but also scientifically measure the robustness of the benchmark model. The test results are shown in column (2) of Table 5. The coefficient of the DE is still significantly positive at the 1% level, which can prove the robustness of the benchmark regression results in this paper. Third, change the model. A self-sampling of 1,000 times was adopted as the alternative model (Tan et al., 2025), and the regression results are shown in column (3) of Table 5. The research finds that the impact coefficient of the DE on GUL remains significantly positive at 1%, which once again indicates that the results of the benchmark regression in this paper are robust.

5.3 Heterogeneity analysis

To further clarify the impact of the DE on GUL, the heterogeneous effects of regression in different regions were explored. This not only enriches the understanding of the application effects of the DE, but also provides a more refined perspective for the future formulation of agricultural environmental policies and agricultural development policies.

Due to the differences in resource endowments and economic development stages among different regions in China, the mechanism of the DE's effect on GUL may present significant geographical heterogeneity (Liu and Xia, 2022; Sasse and Trutnevyte, 2023). For this purpose, in this study, the samples were divided into three major regions: the East, the Middle, and the West for group regression. The results in columns (1)–(3) of Table 6 show that compared with other regions, the promoting effect and effect in the eastern region are more obvious. The DE in the

TABLE 6 Distribution heterogeneity.

Variables	(1) Eastern region	(2) Central region	(3) Western region
DE	0.07*** (6.84)	0.01 (1.27)	0.02** (2.53)
Control variables	Control	Control	Control
Fixed effects	Control	Control	Control
Cons	0.56*** (3.29)	−0.06 (−0.82)	0.13** (2.44)
N	143	104	156

TABLE 7 Indirect effect.

Variables	(1) EA	(2) ICR
DE	0.09*** (4.40)	0.04*** (2.71)
Control variables	Control	Control
Fixed effects	Control	Control
Cons	1.07*** (6.04)	−0.43*** (−3.30)
N	403	403

eastern region shows a significant promoting effect on GUL, and its influence coefficient is significantly positive at the 1% level. The reason lies in that the developed eastern regions have accelerated the transformation and upgrading of traditional land use to green and low-carbon use through the DE. They have optimized land use methods by leveraging digital technologies and, at the same time, better developed low-carbon land by taking advantage of the geographical proximity between cities and suburbs, effectively enhancing land use efficiency and land quality. In addition, as the clean energy and digital infrastructure in the eastern region are more complete than those in other regions, they are more capable of providing technical support for green agricultural production methods, thereby further enhancing the capacity for green and low-carbon land utilization. Although the DE in the central region has shown a promoting effect on GUL, it has not passed the significance test, reflecting that the digital finance in this region is still in the stage of scale expansion. Although the utilization efficiency of some resources has been enhanced through industrial integration, the development mechanism for low-carbon land use is still not well established. The depth of research and application of green and low-carbon land technologies is insufficient, which has led to the failure to fully unleash the promoting effect of the DE in GUL. Furthermore, the functional positioning of the central region as a major grain-producing area makes it face more constraints in the process of balancing food security and GUL. The DE in the western region also shows a significant promoting effect on the GUL, with the influence coefficient being significantly positive at the 5% level. This is mainly attributed to the region's innovative promotion of the deep integration of digital technology and land governance, with the smart agriculture platform precisely guiding the fallow rotation of cultivated land and ecological restoration. In addition, the development of e-commerce for characteristic agricultural products has given rise to the shared cold chain logistics model, as well as the widespread application of intelligent irrigation systems in hilly and mountainous areas. Especially in the western region, which is a karst landform area, the construction of an integrated monitoring network for low-carbon land utilization has enabled the DE to effectively resolve the predicament of fragmented land operation and form a new path for enhancing the low-carbon productivity of land through digital empowerment.

5.4 Mediating effect

5.4.1 Entrepreneurial activity level

This study will explore the mediating role of entrepreneurial activities using Formula 2 and conduct regression using the two-step mediating method. The results in column (3) of Table 7 show that entrepreneurial activity has a significant mediating effect on the impact of the DE on GUL. The DE provides a systematic solution for the low-carbon use of land by stimulating the key transmission hub of entrepreneurial activity. The enhancement of entrepreneurial activities promotes the dual empowerment of technological penetration and institutional innovation, further reshaping the transformation of the allocation model of low-carbon land factors.

Firstly, the DE has restructured the dynamic coupling relationship among land, technology, and capital through entrepreneurial activity, promoting the transformation of the traditional high-carbon land use model to a smart and green low-carbon paradigm. In addition, entrepreneurial activities have given rise to innovative business forms for low-carbon land utilization. Through digital platforms, fragmented land resources are integrated to build a governance system that collaborates with new green technologies. In this digitalization process, land elements are concentrating on high-efficiency and green low-carbon industries. Traditional labor is undergoing a deep transformation from extensive farming to digital carbon management services. By deeply integrating data empowerment with ecological constraints, land resources are promoting a coordinated development towards carbon reduction and efficiency improvement.

Secondly, the entrepreneurial activity has established a collaborative governance system for low-carbon land utilization by amplifying the scale effect of digital emission reduction technologies. The wave of digital entrepreneurship has given rise to a rapid growth in the demand for low-carbon technologies, promoting technological innovation in land management and the coordinated upgrading of the human skill structure. Supported by the digital governance platform, the entrepreneurial entities have achieved real-time monitoring and precise regulation of land carbon emission data throughout the process through the linkage

mechanism of digital technology and land system adaptation, thereby further enhancing GUL.

Finally, the entrepreneurial activity has catalyzed the adaptive transformation of low-carbon land governance, establishing a regulatory system and policy framework that combines data-driven and market incentives. The entrepreneurial ecosystem driven by the DE promotes the formation of a collaborative land green and low-carbon governance framework with local governments as the leaders, agricultural enterprises as the implementation objects, and consumers as the actual supervisors. In addition, local governments should also rely on entrepreneurial platforms to build an intelligent carbon performance supervision system. New agricultural business entities should introduce cutting-edge grain technologies through digital certification to further promote the green, low-carbon and sustainable development of land.

5.4.2 Internet penetration rate

This study will once again use Formula 2 to explore the mediating role of Internet coverage and also conduct regression using the two-step mediating method. The results in column (2) of Table 7 show that the popularity of the Internet has a significant mediating effect on the impact of the DE on GUL. With the further popularization of the Internet, the structure of information acquisition and digital capabilities has been reshaped. It not only directly breaks down the information barriers for the low-carbon transformation of land, but also relies on the synergy effect of digital technology research and development and technology penetration to comprehensively enhance the internal driving force for the green utilization of land.

Firstly, by improving the digital infrastructure to reconstruct the digital organizational form of land elements, the problems of information silos and regulatory failures existing in traditional land use can be solved, and the high-carbon land use model can be transformed and upgraded towards a green and low-carbon direction. Meanwhile, by optimizing the resource allocation structure through the flow of data elements, the digital infrastructure has been continuously upgraded. This not only effectively promotes the construction of the intelligent land detection platform, facilitating the transformation of land use from the traditional extensive land expansion model to a precise carbon reduction model, but also promotes the construction of high-standard farmland in China, significantly reducing the mechanical energy consumption and chemical dependence per unit of land.

Secondly, with the increase in Internet coverage, the network synergy of digital carbon reduction technologies has been strengthened, significantly enhancing the economies of scale in GUL. In addition, the DE has given rise to the demand for intelligent land governance, further precisely regulating and systematically applying green emission reduction technologies, and promoting the improvement of the skill structure of land use entities towards enhancing land ecological data analysis and land ecological protection decision-making. Meanwhile, the popularization of the Internet can reduce the cost of deeply integrating low-carbon technologies into land production, which is conducive to achieving the simultaneous reduction of resource consumption and carbon emissions.

6 Conclusions and policy recommendations

6.1 Conclusion

In this paper, we have constructed a measurement system for the DE and GUL, explained the promoting role of the DE and GUL from a theoretical perspective, and explored the mechanism of their action. In addition, the panel data of 31 provinces in China from 2011 to 2023 were selected as the empirical evidence for this paper. Three models, namely the panel fixed model, the quantile model, and the mediating model, were respectively used to examine the influence effect, influence mechanism, and heterogeneity between the DE and GUL from multiple perspectives. The main findings are as follows:

First, the results of the benchmark regression indicate that the direct impact of the DE and GUL shows a significant promoting effect. Moreover, after adding various control variables, no significant change was found in this result. Furthermore, after testing endogeneity, we believe that the benchmark regression is scientific and reasonable. We conducted robustness tests through two methods: replacing the model and adding a lag term to the control variables. We found that the core conclusion that the DE promotes GUL has not changed significantly. This conclusion emphasizes that the state should enhance the application of the digital economy in land to promote the green and low-carbon utilization level of land, and is consistent with existing literature. This indicates that the state should vigorously develop the digital economy to improve the green and low-carbon utilization level of land, which can not only better promote economic development but also maintain ecological security.

Secondly, the results of the mediating effect indicate that entrepreneurial activity and Internet penetration rate have significant mediating roles in the assessment of the impact of the DE on GUL. Among them, the increase in entrepreneurial activity and the penetration rate of the Internet is conducive to the exertion of the roles of land production factors and green technology factors, which can reduce the generation of land pollution and provide important support for improving the level of green and low-carbon land utilization. This conclusion provides a specific direction for the Chinese government's future financial input and practical experience for developing countries. It is highly consistent with the existing published literature. This indicates that the country can make good use of the advantages of entrepreneurial activity and the Internet penetration rate to provide a good boost for the development of the digital economy and further reduce the generation of carbon emissions in land use. This ensures the security of the national ecological environment.

Thirdly, the heterogeneity regression results show that in the eastern and western regions of China, the DE has a significant promoting effect on GUL, but it shows no significant effect in the central region. This result indicates that in regions with developed economies and more advanced digital technologies, the advantages of the DE in promoting GUL are more prominent. It further demonstrates that promoting the application of the DE and digital green technologies can more effectively achieve the core goal of low-carbon transformation of land and agriculture. The emergence of this conclusion reflects the imbalance in development

among different regions in China, which is consistent with the conclusion of many scholars' research. It can be said that if China wants to achieve green and low-carbon land utilization, it needs to take advantage of the digital economy based on the development status of different regions.

6.2 Policy recommendations

First, develop the capacity for digital land governance and improve the low-carbon land management and control system. The depth of application of digital technology in the land sector is a key support for unleashing GUL and promoting the transformation of land use patterns. We should promote the digital collaboration of coordinating the allocation of land resource elements and carbon emission management, optimize the intelligent collaboration of territorial space planning and ecological carbon sink functions, and accelerate the construction of a digital low-carbon governance system featuring digital agricultural bases, smart energy facilities, and carbon data monitoring networks. Government departments should enhance the digital empowerment level of land low-carbon utilization, leverage the policy guidance role of the digital economy, improve the digital implementation details and intelligent supervision mechanism of land low-carbon utilization regulations, and form a full-process digital monitoring and regulation system for land low-carbon utilization.

Second, build regional differentiated empowerment paths to break through the constraints of the digital divide. In the eastern region, efforts should be made to strengthen the dual-wheel drive of technological adaptation and institutional innovation. Relying on the advantages of digital infrastructure, promote intelligent decision-making systems, pilot "digital land banks" to integrate fragmented and idle land, and release the carbon reduction potential of existing land. Explore the mechanism linking carbon emission rights trading with land development indicators simultaneously. In the western regions, priority should be given to the layout of inclusive digital infrastructure. In the central region, efforts should be focused on breaking through the bottleneck of "technology-system" synergy. In response to the functional constraints of major grain-producing areas, develop a balance model between food security and low-carbon land use; Establish a digital agriculture entrepreneurship incubation park to guide technology to sink to counties at a medium level of development. It is suggested that the government increase investment in the digital technology empowerment and intelligent monitoring platform construction for the low-carbon utilization of land, accelerate the establishment and implementation of data standards and intelligent regulatory systems related to the low-carbon utilization of land, which can not only significantly improve the efficiency of land use and the accuracy of carbon emission control, but also effectively reduce the hidden carbon footprint in the process of agricultural production and construction. Achieve a win-win situation of low-carbon land utilization efficiency and ecological health.

Third, activate the dual intermediary engines of entrepreneurship and the Internet, and enhance the depth of technological penetration. The entrepreneurial activity has been enhanced. A land green technology venture capital fund has been established, and tax credits are provided to agricultural enterprises that adopt technologies such as blockchain traceability and intelligent irrigation. Build a "Digital Agricultural Service crowd sourcing Platform" to guide the labor force to shift from traditional farming to carbon management services. Focus on enhancing the coverage rate of gigabit optical networks and 5G base stations in rural areas of the central and western regions. Establish digital technology promotion stations and, through targeted training, lower the threshold for farmers to apply the smart agriculture platform, thereby solving the problem of implementing green agricultural technologies. It is suggested that the government strengthen the systematic training of digital technology application capabilities for agricultural producers and operators. Through policy guidance and technical support, it should popularize knowledge on data monitoring, intelligent analysis and precise management of low-carbon land use, cultivate compound talents in low-carbon land management who master digital tools, and fully release the comprehensive efficiency of low-carbon land use driven by digital technology.

6.3 Research deficiencies and prospects

Future research can be deepened and expanded from the following two dimensions: First, refine the observation scale and data dimensions. This study uses provincial panel data to reveal the macro impact of the DE on GUL, but the micro transmission mechanism still needs to be analyzed in depth. Subsequently, operational data at the prefectural, county and enterprise levels can be collected. By combining the scale of land transfer, the skills of the labor force and the differences in the integration models of various business entities, the micro-level role path of the DE in GUL can be revealed. Second, strengthen the research on the dynamic coupling of digital economy policies and land policies. The measurement of the digital economy and the green and low-carbon utilization of land in this paper may not be comprehensive. Future research can further construct a dynamic system model that combines climate conditions, technological progress, labor force and land quality, especially the nonlinear matching relationship between the diffusion of green and low-carbon technologies and land use. A more in-depth refinement of the measurement system for the digital economy and the green and low-carbon utilization of land can further reveal the long-term mechanism and spatio-temporal heterogeneity characteristics of the digital economy in the green and low-carbon utilization of land, providing more precise theoretical support for improving the land governance system and achieving ecological and environmental security.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

TL: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft , Writing – review and editing.

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EDITED BY
Lingli Qing,
Guangzhou College of Commerce, China

REVIEWED BY
Roberto Alonso González-Lezcano,
CEU San Pablo University, Spain
Boyao Song,
Beijing Forestry University, China
Guang Yang,
Beijing Forestry University, China
Longbo Ma,
Qingdao Agricultural University, China

*CORRESPONDENCE
Hanxiang Luo
lhx1997@webmail.hzau.edu.cn

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Impact of collective forestland tenure reform on household forestry production efficiency: micro-level evidence from China

Jian Wei[1], Fangzheng Wang[1], Tianwei Xie[2] and Hanxiang Luo[3]*

[1]Fujian Agriculture and Forestry University, Fuzhou, China, [2]Graduate School of Business Administration, Dong Shin University, Naju, Republic of Korea, [3]College of Economics and Management, Huazhong Agricultural University, Wuhan, China

Improving forestry production efficiency is crucial for advancing rural economic development and ecological modernization in China. Using panel data from 13,536 rural households in 18 counties across nine provinces during 2003 and 2007–2019, this study investigates the impact of collective forestland tenure reform on household-level forestry production efficiency. A translog stochastic frontier production function model is applied to estimate efficiency, while Tobit and mediation effect models are used to explore the underlying mechanisms. The results show that tenure reform significantly enhances forestry production efficiency, primarily by increasing production inputs, expanding forestland management scale, and improving access to credit. Further heterogeneity analysis indicates that the positive effects are more pronounced among households with pure farming livelihoods, bamboo or economic forest cultivation, and in less-developed or forest-rich regions. These findings highlight the importance of tenure security in stimulating investment incentives, promoting efficient resource reallocation, and facilitating financial inclusion in rural forestry. Policy implications include strengthening forestland tenure security, developing transparent forestland transfer markets, and innovating credit systems, with particular emphasis on supporting the sustainable management of long-cycle timber forests to balance economic benefits with ecological goals.

KEYWORDS

collective forest tenure reform, forestry production efficiency, production inputs, management scale, credit accessibility, livelihood strategies

1 Introduction and literature review

Since the 18th National Congress of the Communist Party of China, the concept that "lucid waters and lush mountains are invaluable assets" has become a central tenet of ecological civilization. Forests, as critical ecological and economic resources, play a dual role in ensuring national ecological security and supporting rural livelihoods. However, challenges such as slow forest resource accumulation, limited income contribution to farmers, and insufficient ecological product supply have exposed deep-rooted structural problems, notably the low productivity of forestland. These issues stem from institutional deficiencies in property rights definition and protection within China's collective forest system. In response, the Chinese government launched a new round of collective forest rights reform, officially implemented nationwide in 2008, with the aim of clarifying tenure and granting farmers greater autonomy over forestland management. The latest policy blueprint—The Plan for Deepening the Reform of the Collective Forest Rights System (2023)—further emphasizes clarity of ownership, strict

protection, orderly transfer, and effective oversight by 2025. Given that farmers are the most immediate actors in forest production, changes in property rights institutions directly influence their factor allocation decisions and management efficiency. Against this backdrop, this study investigates the impact of forest rights reform on farmers' forestry production efficiency and explores its underlying mechanisms. By identifying the behavioral pathways through which reform affects efficiency, the study contributes to the literature on institutional change in rural resource governance and offers practical guidance for promoting sustainable forestry development under China's evolving policy framework.

Research on forestry production efficiency is extensive. From the perspective of resource endowment, factors such as natural capital (Liang et al., 2022; Shi et al., 2024), human capital (Xue and Yao, 2017; Yang et al., 2018; Zhu et al., 2018), and financial capital (Xue and Yao, 2014) all affect farmers' forestry production efficiency. From the perspective of natural environmental factors, due to the unique natural attributes of forestry, natural elements such as heat, water, light, and soil nutrients that influence tree growth also have an impact on farmers' forestry production efficiency (Lu et al., 2018). In addition to resource endowment and natural environmental factors, differences in time, space, tree species, and management scale also produce heterogeneous effects on farmers' forestry production efficiency (Zhang and Jiang, 2023; Huang et al., 2016; Li et al., 2010; Li et al., 2014; Tian and Shi, 2017). However, the most widely discussed and academically emphasized factor is the institutional arrangement of forest land property rights (Li, 2010; Liu and Ravenscroft, 2016), which directly relates to the input–output level and operational efficiency of economic agents (Liu and Yu, 2007). Clear and stable forest property rights can motivate farmers to manage forest land more effectively, improve the refinement level of forestry production, and thereby enhance forestry production efficiency (Deacon, 1994; Gao, 2007). Correspondingly, without secure and long-term forest property rights, farmers are often reluctant to make long-term investments, thus reducing the efficiency of production factor allocation (Long, 2009; Wang et al., 2010). It is thus evident that ineffective property rights arrangements are a key cause of low forestry production efficiency (Das, 2022). Recent empirical evidence further substantiates this perspective. For instance, Yi (2023) finds that the devolution of forestland tenure significantly increased farmers' labor and capital inputs in afforestation and silviculture, stimulated long-term management incentives, and consequently improved forest resource conditions—manifested in higher average tree height, crown width, and stand volume, alongside enhanced ecological functions. Similarly, Xu and Hyde (2019) emphasize that China's second round of collective forest tenure reform, through enhancing policy stability, clarifying tenure boundaries, and extending contract periods, effectively boosted farmers' investment incentives and led to improved forestry management performance. In addition, some studies have shown that the type of ownership has a significant impact on farmers' forestry production efficiency (Qin and Xu, 2013; Wallace and Newman, 1986). When forest property rights are categorized by ownership into joint ownership and individual ownership, individual ownership has a significantly positive impact on forestry production efficiency compared to joint ownership (Wang et al., 2010; Zhang and Yu, 2009) which aligns with Gao (2007)'s view that forestry production efficiency under decentralized management is not necessarily lower than that under joint management. However, some studies argue that reclaiming self-managed forest land that is divided but not properly managed and placing it under unified collective management can also effectively improve forestry production efficiency (Yiwen, 2024).

A review of existing literature helps to clarify the relationship between forest rights reform and farmers' forestry production efficiency, offering important insights for this study. Most current research evaluating the policy effects of forest rights reform focuses on aspects such as forestland transfer, forestry production investment, and farmers' income growth. While many studies have investigated the economic impacts of forest rights reform—including forestland transfer, forestry investment, and income generation—few have directly examined its influence on forestry production efficiency at the household level. Yet households are the fundamental decision-making units in forest use and management, and their choices directly determine the allocation of production factors, investment horizons, and efficiency outcomes. Overlooking this level risks obscuring substantial heterogeneity in how reforms affect forest use. Moreover, among the limited studies that touch on production efficiency, most tend to treat it as a secondary outcome, without systematically exploring the underlying mechanisms. That is, the pathways through which forest rights reform affects farmers' forestry production efficiency have not yet been adequately revealed.

This study aims to fill these gaps by explicitly focusing on the household level and by constructing a theoretical framework that explains how forest rights reform influences forestry production efficiency. Drawing on household survey data from 18 counties across 9 provinces in China, the analysis considers both the direct and indirect effects of forest rights reform on forestry efficiency through the use of a mediation effect model, thereby enhancing our understanding of the policy's impact mechanisms. By doing so, this paper not only complements existing macro-level research but also provides a micro-level perspective that reveals behavioral heterogeneity and decision-making dynamics often hidden in aggregate analyses. Furthermore, the study explores the heterogeneous policy effects under varying conditions of forest resource endowment and regional economic development, as well as household livelihood strategies and planting structures—providing more targeted recommendations for policy design and contributing unique empirical evidence to the broader debate on institutional reforms and sustainable forest management.

2 Institutional background and research hypotheses

2.1 Institutional background

Since the 1980s, many countries—including China—have implemented forestland tenure reforms through decentralization (Akinola and Wissink, 2019). The primary goal of decentralization in forest governance is to reduce management costs and improve operational efficiency in forestry (De Soto and Diaz, 2002). However, due to inadequate tenure clarification and weak property rights protection in many developing countries (Yeh, 2004), forest decentralization has often failed to improve forest resource management effectively (Sunseri, 2003), and most tenure reforms have not achieved their intended outcomes (Edmunds and Wollenberg,

2001; Larson et al., 2007). China's new round of collective forest tenure reform (hereinafter referred to as "forest rights reform") represents an important component of its rural property rights reform. In 1981, the reform began with the "Three Fixes" policy, which marked the start of de facto household allocation of collective forestland. However, widespread deforestation and over-exploitation led to the suspension of the reform in 1987. In the late 1990s, the marketization of China's forestry sector drove up timber prices, increasing farmers' demand for secure property rights over forest resources. In 2003, the Central Committee of the Communist Party of China and the State Council issued the Decision on Accelerating Forestry Development, launching pilot programs in provinces such as Zhejiang, Jiangxi, Fujian, and Liaoning. These pilots sought to allocate use rights over collectively managed forestland to households through formal tenure confirmation. Building on the successes of the pilot programs, in 2008, the central government issued the Opinions on Comprehensively Promoting the Reform of the Collective Forest Tenure System, which marked the nationwide implementation of forest rights reform. This policy emphasized contracting collective forestland to households and granting them secure forestland use rights, including the rights to transfer, mortgage, and manage their holdings. In September 2023, the Plan for Deepening the Reform of the Collective Forest Rights System was issued by the CPC Central Committee and the State Council. The plan aims to establish, by 2025, a collective forest tenure system characterized by clear ownership, unified rights and responsibilities, strict protection, orderly transfer, and effective supervision. The new reform stage emphasizes easing governmental restrictions on forestland transfers and mortgages to diversify channels for realizing the value of forest property rights. Together with the confirmation and certification of tenure, mechanisms for circulation and mortgage have now become integral components of the reform's incentive structure. The 20th National Congress of the Communist Party of China also explicitly called for deepening the reform of the collective forest tenure system, reflecting the state's high-level policy commitment. It is evident that achieving high-quality development in China's forestry sector requires further improvements to the collective forest tenure system to enhance its attractiveness for long-term investment. This, in turn, provides a practical opportunity to improve the efficiency and productivity of forestland.

Against this backdrop, this paper investigates how forest rights reform affects farmers' forestry production efficiency under the new institutional context. The study offers both theoretical and practical value for strengthening farmers' capacity for sustainable forest management in the current policy environment.

2.2 Theoretical mechanisms and research hypotheses

2.2.1 Forest rights reform, forestry production investment, and farmers' forestry production efficiency

Clear and stable forest property rights help strengthen farmers' perception of tenure security, induce stable expectations, and incentivize increases in forestry capital and labor inputs, which in turn promote improvements in forestry production efficiency. Specifically, first, they enhance the exclusivity of forest property rights. Stable forest tenure can effectively reduce the risk of land being expropriated by governments, institutions, or other individuals (Demsetz, 1967), strengthen the actual control of operators over forestland, lower the risk of operational interruptions in forestry production, and stimulate farmers' willingness to increase forestry investment, However, it is important to note that increased investment alone does not automatically result in efficiency gains. According to the theory of capital deepening (Solow, 1956), investment improves efficiency only when capital is effectively allocated relative to labor and land. In forestry, this requires that additional investment be directed toward productivity-enhancing inputs such as advanced planting techniques, better seedlings, or improved soil management (Zhang et al., 2004). Moreover, stable property rights not only increase the volume of investment but also improve its quality and long-term orientation, reducing risk and encouraging more rational resource allocation. This combination of quantity and quality in investment contributes to more efficient use of production factors, thus enhancing overall production efficiency. Second, they enable the liberalization of property rights transactions. Strengthening the security of forest tenure can effectively reduce transaction costs and uncertainties, and by facilitating the effective physical concentration of forestland or its transfer to more capable operators, it encourages farmers to expand long-term forestry investments, thus optimizing the allocation efficiency of forestry production factors. Finally, they ensure the internalization of forestry returns. Forest rights reform, by clarifying property boundaries and the attributes of forestland as private property, limits the dissipation of rent in the public domain caused by ambiguous property rights, minimizes the risk of losing anticipated investment returns in forestry production, and enhances farmers' willingness to invest production factors, thereby exerting a positive impact on forestry production efficiency.

> *H1:* Forest rights reform incentivizes increased forestry input, thereby improving production efficiency.

2.2.2 Forest rights reform, expansion of forestland management scale, and farmers' forestry production efficiency

Forest rights reform improves forestry production efficiency by reducing forestland transaction costs and risks, thereby guiding farmers to expand their forestland management scale. First, forest rights reform facilitates the effective reallocation of forestland resources by promoting the transfer of land from farmers with low production efficiency to those with higher efficiency, which enhances the coordination and matching of key factors such as land, capital, and labor, thus improving forestry production efficiency. Second, strengthening the stability of forest property rights helps cultivate and improve the forestland transfer market. When farmers have the willingness to expand their forestland management scale, they are more likely to find lessors through a more transparent and well-functioning transfer market, which encourages greater investment in forestry production and promotes efficiency improvements. Finally, the current distribution of forestland based on equal shares per capita has led to fragmented and scattered forestland layout structures, resulting in high unit input costs per plot and limiting gains in production efficiency. Through forestland inflow, farmers can increase their management scale to approach or reach an optimal level, which not only helps reduce unit input costs and achieve moderate

economies of scale, but also facilitates the introduction of more advanced technologies and management practices to optimize forestry production structures and ultimately enhance forestry production efficiency.

> *H2:* Forest rights reform promotes efficiency gains by incentivizing larger-scale forestland operations.

2.2.3 Forest rights reform, enhanced credit accessibility, and farmers' forestry production efficiency

Forest rights reform signifies that forest property rights receive credible recognition and protection through formal institutions on a long-term and stable basis. On this foundation, the reform further grants forestland the rights to be used as collateral and guarantees under contractual arrangements, significantly enhancing the liquidity of forest resources and the market value of forest property rights. On one hand, strengthening the stability of forest property rights can effectively overcome problems of adverse selection and moral hazard in the credit market caused by information asymmetry, reduce the contract supervision costs for financial institutions, as well as the costs of contract enforcement in cases of default, thereby increasing their willingness to supply credit. On the other hand, forest rights mortgage loans, as an extended mechanism of collateralization, help activate forestry assets to increase household wealth and strengthen financial institutions' confidence in the collateral value of forestry assets, thus alleviating the difficulty rural households face in lacking traditional effective collateral. Therefore, forest rights reform, by enhancing the credit accessibility of forest property rights, significantly improves the credit supply–demand relationship in rural forestry financial markets. This not only optimizes the allocation efficiency of forestry production factors such as land, capital, and labor, but also strengthens farmers' investment capacity in forestry, thereby improving forestry production efficiency. The relationship between credit access and efficiency can be explained through the theory of credit constraints (Feder et al., 1990; Petrick, 2004), which suggests that limited access to formal financing channels prevents rural households from acquiring timely inputs or adopting advanced technologies. When credit is made more accessible through the formal recognition of collateralized forest rights, farmers can overcome liquidity constraints and smooth consumption and investment cycles. Additionally, improved credit access enhances risk-taking capacity and allows for longer-term planning, both of which are essential for efficiency gains in forestry operations. In this context, forest rights reform not only increases credit availability but also indirectly promotes optimal input allocation and technological upgrading, further contributing to improvements in forestry production efficiency.

> *H3:* Forest rights reform enhances forestry production efficiency via improved credit access.

3 Research design

3.1 Data sources

The data used in this study are derived from the large-scale long-term household survey database established by the Development Research Center of the National Forestry and Grassland Administration. To ensure data accuracy, a stratified random sampling technique was employed. Nine provinces (regions)—Liaoning, Henan, Shandong, Sichuan, Guangxi, Hunan, Jiangxi, Zhejiang, and Fujian—were selected as the study areas. In each province (region), two counties were chosen; in each county, three townships were selected; in each township, three administrative villages were sampled; and in each village, 15 sample households were randomly selected. After removing invalid samples with inconsistent observation periods or contradictory questionnaire information, the final dataset consists of 13,536 household observations from the years 2003 and 2007–2019. Household-level data for 2004–2006 are unavailable because the national survey project was temporarily suspended during this period due to funding and organizational adjustments, and it resumed in 2007.

Using the rural means of production price index and the rural consumer price index, the data for relevant variables were converted into constant 1994 prices. Specifically, provincial-level rural Consumer Price Indices (CPI) published by the National Bureau of Statistics were used to deflate monetary variables, with 1994 set as the base year. This adjustment was applied to all value-related indicators, including forestry income, production inputs, and household expenditure. Using province-specific indices ensures that the spatial and temporal differences in inflation levels are accurately captured, thereby enhancing the intertemporal and interregional comparability of the micro-level data.

The selection of the nine provinces (regions) was based on their representativeness in terms of forest resource endowment, collective forestland distribution, and the progress of forest rights reform implementation. These provinces span different geographical regions (e.g., Northeast, Central, Southwest, and Southeast China) and ecological zones, and they cover most of the dominant collective forest types (e.g., coniferous, broadleaf, and mixed forests) as well as diverse tenure arrangements. Therefore, they provide a broadly representative picture of China's major collective forest areas. However, it should be noted that they do not fully capture contexts such as arid regions or areas dominated by state-owned forests in western China, where tenure systems and ecological conditions differ substantially. Hence, the results should be interpreted as representative of collective forest regions, and caution is warranted in making generalizations to other tenure contexts.

3.2 Variable selection

3.2.1 Dependent variable

This study uses the forestry production efficiency loss estimated by the translog stochastic frontier production function model as the representative variable for forestry production efficiency. The forestry input indicators include forestland management scale, forestry capital input, and forestry labor input, while the output indicator is the total value of forestry production. To ensure data stability, the logarithmic transformation of forestry production efficiency is applied in this study.

3.2.2 Core explanatory variable

The core explanatory variable in this study is forest rights reform. The primary mechanism through which the reform achieves the "allocation of forestland to individual households"

is the confirmation and certification of tenure rights. At present, the majority of farmers have obtained forest tenure certificates for all their forestland plots, with property rights clearly defined. Only a small portion of farmers hold equity certificates—documents similar in function to forest tenure certificates—for a limited number of plots, while most of their forestland has already been confirmed and certified with forest tenure certificates. Although the government has recently promoted the issuance of real estate certificates and forest management right certificates based on the existing tenure system, their overall issuance rates remain low. Forest tenure certificates still constitute the dominant form of certification for collective forestland. Therefore, using the status of tenure confirmation and receipt of a forest tenure certificate as the policy variable for the new round of forest rights reform is both appropriate and representative. In this study, households that have completed tenure confirmation and obtained a forest tenure certificate are assigned a value of 1, while those that have not are assigned a value of 0.

3.2.3 Mediating variables

The mediating variables in this study include forestry production input, expansion of forestland management scale, and enhancement of credit accessibility. Forestry production input is represented by the household's forestry capital and labor inputs. Expansion of forestland management scale is represented by whether the household has transferred in forestland. Enhancement of credit accessibility is represented by whether the household has obtained a forest rights mortgage loan from a financial institution.

3.2.4 Control variables

The control variables in this study are categorized into four groups. First, market characteristic variables, including the price of non-agricultural labor and the price of timber. Second, household characteristic variables, including the age, gender, years of education, and health status of the household head, whether the household head is a village cadre, household size, proportion of labor force in the household, total household income, proportion of forestry income, and whether the household engages in non-agricultural employment. Third, resource characteristic variables, including forestland area. Fourth, village characteristic variables, including whether the road is paved, whether the village is located in a mountainous area, and the distance from the county seat. It should be noted that if a control variable is binary, it is coded as 0 or 1; otherwise, continuous variables are log-transformed. Detailed variable descriptions and descriptive statistics are provided in Table 1.

3.3 Model specification

3.3.1 Baseline model specification

Among the various methods for measuring production efficiency, Stochastic Frontier Analysis (SFA) is one of the most

TABLE 1 Variable definitions and descriptive statistics.

Variable Name	Variable definition	Mean	Standard deviation
Forestry production efficiency	Forestry production efficiency loss based on SFA model	0.6852	0.2001
Forest rights reform	Forest rights confirmed and certificate Issued (yes = 1; no = 0)	0.6162	0.4863
Forestry capital input	Total investment in forestry management (Yuan)	622.6112	3045.001
Forestry labor input	Total time spent on forestry management (person-days)	31.9945	65.6863
Expansion of forestland management scale	Whether the household transferred in forestland (Yes = 1; No = 0)	0.0725	0.2593
Enhanced credit accessibility	Whether the household obtained a forest rights mortgage loan (yes = 1; no = 0)	0.0165	0.1272
Livelihood strategy	Pure farming = 1; mixed farming = 2; Non-farming = 3	2.0287	0.7315
Non-agricultural labor price	Unit: yuan	52.8723	21.5415
Timber price	Unit: yuan	439.3289	97.3423
Age	Unit: years	52.149	11.0257
Gender	Male = 1; female = 0	0.9694	0.1721
Years of education of household Head	Unit: years	7.3187	2.8496
Health status	Healthy = 1; not healthy = 0	0.8951	0.3064
Household head is village cadre	Yes = 1; no = 0	0.2428	0.4288
Household size	Unit: people	3.9328	1.5076
Number of household laborers	Unit: people	2.7074	1.2344
Total household income	Unit: yuan	16946.2931	22027.3811
Proportion of forestry income	Unit: %	0.1123	0.2090
Non-agricultural employment	Yes = 1; no = 0	0.6923	0.4616
Forestland area	Unit: mu (1 Mu = 0.0667 Hectares)	38.3976	73.138
Paved road surface	Yes = 1; no = 0	0.7674	0.4225
Mountainous area	Yes = 1; no = 0	0.5580	0.4966
Distance to county seat	Unit: km	35.4196	31.3447

widely adopted approaches. SFA, initially developed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977), enables the decomposition of deviations from potential output into two components: random noise and inefficiency. This is particularly important in forestry production, where output fluctuations are not solely attributable to farmers' decisions but are also significantly affected by uncontrollable environmental factors such as weather, pests, and soil variability.

In recent years, SFA has been widely applied in studies on agricultural and forestry production efficiency, especially in the context of institutional reforms and land tenure security. For instance, Yu et al. (2021) used SFA to examine the technical efficiency of collective forest operators in China, finding that collective forest tenure reform had a significant effect on efficiency outcomes. Similarly, Zhang and Chen (2022) applied SFA to assess the impact of land tenure on agricultural productivity. These studies demonstrate the suitability of the SFA approach in empirical contexts that involve property rights structures and natural resource-based production.

In specifying the production frontier, this study adopts a translog functional form rather than the commonly used Cobb–Douglas function. The translog form offers greater flexibility by not imposing restrictive assumptions such as constant returns to scale or unitary elasticity of substitution among inputs. This allows us to capture non-linear relationships as well as substitution and complementarity effects among production factors such as labor, land, and capital—features that are particularly relevant in forestry production, where input interactions are heterogeneous and complex. Thus, the translog SFA specification provides a more accurate and realistic representation of farmers' production technology.

Therefore, this study adopts a translog-form stochastic frontier production function model to estimate farmers' forestry production efficiency. The model is constructed as follows:

$$\begin{aligned}\ln Y_{it} = {} & \beta_0 + \beta_1 \ln S_{it} + \beta_2 \ln K_{it} + \beta_3 \ln L_{it} + \beta_4 \ln S_{it}^2 + \\ & \beta_5 \ln K_{it}^2 + \beta_6 \ln L_{it}^2 + \beta_7 \left(\ln S_{it}\right)\left(\ln K_{it}\right) + \\ & \beta_8 \left(\ln S_{it}\right)\left(\ln L_{it}\right) + \beta_9 \left(\ln K_{it}\right)\left(\ln L_{it}\right) + V_{it} - U_{it}\end{aligned} \tag{1}$$

In Equation 1, Y denotes forestry output; S denotes the area of forestland managed; K represents forestry capital input; L denotes forestry labor input; i represents the i-th household; t is the time variable; $\beta_0, \beta_1, \beta_2 \cdots \beta_9$ are the parameters to be estimated; V_{it} is the random error term, which follows an independent normal distribution with a mean of zero and variance of σ_v^2; That is, $V_{it} \sim N\left(0, \sigma_v^2\right)$; U_{it} represents the forestry production efficiency that is, the gap between actual output and the maximum attainable output on the production frontier. Loss term for farmers. It is assumed that U_{it} follows a truncated normal distribution, i.e., $U_{it} \sim N\left(u, \sigma_u^2\right)$, thereby reflecting the loss in forestry production efficiency.

Since the values of forestry production efficiency loss lie within the interval [0, 1], they represent censored data. Therefore, this study employs the Tobit model for econometric analysis. This is because the inefficiency term is a limited dependent variable, and applying ordinary least squares (OLS) would result in biased and inconsistent estimates. The Tobit model is more appropriate for dealing with censored outcomes and is widely adopted in two-stage stochastic frontier analysis frameworks (e.g., Battese and Coelli, 1995), where the inefficiency scores are treated as latent variables constrained within a specific range. Referring to the empirical model of Qian (2017), the baseline model is specified as follows:

$$u_{it} = \delta_0 + \delta_1 D_{it} + \delta_2 X_{it} + \theta_i + \varepsilon_{it} \tag{2}$$

In Equation 2, u_{it} represents the forestry production efficiency loss of farmers, indicating the gap between actual output and the output under the optimal technological level. D denotes whether the farmer has completed tenure confirmation and obtained a forest rights certificate; if yes, then $D_{it}=1$, otherwise $D_{it}=0$, X is the vector of control variables; $\ddot{a}_0$ is the constant term; δ_1, δ_2 are parameters to be estimated, if δ is negative, it indicates that the corresponding variable has a positive effect on forestry production efficiency; conversely, if δ is positive, it indicates a negative effect; θ_i represents time fixed effects; ε_{it} is the random error term.

All parameter estimates of the stochastic frontier production function model determined by Equations 1, 2 can be obtained using the maximum likelihood estimation (MLE) method. The maximum likelihood function utilizes two variance parameters:

$$\gamma = \sigma_u^2 / \sigma_v^2 + \sigma_u^2 \left(0 \le \gamma \le 1\right) \tag{3}$$

In Equation 3, ā reflects the proportion of the production efficiency loss component within the composite error term. When ā pproaches 0, it indicates that the gap between actual output and the maximum possible output is primarily due to uncontrollable random factors, suggesting the absence of significant efficiency differences; in this case, the use of the stochastic frontier production function model may be inappropriate, indicating model misspecification. Conversely, when ā approaches 1, it implies that the gap is mainly attributable to production efficiency loss, making the application of the stochastic frontier production function model more appropriate.

3.3.2 Mediation effect model

This study primarily draws on the methodology proposed by Ye et al. (2002), and the mediation effect model is constructed as follows:

$$tran_{it} = \alpha_0 + \alpha_1 D_{it} + \alpha_2 X_{it} + \theta_i + \varepsilon_{it} \tag{4}$$

$$u_{it} = \gamma_0 + \gamma_1 D_{it} + \gamma_2 tran_{it} + \gamma_3 X_{it} + \theta_i + \varepsilon_{it} \tag{5}$$

In Equations 4, 5, $tran_{it}$ represents the mediating variable, α_1, γ_1, and γ_2 re parameters to be estimated, α_0, γ_0 are constant terms, and other variables are defined as above. The basic procedure for testing the mediation effect is as follows: first, test the estimated coefficient δ_1 in Equation 2; if δ_1 is statistically significant, then proceed to the second step, otherwise stop the test. Second, test the estimated coefficient α_1 in Equation 4; if α_1 is significant, proceed to the third step. Third, test the estimated coefficient γ_2 in Equation 5; if γ_2 is significant, a mediation effect is considered to exist.

4 Empirical results analysis

4.1 Regression results of the translog stochastic frontier production function

The regression analysis of Equation 1 is conducted using Stata software. As shown in Table 2, the Wald chi2(9) statistic for testing the null hypothesis of "no production efficiency loss" is 1231.15, with a *p*-value of 0.0000, indicating that the null hypothesis is rejected at the 1% significance level and confirming the existence of production efficiency loss. Based on the estimated values of parameters σ_v and σ_u from the regression results, the coefficient value of γ is calculated as 0.9925, suggesting that 99.25% of the composite error term originates from the production efficiency loss U, while the random error V accounts for only 0.75%. This indicates that the translog stochastic frontier production function provides a good fit for estimating the input–output relationship in farmers' forestry production.

4.2 Analysis of factors influencing farmers' forestry production efficiency

Table 3 reports the regression results of factors influencing farmers' forestry production efficiency. The results show that forest rights reform has a significant negative effect on forestry production efficiency loss at the 1% statistical level, indicating that the reform has a positive impact on improving farmers' forestry production efficiency. Timber prices also exhibit a negative effect on efficiency loss, suggesting that expanding the profit margin of forest products is an important driving force for improving production efficiency.

Among the control variables, several demonstrate effects consistent with theoretical expectations. Years of education of the household head, household size, and whether the head is a village cadre all show significant negative effects on efficiency loss at the 1% level, indicating that both human capital and social capital play vital roles in enhancing production efficiency. Total household income and the proportion of forestry income also exhibit significant negative coefficients, suggesting that the availability of material capital—especially income derived from forestry—is critical to sustaining efficient forestry practices. Forestland area shows a significantly negative relationship with efficiency loss, supporting the view that managing larger-scale forest plots (i.e., lower forest fragmentation) helps reduce inefficiencies, likely by enabling economies of scale and more intensive management.

Conversely, participation in non-agricultural employment significantly increases production efficiency loss. This finding may reflect the labor diversion effect: as household labor shifts toward non-forestry jobs, less attention is given to forest management, resulting in more extensive and less efficient forestry practices. Additionally, some natural and infrastructural variables show significant effects. For instance, paved road surface is negatively associated with efficiency loss, highlighting the importance of transportation infrastructure in improving market access and reducing transaction costs. Meanwhile, the coefficient for mountainous area is significantly negative, indicating that favorable agroecological conditions—such as sunlight, water, and heat—can support higher productivity in forestry operations.

4.3 Robustness check

To verify the reliability and consistency of the empirical findings presented in Section 4.2—particularly the effect of forest rights reform on forestry production efficiency—we conduct a series of robustness checks in this section. These tests aim to address potential endogeneity, sample selection bias, and omitted variable bias that may affect the baseline regression estimates. To ensure the robustness of the baseline regression results, a series of robustness checks were conducted (Table 4). First, the proportion of forestland with confirmed rights at the county level was used as a proxy for forest rights reform instead of the household-level variable, which helps to mitigate potential self-selection bias that may arise during pilot implementations of the reform. The results show that forest rights reform continues to have a significant positive effect on farmers' forestry production efficiency, confirming the robustness of the findings. Second, provinces that implemented forest rights reform earlier as pilot regions may be more representative than others; thus, after excluding the four earliest pilot provinces—Liaoning, Zhejiang, Fujian,

TABLE 2 Regression results of the stochastic frontier production function for farmers' forestry input and output.

Variable	Estimated coefficient	Standard error	Z-statistic	Variable	Estimated coefficient	Standard error	Z-statistic
Constant	6.8111***	0.1414	48.16	Forestland area × Forestry labor	−0.0002	0.0018	−0.13
Forestland area	0.0244	0.0224	1.09	Forestry production costs × Forestry labor	−0.0041***	0.0007	−5.90
Forestry production costs	0.1692***	0.0108	15.62	σ_v	0.8136***	0.0213	38.17
Forestry labor	0.1975***	0.0161	12.30	σ_u	9.3586***	0.0874	107.06
Squared forestland area	0.0331***	0.0023	14.31	Log likelihood	−42297.67		
Squared forestry production costs	0.0188***	0.0014	13.67	Wald chi2(9)	1231.15		
Squared forestry labor	0.0313***	0.0027	11.76	Prob > chi2	0.0000		
Forestland area × Forestry production costs	−0.0080***	0.0024	−3.29	Number of observations	13,536		

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 3 Regression results of factors influencing farmers' forestry production efficiency.

Variable	Estimated coefficient	Standard error	T-statistic	Variable	Estimated coefficient	Standard error	T-statistic
Forest rights reform	−0.0209***	0.0019	−10.90	Non-agricultural employment	0.2475***	0.0210	11.81
Non-agricultural labor price	0.0000	0.0005	0.10	Forestland area	−0.0007***	0.0001	−5.61
Timber price	−0.0009***	0.0001	−8.32	Paved road surface	−0.0356*	0.0208	−1.71
Age	−0.0007	0.0009	−0.70	Mountainous area	−0.2094***	0.0179	−11.68
Gender	0.0705	0.0471	1.50	Distance to county seat	0.0003	0.0003	1.07
Years of education of household head	−0.0215***	0.0031	−6.88	Constant	3.7372***	0.1068	34.98
Health status	−0.0381	0.0358	−1.06	Year fixed effects	Yes		
Household head is village cadre	−0.1117***	0.0197	−5.68	Regional fixed effects	Yes		
Household size	−0.0237***	0.0061	−3.88	Log likelihood	−16234.311		
Number of household laborers	−0.0479	0.0376	−1.27	Prob > chi2	0.0000		
Total household income	−0.1512***	0.0074	−20.48	Number of observations	13,536		
Proportion of forestry income in household income	−3.9079***	0.0466	−83.80	Pseudo R^2	0.199		

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 4 Robustness check.

Variable	Substitution of core explanatory variable	Exclusion of pilot provinces	Exclusion of confounding policy effects
Forest rights reform	−0.0183*** (0.0032)	−0.0149*** (0.0024)	−0.0169*** (0.0019)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes
Constant	3.7175*** (0.1075)	3.4559*** (0.1446)	3.6739*** (0.1057)
Number of observations	13,536	7,752	13,536
Pseudo R^2	0.197	0.220	0.206

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

and Jiangxi—the results still indicate a significant positive effect of forest rights reform on forestry production efficiency. Third, during the implementation of forest rights reform, other related policies affecting farmers' forestry production efficiency may have been introduced concurrently, potentially confounding the estimated effects. The results show that after controlling for policies such as the logging quota management system, forest insurance programs, and participation in forestry cooperatives, the positive effect of forest rights reform on forestry production efficiency remains significant.

4.4 Endogeneity check

Given that endogeneity may affect the stability of parameter estimates, this study employs the instrumental variable Tobit (IV-Tobit) model to address the potential endogeneity of forest rights reform. For the choice of instrumental variable, this paper uses forestland adjustment, based on two main considerations. First, forestland adjustment is closely related to forest rights reform, as the government may select pilot areas for reform based on the historical frequency of forestland adjustments within a village. In villages that have undergone such adjustments, the implementation of forest rights reform may serve different purposes: where land-use conflicts are severe, the reform helps accumulate experience in tenure clarification; where such conflicts are relatively mild, the reform is easier to carry out. Therefore, regardless of the severity of land-use conflicts, villages with a history of forestland adjustment are more likely to be selected as reform pilots, satisfying the relevance condition of the instrumental variable. Second, forestland adjustment does not directly affect farmers' forestry production efficiency, but it is highly likely to influence it through forest rights reform. Specifically, what may affect farmers' efficiency is not the past occurrence of land adjustment per

se, but the perceived likelihood of future adjustments. The expectation of future adjustments may undermine tenure stability and security, thereby reducing farmers' willingness to invest in and manage forestland. Forest rights reform, by reducing the uncertainty of future land adjustments, can enhance tenure stability and security. This satisfies the exclusion restriction required for instrument exogeneity (Table 5).

The estimation results using the instrumental variable approach are presented in Table 5. In the IV-Tobit model, the first-stage regression involves an ordinary least squares (OLS) regression of the instrumental variable—forestland adjustment. The coefficient of the instrument is positive and statistically significant at the 1% level. Furthermore, the F-statistic of the first-stage regression exceeds the conventional threshold of 10 and is significant at the 1% level, thereby rejecting the null hypothesis of a weak instrument. This indicates that forestland adjustment is strongly and positively associated with forest rights reform and can serve as a valid instrument, effectively addressing the potential endogeneity of the reform variable.

The second-stage regression results show that the exogeneity assumption of forest rights reform is rejected based on the Wald test for exogeneity, which is significant at the 1% level. This confirms the presence of endogeneity in forest rights reform, underscoring the necessity of using an instrumental variable approach. After correcting for endogeneity, the coefficient on forest rights reform remains significantly positive, indicating that the reform continues to exert a robust and favorable effect on farmers' forestry production efficiency. These findings affirm the validity of the study's core conclusion.

5 Further analysis

5.1 Mechanism analysis

To identify the role of the mediation effect, it is first necessary to estimate the impact of forest rights reform on the mediating variables (Table 6).

Table 6 reports the regression results of how forest rights reform influences farmers' forestry production efficiency through mediating variables. First, forest rights reform significantly promotes increased investment in forestry capital and labor [Table 5, columns (1)–(2)], and both forestry capital and labor have a significant negative effect on farmers' forestry production efficiency. After incorporating forestry capital and labor inputs, the positive effect of forest rights reform on farmers' forestry production efficiency remains significant [Table 6, columns (1)–(2)]. Therefore, it can be concluded that forestry capital and labor inputs play a mediating role, meaning that forest rights reform enhances farmers' forestry production efficiency by incentivizing increased forestry production inputs, which is consistent with the theoretical analysis and supports H1. Second, forest rights reform has a significant positive effect on farmers' expansion of forestland management scale [Table 5, column (3)], and both forest rights reform and the expansion of forestland management scale have a significant positive effect on farmers' forestry production efficiency [Table 6, column (3)]. This indicates that the expansion of forestland management scale plays a mediating role, meaning that forest rights reform improves forestry production efficiency by guiding farmers to expand forestland management scale, which aligns with the theoretical analysis and supports H2. Finally, forest rights reform has a significant positive effect on farmers' credit accessibility [Table 5, column (4)], and both forest rights reform and credit accessibility have a significant positive effect on farmers' forestry production efficiency [Table 7, column (4)]. Thus, credit accessibility plays a mediating role, meaning that forest rights reform improves farmers' forestry production efficiency by enhancing credit accessibility, which is consistent with the theoretical analysis and supports H3. In conclusion, under the constraints of initial resource endowment in forestry production, farmers' behavioral decisions have already formed inherent path dependencies. The changes in the allocation of production factors and management decisions brought about by forest rights reform have, to some extent, broken through the boundary of resource allocation capability, thus improving farmers' forestry production efficiency.

5.2 Extension analysis

It has been confirmed in the previous sections that forest rights reform has a significant positive effect on farmers' forestry production efficiency. However, does the actual effect of forest rights reform on forestry production efficiency vary among different farmers? To address this question, this section attempts to examine the heterogeneous effects of the forest rights reform policy from two

TABLE 5 Results of the endogenous regression.

Variables	Instrumental variable first-stage regression	Instrumental variable second-stage regression
Forestland adjustment	0.0463*** (0.0014)	
Forest rights reform		−0.0394*** (0.0069)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
Regional fixed effects	Yes	Yes
Constant	0.0233 (0.0477)	3.7242*** (0.1073)
F	214.12***	
Wald test		9661.76***
Wald test of exogeneity		7.90*** (0.0050)
Number of observations	13,536	13,536

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6 The impact of forest rights reform on mediating variables.

Variable	Forestry capital	Forestry labor	Expansion of forestland management scale	Enhanced credit accessibility
	(1)	(2)	(3)	(4)
Forest rights reform	0.1687*** (0.0159)	0.1903*** (0.0122)	0.0363*** (0.0046)	0.0648*** (0.0137)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes
Constant	−1.6167*** (0.0891)	−0.9796*** (0.0685)	−3.1097*** (0.2997)	−4.3845*** (0.5393)
Number of observations	13,536	13,536	13,536	13,536
Pseudo R^2	0.168	0.164	0.102	0.311

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 7 Forest rights reform, mediating variables, and farmers' forestry production efficiency.

Variable	Forestry production efficiency			
	(1)	(2)	(3)	(4)
Forest rights reform	−0.0217* (0.0114)	−0.0200*** (0.0019)	−0.0204*** (0.0057)	−0.0153*** (0.0055)
Forestry capital	−0.0841*** (0.0270)			
Forestry labor		−0.0501*** (0.0140)		
Expansion of forestland management scale			−0.0996** (0.0450)	
Enhanced credit accessibility				−0.1180*** (0.0440)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes	Yes
Constant	3.7838*** (0.4105)	3.6862*** (0.1076)	4.5627*** (0.4149)	5.3176*** (0.3102)
Number of observations	13,536	13,536	13,536	13,536
Pseudo R^2	0.223	0.199	0.211	0.211

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

perspectives: the differences in land livelihood strategies and forestry planting structures at the household level, and the differences in forest resource abundance and economic development levels at the regional level.

5.2.1 Heterogeneity of livelihood strategies

Farmers with different resource endowments develop heterogeneous livelihood strategies by aligning their household resources with their labor advantages. This inevitably leads to significant differences in farmers' forestry management levels, which is an important factor affecting forestry production efficiency. This study, referring to Liu (2020), measures livelihood strategies based on the occupational types reflecting the production and management structure of farmers' households. The classification is made according to the proportion of non-agricultural employment in the household labor allocation, dividing farmers into pure farming households, mixed farming households, and non-farming households. Table 8 reports the impact of forest rights reform on farmers' forestry production efficiency under different livelihood strategies. The results show that the effect of forest rights reform weakens as the degree of non-agriculture in the livelihood strategy increases. Among samples with a low degree of non-agricultural livelihood strategies, such as pure farming households, forest rights reform has a greater positive effect on forestry production efficiency. However, for non-farming households, the reform does not show significant effects. Therefore, the positive feedback effect of forest rights reform on farmers' forestry production efficiency increases as the degree of non-agriculture in the livelihood strategy decreases.

This finding has broader implications for rural migration and labor transitions. The absence of significant reform effects among non-farming households indicates that as more rural labor shifts to off-farm employment, households become less responsive to forestry-related institutional incentives. This reflects a livelihood diversification trend in which non-farm households prioritize stable wage income over long-cycle forestry investment. From a policy perspective, this suggests the need for differentiated approaches: while tenure security and ecological compensation may further encourage forestry engagement among farming households, non-farming households may benefit more from policies facilitating forestland transfer, cooperative management arrangements, or mechanisms linking forestry rights with off-farm income opportunities. Such tailored measures can ensure that forest resources remain effectively utilized while also supporting rural households in their broader livelihood transitions.

TABLE 8 Policy effects of forest rights reform under different livelihood strategies.

Variable	Pure farming households	Mixed farming households	Non-farming households
Forest rights reform	−0.0123** (0.0055)	−0.0070** (0.0034)	−0.0022 (0.0124)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Regional fixed effects	Yes	Yes	Yes
Constant	3.2817*** (0.2581)	2.9469*** (0.2169)	6.4634*** (0.5083)
Number of observations	3,786	5,132	4,618
Pseudo R^2	0.359	0.221	0.304

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

5.2.2 Heterogeneity in forestry planting structures

Table 9 reports the effects of forest rights reform on farmers' forestry production efficiency under different forestry planting structures. The results show that forest rights reform has a significant positive effect on the forestry production efficiency of households engaged in bamboo and economic forest cultivation, but no significant policy effect on those managing timber forests. This suggests that after the reform, farmers still tend to prefer managing bamboo and economic forests, which are characterized by shorter growth cycles, higher levels of intensive management, and shorter investment recovery periods. Their traditional management mindset has not undergone a significant shift, and the enthusiasm for managing timber forests—which have longer growth cycles, lower levels of intensification, and extended economic return periods—has not been fully stimulated. To further confirm this finding, we subdivide the timber forest category into fast-growing and high-yield timber forests and general timber forests. The results indicate that forest rights reform has a significant positive effect on the forestry production efficiency of households managing fast-growing timber forests with shorter growth cycles, but no significant positive impact on those managing general timber forests with longer growth cycles. This further supports the above conclusion.

These results carry important policy implications. Although timber forests contribute less to short-term household efficiency, they play a critical role in long-term carbon sequestration, biodiversity conservation, and climate change mitigation. The weaker reform effects observed in this category suggest that existing incentives are insufficient to encourage households to invest in long-cycle timber forests. To better align economic and ecological objectives, future reforms could incorporate mechanisms such as carbon credit trading, ecological compensation, and enhanced tenure security to strengthen farmers' incentives for sustainable timber forest management. In this way, forest rights reform can contribute not only to rural livelihoods but also to national carbon neutrality and climate goals.

5.2.3 Heterogeneity in economic development level and forest resource abundance

Table 10 reports the estimated effects of forest rights reform on farmers' forestry production efficiency under different levels of economic development and forest resource abundance. Specifically, farmers are categorized by regional economic development level into those in the central and western regions and those in the eastern region, and by forest resource abundance into those in forest-rich southern regions and forest-scarce northern regions. The results show that forest rights reform has a significant positive effect on forestry production efficiency for farmers in the central and western regions as well as those in the southern forest-rich regions. In contrast, the reform does not have a significant effect on farmers in the eastern or northern regions. These findings indicate that differences in regional location lead to substantial variation in the market and natural environments faced by farmers, resulting in different production preferences and capabilities, which in turn shape heterogeneous production structures and income-generating capacities. Therefore, farmers in economically less developed and forest-rich regions tend to have a higher dependence on forest resources, which is more conducive to leveraging the comparative advantage of forestry production, enhancing efficiency, and expanding the profitability of forestry.

In particular, the more pronounced effect observed in central and western (often poverty-stricken) regions may be attributed to lower initial production efficiency, which allows forest rights reform to generate greater marginal improvements through enhanced tenure security and institutional incentives. These regions often face structural constraints in accessing capital, technology, and markets, so policy-driven improvements in forest property rights directly address key barriers to productive investment. Furthermore, poverty-alleviation programs and ecological compensation policies tend to concentrate in these areas, creating a synergistic environment that reinforces the reform's effect. These mechanisms together help explain why the efficiency gains from forest rights reform are more prominent in less developed areas.

5.2.4 Heterogeneity in the degree of forest tenure certification

The view that secure forestland tenure can enhance farmers' forestry production efficiency is widely supported in the academic literature (Li et al., 2014; Liu and Lv, 2007), and the findings of this study also confirm this perspective. At the national level, forest rights reform has contributed to improvements in farmers' forestry production efficiency. However, in the implementation process, the reform has been largely guided by a standardized approach to the delineation of collective forestland ownership and use rights. For example, one of the key indicators used to evaluate the reform's progress is the certification rate of collective forestland. Field investigations reveal that most farmers have received forest tenure certificates for all of their forestland plots, with ownership clearly defined. However, a small portion of farmers have not received

TABLE 9 Policy effects of forest rights reform under different forestry planting structures.

Variable	Bamboo forest	Economic forest	Timber forest	Fast-growing high-yield timber forest	General timber forest
Forest rights reform	−0.0209*** (0.0019)	−0.0211*** (0.0019)	−0.0378 (0.1180)	−0.0216*** (0.0019)	0.0062 (0.0138)
Control variables	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	3.7287*** (0.1069)	3.7375*** (0.1071)	3.5700*** (0.6388)	3.7451*** (0.1080)	3.5341*** (0.7847)
Number of observations	13,536	13,536	13,536	13,536	13,536
Pseudo R^2	0.199	0.199	0.215	0.200	0.215

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

TABLE 10 Policy effects of forest rights reform under differences in economic development level and forest resource abundance.

Variable	Economic development level		Forest resource endowment	
	Eastern region	Central and western region	Northern region	Southern region
Forest rights reform	−0.0181 (0.0129)	−0.0267*** (0.0029)	−0.0103 (0.0343)	−0.0215*** (0.0024)
Control variables	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Constant	5.1074*** (0.3725)	4.2746*** (0.1719)	3.2595*** (0.2091)	3.8065*** (0.1303)
Number of observations	5,856	7,680	4,416	9,120
Pseudo R^2	0.1852	0.2463	0.2112	0.1797

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

certificates for all of their forestland. Although the majority of their plots have been certified, the remaining uncertified plots are still under their management, and the associated income remains with the farmers. This raises an important question: does the proportion of certified forestland affect farmers' investment decisions, and thereby influence forestry production efficiency? As shown in Table 11, a higher certification ratio of collective forestland is associated with a greater improvement in forestry production efficiency. This finding suggests that even though farmers retain the income rights to uncertified plots, certified plots exert a stronger policy incentive effect on their forestry behavior and efficiency outcomes.

6 Conclusion and policy recommendations

6.1 Conclusion and discussion

Based on nationally representative rural household survey data from China, this study aims to explore the impact and underlying mechanisms of forest rights reform on farmers' forestry production efficiency from the perspective of household behavior. The main findings and their broader implications are discussed below.

First, forest rights reform has a significant promoting effect on farmers' forestry production efficiency, indicating that the reform has led to a qualitative improvement in farmers' production decision-making without causing an over-concentration of production factors. This finding is consistent with the conclusions of Li et al. (2014). However, building upon existing research, this study further analyzes the underlying reasons behind the positive correlation between forest rights reform and forestry production efficiency. It finds that increased forestland investment, expansion of forestland management scale, and enhanced credit accessibility play important mediating roles in the process through which forest rights reform improves production efficiency. Nonetheless, the efficiency-enhancing effect of forest rights reform faces several challenges amid the evolving socio-economic environment and changing forestry-related policies. For example, rising factor prices may reduce farmers' willingness to invest in forestry; irregularities in the forestland transfer market may lead to a low rate of land inflow; and alternative credit channels with interest rates comparable to or even lower than forest rights mortgage loans—without requiring physical collateral—may diminish the advantages of such loans. These realities not only weaken the positive effects of forest rights reform on production efficiency but also constrain the transformation of traditional self-sufficient smallholders into specialized and professionalized forestry operators, such as large-scale forestry households, cooperatives, family forest farms, and forestry enterprises. Moreover, they also hinder the development of emerging forestry-related industries such as forest tourism and forest wellness services.

Second, regarding the heterogeneous effects of forest rights reform on farmers' forestry production efficiency under different forestry planting structures, the reason why forest rights reform significantly improves the production efficiency of farmers cultivating bamboo forests, economic forests, and fast-growing high-yield timber forests—but not those managing general timber forests—lies in the risk perception associated with insecure forest property rights. In general, the lack of secure property rights increases the risk of forestry investment for farmers, often resulting in short-sighted behavior and a preference for planting tree species with shorter growth cycles. Bamboo, economic forests, and fast-growing timber forests are characterized by short growth cycles, a high degree of intensive management, and short investment recovery periods, whereas general timber forests are the opposite. Therefore, the differences in growth

TABLE 11 The impact of the certification ratio of collective forestland on farmers' forestry production efficiency.

Variable	Forestry production efficiency	
	(1)	(2)
Collective forestland certification ratio	−0.0513*** (0.0029)	−0.0325*** (0.0023)
Control variables		Yes
Year fixed effects		Yes
Regional fixed effects		Yes
Constant	2.0333*** (0.0259)	3.8453*** (0.1066)
Number of observations	13,536	13,536
Pseudo R^2	0.008	0.201

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

cycles among tree species lead to variations in management levels. Although forest rights reform has strengthened the de facto stability of forest property rights, farmers still tend to prioritize economic returns and thus prefer species with shorter production and management cycles, showing limited enthusiasm for cultivating general timber forests with long production cycles. Their traditional management mindset has not fundamentally changed.

This raises an important issue: whether planting bamboo, economic forests, or fast-growing timber forests, these types of management typically require intensive cultivation involving human intervention and excessive use of chemical fertilizers and pesticides to shorten the growth period and quickly obtain economic benefits. Such practices inevitably lead to overly homogeneous forest structures, which are detrimental to the long-term provision of ecosystem services and the sustainable management of forests. Especially in the current stage, as China transitions toward its "dual carbon" goals, timber forests—which account for more than 50% of total forestland—play a crucial role in ecological functions such as soil and water conservation, climate regulation, and carbon sequestration. For general timber forests with longer growth cycles, their carbon sequestration capacity and total carbon storage increase over time, thereby enhancing the ecological value of natural resources. As such, balancing national ecological goals with farmers' economic interests remains a key practical issue that forest rights reform must address.

Third, as the degree of non-agriculture in livelihood strategies decreases, the positive effect of forest rights reform on farmers' forestry production efficiency shows an increasing trend. For pure farming households, since forestry income occupies an important position in their household income structure, strengthening the stability of forest property rights will encourage farmers to improve forestry production efficiency by increasing forestry production inputs or optimizing the allocation of forestry production factors, thus enhancing their comparative advantage in forestry production. It is noteworthy that the lower the degree of non-agriculture in livelihood strategies, meaning the more singular the source of household livelihood, the higher the farmers' dependence on forestry production, making them more vulnerable to shocks from changes in the market environment. Fortunately, farmers with a comparative advantage in forestry production are more likely to transition from traditional smallholders to new forestry operators such as large forestry households, forestry enterprises, family forest farms, and forestry cooperatives after forest rights reform, thus gaining economies of scale by improving forestry production efficiency.

For mixed farming households, their reliance on forestry production is relatively weaker than that of pure farming households. Therefore, the effect of forest rights reform on improving mixed farming households' forestry production efficiency is relatively weaker, mainly due to the combined effects of the "push" of disadvantages in forestry production comparative returns and the "pull" of the advantages of non-agricultural employment comparative returns, which further enables the effective linkage between rural labor force and the non-agricultural employment market. This leads to a weakening of the incentive effect for forestry production investment caused by the labor force's non-agricultural migration. For non-farming households, their dependence on forestry production is even smaller, and they generally do not rely on forestry production as their primary source of livelihood, resulting in less investment in forestland production. Clearly, the higher the degree of non-agriculture in livelihood strategies, the more non-farming households with a comparative advantage in non-agricultural employment will tend to accelerate the further non-agricultural migration of household labor to strengthen their comparative advantage in non-agricultural employment. This leads to a relative increase in non-agricultural income, which gradually weakens the economic security function of forestland, causing forest rights reform to have no significant effect on their forestry production efficiency.

This finding also resonates with international experience. In Africa and Latin America, tenure reforms have been shown to enhance investment incentives primarily among households that continue to rely on land and forests, whereas those transitioning to non-farm livelihoods benefit less unless complemented by land transfer markets, cooperatives, or ecological compensation programs. This suggests that China's forest rights reform could further benefit from differentiated strategies that account for household livelihood diversification and migration trends.

Finally, several limitations of this study should be acknowledged. First, although the data used are drawn from nationally representative rural household surveys, the specific sample areas primarily cover forest-rich regions in southern China. This may limit the generalizability of the findings to other regions with different forest tenure structures, ecological conditions, or institutional environments. Second, while the model includes a broad range of control variables to account for household heterogeneity, potential omitted variables—such as detailed forestland quality indicators, farmers' risk attitudes, or access to forestry extension services—may still influence the relationship between forest rights reform and production efficiency. These unobserved factors may introduce bias into the estimation results. Future studies could consider applying panel data and advanced identification strategies (e.g., instrumental variables or natural experiments) to improve internal validity and assess the robustness of these findings across regions and time.

6.2 Policy recommendations

1) Consolidate forest tenure security and ensure long-term policy consistency

While forest rights reform has significantly improved farmers' forestry production efficiency, several implementation challenges remain. These include incomplete tenure confirmation and certification, unresolved disputes over overlapping claims on collective forestland, and uncertain future policy orientations—all of which weaken farmers' expectations of long-term returns and deter investment in sustainable forest management. The government should accelerate the completion of forestland rights confirmation, registration, and certification, while further reinforcing the long-term stability of forest tenure. Institutional mechanisms must be established to protect farmers' lawful rights over contracted forestland, thus strengthening their intrinsic motivation to engage in both ecological conservation and productive forest management.

2) Promote standardization and marketization of forestland transfers

To improve the efficiency of forestland allocation, it is critical to support the development of intermediary service organizations in the forestland transfer market, improve the legal and institutional frameworks governing forest property rights transactions, and encourage the aggregation of forestland to farmers or enterprises with comparative advantages. In particular, differentiated policies should be considered to support the transfer and consolidation of long-cycle timber forest plots, which often require larger scales of operation to justify long-term investment and generate ecological value.

3) Innovate forest rights-based financing mechanisms

The current forest rights mortgage system is constrained by high transaction costs and risk perceptions among financial institutions. Through institutional innovation, these barriers should be lowered by enhancing risk-sharing mechanisms, strengthening forest asset valuation standards, and developing inclusive financial products tailored for forestry. Especially for long-rotation timber forests, which have limited short-term liquidity but considerable ecological and future economic value, specialized credit instruments and government-backed guarantees may be necessary to unlock financing potential.

In practical terms, local rural commercial banks could establish dedicated forest-rights mortgage loan programs, in which certified forest tenure certificates serve as collateral and repayment schedules are aligned with the long growth cycles of forestry production. Rural credit cooperatives could adopt collective-guarantee models to reduce default risk, enabling smallholders without sufficient collateral to access credit. Forestry cooperatives and associations could further serve as intermediaries, securing bulk credit lines from financial institutions and redistributing funds to member households based on their production needs. In addition, integrating carbon credit trading and ecological compensation schemes into rural finance systems could provide farmers—particularly those managing long-cycle timber forests—with advance payments or low-interest loans linked to the expected ecological value of their forests. These concrete mechanisms would strengthen the connection between tenure security and financing access, thereby amplifying the positive effects of forest rights reform on forestry production efficiency.

4) Enhance differentiated policy support to balance ecological and economic goals

Greater attention should be given to farmers with low capacity to engage in non-agricultural livelihoods. Targeted support should encourage their transformation into professional forestry operators such as large-scale households, family forest farms, and forestry enterprises. Site-specific guidance on tree species selection and diversified forest management models—such as agroforestry, forest-based health services, and undergrowth economy—should be promoted to raise land-use efficiency and economic resilience. In particular, a differentiated ecological compensation system should be established to reward households engaged in long-cycle ecological forestry. Subsidy standards can be calibrated based on forest type, growth cycle, and expected ecological benefits, thereby incentivizing sustained investment in ecological forestry and facilitating a synergy between environmental protection and economic development.

5) Promote ecologically sustainable forestry through incentive-based regulation and structural guidance

To balance economic efficiency and ecological sustainability, differentiated ecological compensation mechanisms should be further developed to support the cultivation of long-rotation timber forests with high ecological value. This can include payment schemes for ecosystem services (PES), subsidies linked to carbon sequestration performance, or tax incentives for biodiversity-friendly forestry practices. In practical terms, compensation can be structured in multiple ways—for example, per hectare of forestland to provide a stable baseline subsidy, per ton of carbon sequestered to directly support climate goals, or based on biodiversity and ecosystem service indicators (such as species diversity or soil and water conservation capacity) to encourage broader ecological outcomes. A hybrid design that combines area-based payments with performance-based bonuses could balance simplicity, fairness, and ecological effectiveness.

Meanwhile, forest management guidelines should encourage species diversification and reduced chemical inputs, especially in areas dominated by short-cycle economic species. In regions undergoing rapid forestland transfer and intensified production, regulatory frameworks should include ecological red lines and minimum reforestation standards. By embedding sustainability into the incentive and regulatory system, it is possible to align farmers' economic interests with long-term ecological goals.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

JW: Writing – original draft, Software, Formal analysis, Conceptualization, Data curation, Methodology, Investigation. FW: Funding acquisition, Methodology, Writing – original draft, Data curation, Investigation, Conceptualization. TX: Conceptualization,

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EDITED BY
Cunyi Yang,
Sun Yat-sen University, China

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Minzhe Du,
South China Normal University, China
He Kai,
Jinan University, China
Athar Marwat,
Iqra National University, Pakistan

*CORRESPONDENCE
Yeon-Soo Shin,
yssin@joongbu.ac.kr

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How does digital economy development influence urban land green efficiency? evidence from China

Huayu Jiang[1], Shang Xiang[2] and Yeon-Soo Shin[3]*

[1]School of Electronic Information Engineering, Inner Mongolia University, Hohhot, China, [2]School of Economics and Finance, South China University of Technology, Guangzhou, China, [3]School of Business Administration, Joongbu University, Goyang, Republic of Korea

Rapid digital economy development is reshaping urban governance and resource allocation, but its impact on urban land green use efficiency (ULGUE) remains insufficiently examined. This study investigates whether and how digital economy development enhances ULGUE in China, focusing on direct effects, mediating mechanisms, and spatial spillovers. Using panel data from 282 prefecture-level cities during 2007–2022, ULGUE is measured with the Super-Slack-Based Measure model. The National E-Commerce Demonstration City policy serves as a quasi-natural experiment within a Differences-in-Differences framework. Complementary analyses include instrumental variable estimation, propensity score matching, and the spatial Durbin model, with robustness checks using 5G population density. Findings indicate that the digital economy and 5G infrastructure significantly improve ULGUE. Mechanism tests highlight green technology innovation and resource efficiency as key channels, with strong spatial spillover effects. Heterogeneity analysis reveals that policy impacts are strongest in eastern and early pilot cities, moderate in central regions, and weakest in western areas. Overall, the study enriches interdisciplinary research on digitalization and sustainability, and provides policy insights suggesting that region-specific green strategies and targeted digital infrastructure deployment are essential to achieve balanced and sustainable urban transitions.

KEYWORDS

digital economy, 5G communication infrastructure, urban land green use efficiency, space spillover effect, differences-in-differences

1 Introduction

Efficient and green land use forms the foundation for high-quality urban development (Jin et al., 2019). However, the accelerating pace of global urbanization has caused negative consequences, including land resource scarcity and ecological degradation. To achieve sustainable development, ULGUE is a crucial statistic for assessing how well environmental protection coordinates with economic growth (Wang et al., 2021; Tan et al., 2021). China is aggressively seeking new catalysts for urban green transformation in line with the United Nations Sustainable Development Goals (SDGs), serving as a prime example of rapid urbanization. Empirical evidence shows that various policy pilots, such as low-carbon cities, smart cities, and innovation cities (Liu et al., 2022; Wang et al., 2021; Zuo and Zhang, 2025), along with environmental regulations (He et al., 2024; Zheng and Chen, 2024) and increased government attention (Lu and Tao, 2024), can all effectively enhance

ULGUE. In addition, Zhang et al. (2023) provide robust evidence that smart city construction significantly contributes to urban green development through industrial restructuring and green technology innovation, while also generating positive spatial spillover effects across neighboring regions. This underscores the importance of incorporating digital and smart city initiatives into the study of land use efficiency.

Thanks to advancements in information technology, the digital economy has emerged as a major driver of urban green growth (Fan et al., 2024; Hao et al., 2023; Cheng et al., 2023). While its positive environmental effects are well established (Cheng et al., 2023; Wen and Sun, 2023), significant research gaps remain. First, regarding research perspectives, ULGUE—a crucial component of urban governance performance—is often overlooked in favor of macro-level environmental metrics, such as carbon emissions and green total factor productivity (Ding and Gao, 2023). In addition, concerning the mechanism, the specific pathways through which the digital economy affects ULGUE remain inadequately examined (Fan et al., 2024; Hao et al., 2023; Cheng et al., 2023). Furthermore, many researchers underestimate the spatial spillover effects produced by the digital economy's network externalities (Chu et al., 2023; Yu et al., 2023).

Compared with prior studies such as Yu et al. (2023), which mainly emphasize environmental spillovers, and Tan et al. (2021), which focus on regional heterogeneity under general policy interventions, this paper innovates by explicitly centering on the urban land dimension and identifying new causal pathways. Therefore, constructing a comprehensive conceptual framework to analyze the digital economy's effect on ULGUE represents an urgent scholarly need.

China's National E-commerce Demonstration Cities (NEDC) policy, a flagship initiative for digital economy development, provides a robust quasi-natural experiment setting for examining this relationship. Unlike earlier studies relying on cross-sectional data or general proxies, this research leverages the staggered rollout of the NEDC policy to rigorously identify causal effects through a DID-based approach. Furthermore, it incorporates 5G infrastructure indicators, such as population density of base stations, into the analysis of ULGUE, offering a novel perspective on how emerging digital technologies shape land-use efficiency. Methodologically, this study also pioneers the use of an SDM-DID model, enabling simultaneous identification of causal impacts and spatial spillovers—a gap not addressed in existing literature.

This study makes three contributions. First, it advances beyond traditional macro-level environmental assessments by incorporating digital economy metrics into the ULGUE framework, thus enhancing the evaluation of sustainability externalities in urban spatial governance systems (Cheng et al., 2023; Zhang et al., 2024). Second, based on rigorous theoretical analysis and empirical modeling, it identifies and verifies two key mediating variables—green technology innovation and resource use efficiency—delineating the "innovation-driven resource allocation optimization" pathway through which the digital economy affects ULGUE (Guo and Zhang, 2024; Hao et al., 2023; Liu et al., 2025). Third, by incorporating spatial spillover analysis, it reveals significant positive radiation effects of digital economy development across regions, highlighting its potential to support coordinated regional development and collaborative green transformation. These insights provide a crucial foundation for the scientific allocation of digital infrastructure and the design of differentiated green transition policies (Chu et al., 2023; Tan et al., 2021).

The structure of the paper is as follows. Section 1 presents the problem statement and research background. Section 2 develops the research hypotheses and theoretical analysis. Section 3 describes the research technique in full. Section 4 provides an analysis of the empirical findings. Section 5 concludes and discusses policy implications.

2 Theoretical foundation and research hypotheses

This study develops its theoretical framework based on General Purpose Technology (GPT) theory (Bresnahan and Trajtenberg, 1995) to explain how the digital economy enhances ULGUE. GPT refers to foundational technologies with broad applicability, continuous evolution, and the ability to generate synergistic innovations and structural transformations. The digital economy represents a modern generation of GPT. It reshapes production functions and the structure of externalities, thus promoting urban green development. Its mechanisms include: (1) Technology Complementarity, which facilitates the integration of green technologies with digital infrastructure; (2) Factor Reallocation, which improves the efficiency of land, capital, and labor allocation; and (3) Spatial Spillovers, which enable the cross-regional diffusion of green practices and resource flows.

Building on this, the digital economy shows distinctive features that reinforce its role in improving ULGUE. Network effects accelerate the diffusion of green technologies and sustainable practices across regions. Data-driven decision-making, through big data, remote sensing, and digital twins, supports precise land management and efficient redevelopment. Smart land governance, via e-government and digital approval systems, enhances transparency and regulatory capacity, reducing idle land and promoting brownfield reuse. These mechanisms indicate that the digital economy, as a GPT, not only reallocates factors but also advances sustainable land use through institutional and technological innovations. Empirical evidence supports this view: Du et al. (2022) show that digitalization in low-carbon city initiatives improves ecological efficiency by fostering green innovation and governance capacity.

Based on this logic, ULGUE is defined as the dependent variable. Two mediating mechanisms are identified: green technology innovation (GTI), which represents R&D and the implementation of green technology, and resource use efficiency (RUE), which measures increased output and ecological performance per unit of resource input.

Our theoretical model positions GPT as the central tenet, as illustrated in Figure 1, and shows that the digital economy indirectly improves ULGUE through GTI and RUE, while also generating spatial spillovers that improve green performance in nearby areas.

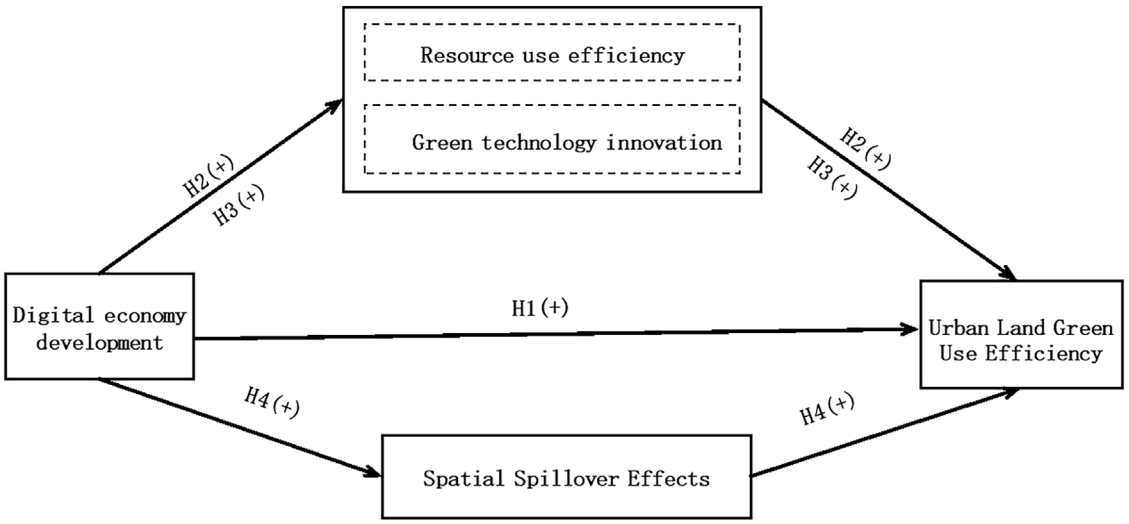


FIGURE 1
Theoretical model.

2.1 Direct influence of digital economy on ULGUE

Drawing on GPT theory (Bresnahan and Trajtenberg, 1995), this study conceptualizes the digital economy as a transformative infrastructure that reshapes the allocation of urban land, capital, and labor under ecological constraints. As a GPT, the digital economy affects ULGUE through technology complementarity, factor reallocation, and altered externality structures.

Empirical evidence strongly supports this theoretical linkage. For example, Zhang et al. (2024) found that the rapid expansion of e-commerce in China significantly reduced carbon emission intensity and increased land-use efficiency by optimizing logistics systems. Within the framework of China's National E-commerce Demonstration Cities (NEDC) policy, Liu et al. (2025) showed that digital infrastructure contributed to more rational urban land use and more efficient resource allocation. Guo and Zhang (2024) found that digital technologies facilitate accurate matching of land resources with complementary production factors, effectively reducing carbon-intensive and extensive land-use patterns. Additionally, Liu and Qiu (2023) confirmed that digital infrastructure applications decrease carbon emissions per unit of GDP, which indicates stronger ecological sustainability. According to Zhang et al.'s (2022) analysis of data from 265 Chinese cities, e-commerce pilot cities performed better than others in pollution control and ULGUE improvement.

In summary, this study conceptualizes the digital economy as a GPT that drives green transformation, highlighting its transformative effect on urban land use for sustainable development. We propose Hypothesis 1:

H1: The growth of the digital economy notably improves ULGUE.

2.2 The mediating role of green technology innovation

From the GPT perspective, the digital economy stimulates green innovation through technology complementarity. As a foundational technology with broad applicability and evolutionary potential, it lowers innovation costs, facilitates cross-firm learning, and provides information infrastructure. Therefore, it accelerates the development and diffusion of eco-friendly technologies. These technologies, in turn, reduce carbon emissions, optimize energy structures, and enhance land-use sustainability.

Numerous studies offer strong support. Liu et al. (2025) found that the NEDC policy, through increased R&D funding and digital infrastructure, significantly drives GTI. Cheng et al. (2023) employed spatial econometrics to confirm that digital economy development suppresses urban carbon emissions, with green technology diffusion showing a 23.7% mediation effect and a spatial spillover coefficient of 0.215. Fan et al. (2024) noted that higher regional digitalization strengthens firms' absorptive capacity for green technologies; the elasticity of green innovation reaches 0.394 in high-tech industries. Hao et al. found a sharp marginal increase in green innovation effects when the digital index exceeded 0.68. Liu and Qiu (2023) reported that green patents accounted for 20.07% of emission reductions under the NEDC policy, and energy consumption per unit of land declined by 14.2%. Yu et al. (2023) highlighted that fiscal incentives, internet infrastructure, and agglomeration effects jointly support the spatial diffusion of green innovation, with a spillover effect up to 1.025.

These findings confirm that the digital economy, as a GPT, enhances ULGUE by promoting the diffusion of green technology innovation across cities. We assume Hypothesis 2:

H2: Innovation in green technologies helps ULGUE by acting as a mediator in the growth of the digital economy.

2.3 The mediating role of resource use efficiency

Another critical feature of GPT is to enhance resource use efficiency. Digital platforms reduce information asymmetry, automate operational processes, and enable real-time optimization of factor allocation. As a result, they decrease energy inefficiencies and improve the productivity of land, labor, and capital inputs. This represents a key pathway toward green and intensive land use.

Liu et al. (2023) used China's e-commerce demonstration city policy as a natural experiment and revealed significant energy-saving effects of digital platforms on economic output. Guo and Zhang (2024) argued that, under energy constraints, digital transformation improves urban resource allocation and has become an endogenous driver of high-quality urban development. Jiang et al. (2024) empirically demonstrated that e-commerce platforms enhance energy–output conversion efficiency from a carbon productivity perspective. Liu and Qiu (2023) further confirmed through econometric analysis that the NEDC policy significantly reduced energy consumption per unit of land, establishing it as an important indirect indicator of ULGUE improvement. Ding and Gao (2023) highlighted from a micro perspective that the digital economy facilitates the dynamic reallocation of labor and capital, which increases overall factor productivity. Ding and Gao (2023) also provided additional evidence that green technologies enhance energy efficiency and Green Total Factor Productivity (Green TFP), further complementing resource optimization.

Collectively, digital economy development improves resource use efficiency, as measured by lower energy and land consumption per unit of GDP, thereby indirectly promoting greener and more intensive urban land use. We suppose Hypothesis 3:

H3: Digital economic growth boosts ULGUE indirectly by optimizing resource use efficiency.

2.4 Spatial spillover effects of digital economy development

The systemic nature of GPT also appears in spatial externalities. Digital infrastructure, platforms, and network structures support knowledge sharing, institutional coordination, and regional collaboration. These mechanisms generate green effects that extend beyond local boundaries and initiate a "diffusion-coordination-progress" mechanism among cities.

Empirical evidence supports this mechanism. According to Zhang et al. (2024), core cities are important channels for the geographical spread of sustainable practices, and digital platforms play an instrumental role in reshaping regional factor flows. Cheng et al. (2023) applied spatial models and found nonlinear spillover effects in carbon emission reduction, with an effect radius exceeding 300 km. Liu et al. (2025) observed that the NEDC policy produces significant intra- and inter-regional effects; through the diffusion of green innovations and fiscal incentives, it affects adjacent cities' green TFP and ULGUE. Zhang and Chen (2024) emphasize the strong regional penetration of e-commerce infrastructure, which supports cross-city green innovation collaboration and increases environmental technology levels across urban clusters. The spatial aggregation and evolutionary trajectory of ULGUE in the Yangtze River Delta are further supported by Tan et al. (2021), who highlight the interdependence of green performance across cities.

Therefore, through platforms, knowledge externalities, and factor flows, the advancement of the digital economy has a major positive spatial spillover effect, enhancing ULGUE in nearby cities. This leads to our final hypothesis:

H4: The expansion of the digital economy exerts a substantial positive spatial spillover effect on the ULGUE of neighboring cities. The study's theoretical model is shown in Figure 1.

3 Methodology

3.1 Model specification

3.1.1 Baseline regression model

Following the analytical framework proposed by Moser and Voena, this study constructs a quasi-natural experiment based on the NEDC program to evaluate the effect of growing digital infrastructure on ULGUE. We determine the causal policy effects using a differences-in-differences (DID) model. In 2011, a collaborative policy document titled "Guidelines on Launching National E-commerce Demonstration Cities," issued by five ministries, including the NDRC, laid the foundation for the three-phase implementation of the NEDC strategy across 70 cities. These phases were launched in 2011, 2014, and 2017, respectively, and show a typical staggered promotion pattern. The NEDC policy has strong exogeneity and institutional shock characteristics. First, pilot cities were designated by the central government through top-down administrative assignment, which eliminates self-selection by local governments and reduces sample selection bias. Second, the clear temporal structure of the policy rollouts facilitates the construction of a progressive DID model. Third, the division between treatment and control groups is explicit, so policy effects can be captured through interaction terms.

To estimate the effect of the development of the digital economy, as represented by the NEDC policy, on ULGUE, the baseline regression model (Equation 1) is created as follows:

$$Lgue_{it} = \alpha_0 + \alpha_1 Did_{it} + \sum \rho control_{it} + u_i + \lambda_t + \varepsilon_{it}, \qquad (1)$$

where i and t denote city and year, respectively; α_0 is a constant term; u_i and λ_t represent area fixed effects and time fixed effects, respectively; and ε_{it} refers to the residual term. The efficiency of land green usage is represented by the explanatory variable ($Lgue_{it}$), and the creation of digital infrastructure is represented by the core explanatory variable (Did_{it}).

3.1.2 Mediating effect model

Using Baron and Kenny's traditional mediation analysis approach, this study systematically developed multiple regression equation sets to examine the role of mediating factors in the policy influence process. To enhance the statistical credibility of the results, Sobel tests and bootstrap repeated sampling techniques were introduced to verify the significance of the mediating pathways.

The specific analysis paths were divided into the following three groups of models (Equations 2–4):

$$Lgue_{it} = \alpha_0 + \alpha_1 Did_{it} + \sum \rho control_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$M_{it} = \beta_0 + \beta_1 Did_{it} + \sum \rho control_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$Lgue_{it} = \gamma_0 + \gamma_1 Did_{it} + \gamma_2 M_{it} + \sum \rho control_{it} + u_i + \lambda_t + \varepsilon_{it}. \quad (4)$$

In this study, M_{it} is set as a mediating variable to reflect green technology innovation or resource use efficiency. When regression model (4) produces a statistically significant coefficient α_2 for the mediating variable, and the coefficient α_1 associated with the core explanatory variable Did_{it} decreases substantially or loses significance relative to model (2), this suggests that the mediating mechanism exists and that the effect of the policy variable on the dependent variable may be partially or fully transmitted through the mediating path.

3.1.3 Spatial durbin differences-in-differences model

This study combines the spatial econometric method proposed by Corrado and Fingleton (2012) to extend the traditional DID Model (Equation 5) by embedding spatial lag variables and spatial weight matrices, thereby constructing the Spatial Durbin DID Model (SDM-DID). This approach systematically identifies regional linkage and spatial spillover effects resulting from policy implementation.

$$\begin{aligned} Lgue_{it} = {} & \gamma_0 + \rho \sum_j W_{ij} Lgue_{jt} + \gamma_1 Did_{it} + \gamma_2 \sum_j W_{ij} Did_{jt} \\ & + \gamma_3 control_{it} \\ & + \gamma_4 \sum_j W_{ij} control_{jt} + u_i + \lambda_t + \varepsilon_{it}, \end{aligned} \quad (5)$$

where ρ is the spatial autoregressive coefficient of ULGUE, $W_{ij}Lgue_{jt}$, W_{ij}, and $W_{ij}control_{jt}$ represent the spatially lagged values of the respective variables, and W_{ij} indicates the element of the spatial weight matrix that captures the spatial linkage between the samples.

3.2 Variable selection

3.2.1 Explained variable (land green use efficiency)

The study focuses on ULGUE as the key variable, aiming to show the correlation between the logical distribution of input elements and the efficiency of outputs in urban land resource development (Xu et al., 2025). Regarding Tone's proposed super-efficiency SBM model, a system has been developed for practical measurement.

In terms of input specification, this study includes four categories of factor variables. First, labor input is quantified using annual year-end employment figures, which reflect the total workforce engaged in productive activities, following the methodology of Wang et al. (2021). This serves as an indicator of human capital utilization. Second, capital input is adapted from Xu et al. (2025), using total fixed asset investment to represent material capital expenditure within the city. Third, science and technology investment is measured as the aggregate of research and development expenditures and educational funding allocations, reflecting the level of knowledge capital investment. Fourth, the energy dimension is represented by annual total water and electricity consumption, which serve as proxy indicators for resource consumption.

For output indicators, this study adopts *per capita* GDP, following the approach of He et al. (2024) and Wang et al. (2021), as a proxy for urban economic development. In response to the unanticipated outcomes, and in line with the method of Wang and Han, environmental effect is measured using three types of industrial emissions: wastewater, sulfur dioxide, and smoke dust. All fluctuating data are sourced from the China Urban Statistical Yearbook, which guarantees reliability, uniformity in breadth, and thoroughness across the time series.

3.2.2 Explanatory variable (digital economy development)

Drawing on the methodological framework of Liu et al. (2023), this study uses a DID estimation strategy to assess the causal effect of NEDC policies on ULGUE. The main identification strategy constructs interaction terms between binary treatment indicators (policy intervention group) and temporal dummy variables (pre/post implementation). Specifically, if a city initiates the policy pilot in a given year, the urban area is included in the treatment group, with the treatment group identification variable set to one. At the same time, the temporal indicator variable is coded as one for all years after policy implementation. Cities not selected for the pilot program serve as the control group, with both treatment and time dummies equal to zero. This interaction term specification allows for rigorous estimation of the policy's causal effects using the difference-in-differences framework.

3.2.3 Mechanism variables

Resource use efficiency. Following Zheng and Chen (2024), resource use efficiency is measured by the amount of energy consumption that corresponds to economic output per person. The calculation method converts different types of energy consumption at the urban level—including total electricity consumption, as well as artificial, natural, and liquefied petroleum gas supplies—into a standard coal equivalent (measured in 100 tons). This value is then divided by the region's *per capita* GDP (measured in yuan) to obtain the energy-to-per capita output ratio. A natural logarithmic transformation is applied to this ratio to represent "resource use efficiency" and to control for the effect of outliers.

Green technology innovation (GTI). Following Fu's (2024) methodological framework, this study includes GTI as a core explanatory variable, measured using city-level counts of green patent applications. The calculation method is as follows: GTI = ln (1 + number of green invention patents + number of green utility model patents). This approach applies a logarithmic transformation to the annual sum of green invention and utility model patents declared by each city. This metric effectively captures regional innovation outputs in green technology, providing both practical applicability and strong representativeness for policy evaluation.

3.2.4 Control variables

The analysis includes several control variables in three important dimensions to reduce the possibility of omitted

TABLE 1 Definitions of the variables.

Variables	Variables name	Definition	Symbols
Explained variable	Land green use efficiency	The super efficiency Slack-Based Measure model is used for measurement	Lgue
Explanatory variables	Digital economy development	• Policy implementation group dummy variable (treat): Cities designated as NEDC pilots during the study period constitute the treatment group (Treatment = 1), while non-pilot cities serve as the control group (Treatment = 0). This binary coding follows a strict intent-to-treat (ITT) assignment based on policy rollout records • Policy implementation time dummy variable (time): If a national e-commerce demonstration city pilot was implemented in a certain year, the value for that year is 1; 0, otherwise • Interaction term (treat): A dummy variable interaction term used to identify whether a city was a national e-commerce demonstration city pilot in a certain year	NEDC
Mediating variables	Resource use efficiency	Total energy consumption (in 100 tons of standard coal) per 100 yuan of regional GDP *per capita* Energy consumption per unit of GDP	RUE
	Green technology innovation	The logarithm of the number of green patents (invention + utility model) filed in that year	GTI
Control variables	Economic development level	Measure by the natural logarithm of real GDP *per capita*	InPGDP
	Industrial structure	Proportion of added value of the tertiary industry to GDP (%)	IS
	Environmental regulation intensity	Environmental protection word frequency and/text total word frequency precise patterns	ERS
	Urban population density	The natural logarithm of population per unit area is used for measurement	InDENS
	Financial development level	The proportion of loans from financial institutions to GDP	FinDev

variable bias and increase the accuracy of model estimation: (1) Economic Development Level (InPGDP): According to He et al. (2024) and Wang et al. (2021), the logarithm of a region's *per capita* real GDP represents its economic output capabilities. (2) Industrial Structure (IS): According to Lu et al. (2020), the degree of service sector dominance is gauged by the tertiary industry's added value as a percentage of the regional GDP. (3) Environmental Regulation Strength (ERS): Referring to Berman and Bui, (1998), an indicator was constructed by obtaining the frequency of occurrence of environment-related terms in policy documents through text analysis methods. (4) Population density (InDENS): It is defined as the natural logarithmic value of the number of permanent residents per unit of land area (Liu et al., 2022). (5) Financial development level (FinDev): Following the idea proposed by Beck et al. (2000), financial resource allocation capacity is proxied by the share of loan balances held by financial institutions relative to GDP. Variable definitions are listed in Table 1.

3.2.5 Sample selection and data processing

A balanced panel data set is constructed, including 282 prefecture-level and above cities in China, with continuous annual data from 2007 to 2022. The study period is selected to balance methodological requirements and data availability. Although the National E-commerce Demonstration City (NEDC) policy was formally introduced in 2011, the analysis extends the starting year to 2007 to provide an adequate pre-policy period, which meets the parallel trends assumption of the DID model. The end year is set as 2022 because it is the most recent year with complete and consistent city-level data, which allows for an assessment of the medium-to long-term policy effects.

To ensure data completeness and consistency in administrative divisions, the final sample includes 67 pilot cities with complete observations—23 from the first batch, 29 from the second, and 15 from the third—as well as 215 non-pilot cities that were never included in the policy. The main data sources are the *China Urban Statistical Yearbook*, *the China Energy Statistical Yearbook*, and statistical bulletins issued by cities at the prefecture level. Missing values for certain years are addressed using group mean imputation or linear interpolation, which aims to improve data integrity and reduce estimation bias. Table 2 displays descriptive statistics for the primary variables.

Additionally, Figure 2 shows the trajectory of ULGUE for various categories during 2007–2022. In terms of trend, ULGUE demonstrates a continuous upward development for the whole country, model cities, and non-model cities. Analyzing various urban clusters indicates a consistent superiority in the efficiency of green land use, with demonstration cities consistently outperforming non-demonstration cities throughout the research period. Between 2011 and 2022, the ULGUE of demonstration cities increased from 0.406 to 0.572, an increase of 40.726%, whereas the growth rate of this metric in cities without demonstrations during that period was 14.316%. The observed disparities suggest a causal linkage to the NEDC policy intervention. Pilot cities show significantly stronger performance gains in green land use intensification, while the divergence from non-pilot counterparts progressively widens.

4 Analysis of empirical test results

4.1 Baseline model regression

Using the DID Model requires adherence to the parallel trend hypothesis. The pre-treatment data show parallel trends in green land use efficiency between the experimental and control cohorts, which satisfies a critical quasi-experimental assumption. To rigorously test this condition and dynamically assess policy effects, we implement an event-study framework and specify the following econometric specification (Equation 6):

TABLE 2 Descriptive results.

Variables	Variable names	Sample size	Mean	Standard deviation	Minimum	Maximum
Explained variable	Green utilization efficiency of land	4,512	0.404	0.089	0.301	0.909
Explanatory variable	Digital economy development	4,512	0.139	0.346	0.000	1.000
Mediating variables	Green technology innovation	4,512	0.982	2.008	0.007	13.123
	Energy efficiency	4,512	0.031	0.022	0.004	0.113
Control variables	Economic development level	4,512	10.591	0.677	8.913	12.061
	Population density	4,512	8.004	0.715	6.110	9.340
	Industrial structure	4,512	0.461	0.110	0.173	0.732
	Intensity of environmental regulation	4,512	0.008	0.003	0.002	0.016
	Financial development level	4,512	0.982	0.568	0.291	3.184

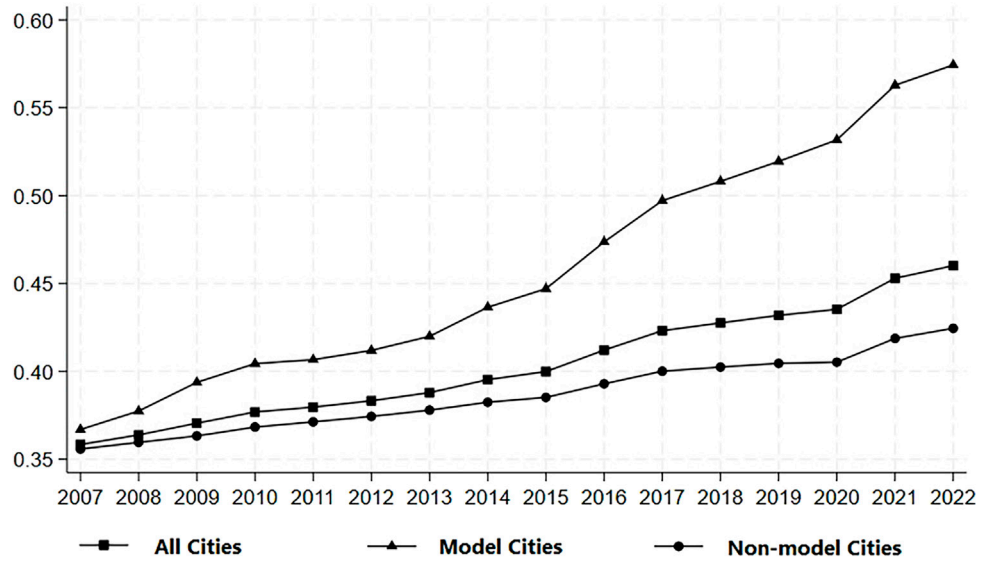


FIGURE 2
ULGUE trend from 2007 to 2022.

$$Y_{it} = \varphi_0 + \sum_{k=-6}^{k=6} \varphi_k D_{it}^k + \sum \rho control_{it} + u_i + \lambda_t + \varepsilon_{it} \quad (6)$$

In this model, D_{it}^k represents a series of dummy variables (including 6 years before policy implementation, the current year, and the subsequent 6 years), where cities not used for demonstrations are given a value of zero, and the estimated coefficient φ_k quantifies the differential in green land use efficiency between treatment and control cohorts during the kth year following NEDC policy implementation.

Figure 3 shows the outcomes of the parallel trend examination. The regression coefficients in the pre-policy period fluctuate around zero and are not statistically significant, which supports the parallel trend condition between the treated and control cities and validates the use of the DID strategy. In the year the policy was introduced, and in the following 2 years, the coefficients remain insignificant, suggesting a delayed policy response. Beginning in the third year after the policy enactment, the regression coefficients show a notable positive trend and continue to rise. The NEDC policy initially shows limited effects on ULGUE, indicating a temporal lag in the digital economy's capacity to increase green land use outcomes. This evidence, combined with the exogenous and staggered rollout of NEDC designations (2011, 2014, and 2017), further reinforces the credibility of the DID strategy.

Table 3 reports the baseline regressions. Columns 1–4 progressively add year and city fixed effects. Across all models, the coefficient of digital economy development is positive and significant at the 1% level, supporting Hypothesis 1. In Model (4), the interaction term (Treat × Post) is 0.060, significant at 1%. This implies that the NEDC policy raised ULGUE in pilot cities by 0.060 units on average, about 14.85% of the sample mean (0.404), reflecting a substantial policy effect. These results align with

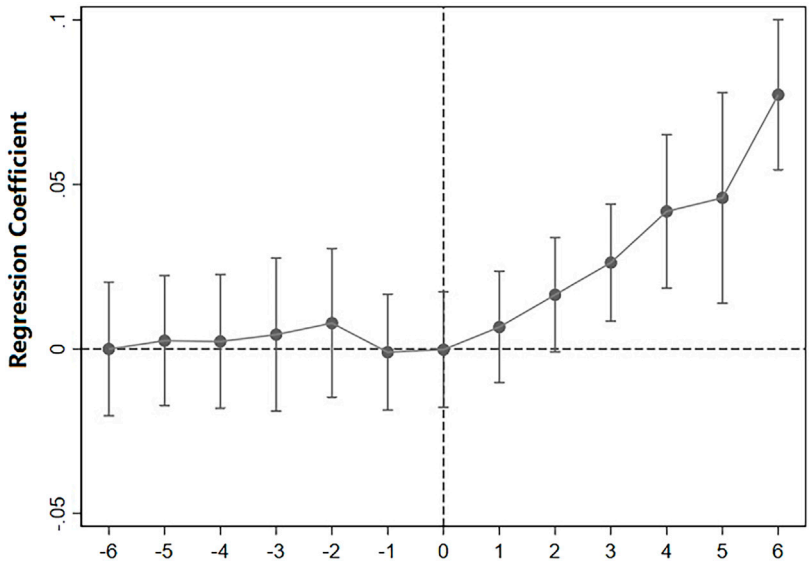


FIGURE 3
Parallel trend and dynamic effect test results. Note: The upper and lower lines of the solid points represent 95% confidence intervals.

TABLE 3 Benchmark regression.

Variables	(1)	(2)	(3)	(4)
	Land green use efficiency	Land green use efficiency	Land green use efficiency	Land green use efficiency
Digital economy development	0.064***	0.082***	0.068***	0.060***
	(15.189)	(14.837)	(15.367)	(14.761)
Economic development level		0.074***	0.031***	−0.054***
		(21.353)	(18.393)	(-9.633)
Population density		0.004***	0.006***	0.002
		(2.830)	(3.515)	(1.584)
Industrial structure		−0.230***	−0.125***	0.071***
		(-14.268)	(-10.532)	(3.912)
Intensity of environmental regulation		−3.166***	−0.934***	−1.339***
		(-8.717)	(-3.676)	(-5.260)
Financial development level		−0.030***	0.020***	−0.017***
		(-11.269)	(6.006)	(-4.805)
Constant term	0.395***	−0.257***	0.063***	0.946***
	(479.526)	(-7.492)	(2.882)	(16.705)
Urban fixed effects	Controlled	Uncontrolled	Controlled	Controlled
Year-fixed effect	Controlled	Controlled	Uncontrolled	Controlled
Sample size	4,512	4,512	4,512	4,512
R^2	0.809	0.408	0.791	0.817

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

Liu et al. (2025), who show that digital infrastructure improves resource allocation efficiency, and with Guo and Zhang (2024), who find that digital technologies enhance factor matching and reduce inefficient land development.

Control variables also matter. Economic development has a significant positive effect, indicating that cities with stronger foundations integrate resources more effectively (Zheng and Chen, 2024). Population density is positive, suggesting that labor supply and urban vitality promote efficiency (Liu et al., 2022). By contrast, environmental regulation intensity is negative and significant, likely due to higher short-term compliance costs or uneven enforcement, reflecting transitional rather than long-term effects. Industrial upgrading and financial development also significantly affect ULGUE.

Overall, the green transformation of land use depends not only on digital tools but also on industrial policies, institutional support, and financial systems.

4.2 Robustness test

4.2.1 Robustness checks

We conduct robustness checks through variable substitution and model extension:

First, regarding the explanatory variables, we introduce three representative indicators of communication infrastructure: Internet penetration, 5G population density, and long-distance cable length per unit area. Although existing empirical studies rarely apply "5G base station population density" directly to urban land green use efficiency, Yang et al. (2018) from the communication engineering field show that base station density is a key factor affecting network performance, especially in urban deployment scenarios, where it determines the transition from noise-limited to interference-limited regimes. Based on this theoretical foundation, we treat 5G population density as a structural proxy for digital infrastructure and include it in the robustness analysis to strengthen the engineering logic behind our green land use model. Following the methodologies of Wang and Wang (2024) and El-Garaihy et al. (2022), we also use Internet penetration rate and fiber-optic cable density (km/km^2) as key infrastructure indicators to examine the consistency of our core conclusions. As shown in Columns (1)–(3) of Table 4, all three infrastructure indicators have significantly positive coefficients at the 1% significance level ($p < 0.01$). The signs and magnitudes of the control variables remain consistent with theoretical expectations, and the model's explanatory power (R^2) varies within ±0.03, which indicates the robustness of the baseline findings across alternative digital economy measures. Second, for the dependent variable, we extend the original Super-SBM model. In addition to the initial specification that includes only the "three industrial wastes" as undesirable outputs, CO_2 emissions are also included as an additional undesirable output to recalculate ULGUE. The regression results reported in Column (4) of Table 4 show that the effect of digital economy development remains positive and statistically significant at the 5% level, which provides further support for the external validity of the core model.

Taken together, these robustness checks, which include both the substitution of explanatory variables and the alternative estimation of the dependent variable, provide strong evidence that digital infrastructure construction significantly contributes to improving ULGUE. Therefore, these results reinforce the reliability and validity of our main conclusions.

4.2.2 Instrumental variable method

This study adopts Guo and Zhang (2024)'s causal inference framework to address endogeneity, focusing on how e-commerce policies affect urban development, and applies the instrumental variable (IV) approach of Li et al. (2016) based on historical communication facilities. The two-stage least squares method (2 S LS) is used. Specifically, we employ the correlation between post office counts and Internet user numbers in 1984 as the key instrument, reflecting early infrastructure foundations of digitalization.

To justify exogeneity, we argue that postal density in 1984 mainly reflected administrative layout and communication demand, not current determinants of ULGUE. At that time, China's land market was undeveloped and the notion of ULGUE did not exist, making a direct effect implausible. Our specification also controls for structural city characteristics such as economic development, population density, industrial structure, and financial development, reducing concerns that postal density captures persistent unobserved traits. From a theoretical standpoint, 1984 postal density is unlikely to correlate with pre-treatment ULGUE, supporting the exclusion restriction.

The instrument's strength is confirmed by the first stage: the IV coefficient is 0.126 ($p < 0.01$), with an F-statistic of 158.049, well above the threshold of 10. The Kleibergen–Paaprk LM statistic ($p = 0.000$) rejects weak-instrument and under-identification concerns. In the second stage (Table 5, Column 2), the policy variable remains positive and significant ($p < 0.01$). After addressing endogeneity, digital economy development continues to enhance ULGUE, indicating robust results.

Overall, combined with strong statistical evidence and consistency with prior studies using historical infrastructure as instruments (Li et al., 2016; Guo and Zhang, 2024), the instrument is both relevant and exogenous, reinforcing the reliability of the baseline estimates.

4.2.3 PSM-DID test

To address potential non-randomness in sample selection, this paper adopts the Propensity Score Matching–Difference-in-Differences (PSM-DID) method following Moser and Voena (2012). A binary variable indicates city participation in the NEDC program (1 for pilot, 0 otherwise). Control variables are included as covariates in a Logit regression to estimate propensity scores. Two strategies are applied: kernel matching, which weights all controls by score distance, and caliper matching with a width of 0.1, conducted with replacement to improve comparability.

Balance tests show that covariate means between treatment and control groups are statistically indistinguishable, with standardized bias below 10%, confirming good match quality. Re-estimated DID regressions on the matched samples (Table 6) indicate that, at the 1% level, NEDC construction continues to exert a significantly positive effect on urban development, supporting the robustness of the baseline findings.

TABLE 4 Robustness checks—alternative variables.

Variables	(1)	(2)	(3)	(4)
	Land green use efficiency	Land green use efficiency	Land green use efficiency	ULGUE (Alternative Estimation)
Internet penetration rate	0.001***			
	(6.044)			
5G population density		0.014***		
		(2.942)		
Long-distance optical cable length per unit area			0.005***	
			(11.587)	
Digital economy development				0.013**
				(2.081)
Level of economic development	−0.059***	−0.024**	−0.059***	−0.089***
	(-9.878)	(-2.057)	(-9.615)	(-6.655)
population density	0.002	0.007**	0.007***	0.005
	(1.390)	(2.411)	(2.666)	(1.057)
Industrial Structure	0.069***	0.112	0.142***	0.010
	(3.681)	(1.347)	(8.139)	(0.210)
Environmental regulation intensity	−1.788***	0.345	−0.853***	1.298*
	(-6.841)	(1.082)	(-3.163)	(1.934)
level of financial development	−0.018***	0.003	−0.010**	−0.017
	(-4.564)	(0.455)	(-2.286)	(-1.586)
constant term	0.996***	0.592***	0.922***	1.392***
	(16.367)	(4.345)	(13.885)	(9.670)
urban fixed effect	control	control	control	control
year fixed effect	control	control	control	control
sample size	4,512	1,128	3102	4,512
R^2	0.801	0.974	0.885	0.729

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

4.2.4 Other robustness tests

Four supplementary tests were conducted to ensure the robustness of the results. First, Propensity Score Matching (PSM) was used to reconstruct the sample by matching treated and untreated cities through kernel and caliper matching methods, which mitigates sample selection bias (see Columns (1) and (2) of Table 6). The findings confirm the reliability of the baseline results by showing that the beneficial effect of digital economy growth on ULGUE is statistically significant. Second, to prevent estimate bias because of inherent locational and resource advantages, key cities—municipalities directly under the central government, provincial capitals, and sub-provincial cities—were excluded from the sample (see Column (3)). Third, the core explanatory variable was lagged by one period to account for the delayed effect of policy implementation and to reduce potential reverse causality (see Column (4)). Lastly, dummy variables for the smart city policy and the low-carbon pilot policy were included to control for interference from concurrent policies that may also affect ULGUE (see Columns (5) and (6)).

The digital economy development coefficient consistently shows significant positive effects in all robustness tests, confirming the stability and reliability of the baseline results. This identification strategy aligns with previous studies. For example, Liu et al. (2025) adopted comparable strategies, such as sample exclusion and lagged variable settings, and found that the NEDC initiative notably enhanced urban green performance. Similarly, Zheng and Chen (2024) used a spatial DID model and placebo testing to verify the favorable effect of low-carbon policies on ULGUE. Liu, Feng, and Wang (2022) highlight the role of green transformation policies in increasing land use efficiency, which supports our inclusion of policy control variables. Together, these studies provide strong theoretical and empirical support for our estimation approach and conclusions.

TABLE 5 Robustness testing - instrumental variable method.

Variables	(1)	(2)
	Digital economy development	Land green use efficiency
tool variable	0.126***	
	(5.158)	
Digital economy development		0.470***
		(7.221)
Level of economic development	−0.100***	−0.016
	(-4.084)	(-1.188)
population density	−0.003	0.002
	(-0334)	(0.469)
Industrial Structure	−0.012	0.075*
	(-0.147)	(1.926)
Environmental regulation intensity	−7.903***	2.178**
	(-5.190)	(2.435)
level of financial development	0.005	−0.018**
	(0.254)	(-2.208)
constant term	1.260***	
	(4.847)	
urban fixed effect	control	control
year fixed effect	control	control
sample size	4,512	4,512
Cragg-Donald Wald F statistic	158.049	
	48.106	
Kleibergen-Paap rk LM statistic	(p-value = 0.000)	

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

According to Table 7, once matching was performed, no covariate differences between the treatment and control samples reached statistical significance ($p > 0.05$), suggesting that the groups achieved adequate balance through the matching process.

4.2.5 Placebo test

Based on the counterfactual idea of placebo testing, this article refers to the study by Wang and Wang, (2024) to construct false policy regions for robustness testing. This study conducts a spatial placebo test by randomly assigning pseudo-treatment status across potential pilot cities. Figure 4 shows the distribution of estimated coefficients and corresponding p-values using kernel density plots, which are derived from 500 random replications of the treatment group assignment. The results show two key findings: first, the mean regression coefficient (0.032) is close to zero, which indicates no systematic treatment effect under randomization; and second, more than 90% of the simulated p-values are above conventional significance thresholds ($p > 0.1$). These patterns confirm that the observed policy effects are unlikely to result from chance spatial correlations, thus supporting the validity of our causal inferences.

These findings are highly consistent with those of Zheng and Chen (2024), who use a spatial DID model to evaluate the effect of China's low-carbon city pilot policy on ULGUE. Their analysis includes a placebo approach to validate the robustness of the identified causal relationship. The results show that when the treatment status is randomly assigned, the statistical significance of the policy effect disappears. This further confirms that the original estimation is not driven by model specification or sample selection bias, but instead reflects a genuine policy effect. Both studies demonstrate that the placebo test, as a counterfactual-based robustness check, is an effective tool for enhancing the credibility of causal inference and strengthening the reliability of empirical conclusions.

4.3 Mechanism effect test

This section examines how the digital economy influences ULGUE through two mediating paths: RUE and green technology innovation (GTI). Drawing on Fu (2024)

TABLE 6 Robustness test.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	PSM match		Cull Central city	Core explanatory variable lags one period	Controlling other policy implications	
	Kernel matching	Caliper matching			Low carbon pilot policy	Smart city construction
Digital economy development	0.039***	0.033***	0.046***	0.061***	0.059***	0.060***
	(8.777)	(6.417)	(9.184)	(14.687)	(14.761)	(14.603)
Low carbon pilot policy					0.006**	
					(2.135)	
Smart City Construction						0.002
						(0.960)
Level of economic development	−0.047***	−0.057***	−0.050***	−0.054***	−0.055***	−0.054***
	(-4.716)	(-4.486)	(-8.905)	(-9.443)	(-9.645)	(-9.694)
population density	0.008**	0.007	0.003**	0.002	0.002	0.002
	(2.482)	(1.522)	(2.290)	(1.324)	(1.623)	(1.561)
Industrial Structure	0.128***	0.115**	0.059***	0.091***	0.070***	0.070***
	3.190)	(2.493)	(3.250)	4.826)	(3.860)	(3.894)
Environmental regulation intensity	−1.837***	−1.789***	−0.920***	−1.269***	−1.327***	−1.354***
	(-3.506)	(-2.782)	(-4.022)	(-4.930)	(-5.212)	(-5.306)
level of financial development	−0.015***	−0.023***	−0.020***	−0.015***	−0.017***	−0.017***
	(-3.502)	(-3.401)	(-5.301)	(-4.209)	(-4.790)	(-4.809)
constant term	0.846***	0.977***	0.880***	0.944***	0.947***	0.948***
	(7.788)	(7.316)	(16.239)	(16.300)	(16.697)	(16.803)
urban fixed effect	control	control	control	control	control	control
year fixed effect	control	control	control	control	control	control
sample size	4,512	1,627	3952	4,230	4,512	4,512
R2	0.827	0.832	0.768	0.833	0.818	0.817

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

and Zheng and Chen (2024), we adopt a parallel mediation model, treating GTI and RUE as independent rather than sequential channels. Although the two may be correlated in practice, the identification relies on the assumption that each captures a distinct pathway from digital economy development to ULGUE, consistent with Liu et al. (2023) and Guo and Zhang (2024).

Regression results in Table 8 show that digital economy development significantly promotes GTI (coef. = 1.539, $p < 0.01$), and GTI positively affects ULGUE (coef. = 0.015, $p < 0.01$), supporting Hypothesis 2. These findings are consistent with Liu et al. (2025) and Cheng et al. (2023). Similarly, the digital economy significantly enhances RUE by reducing energy intensity (coef. = −0.003, $p < 0.01$), while RUE has a strong negative effect on ULGUE (coef. = −0.993, $p < 0.01$). Since RUE is measured as energy consumption per unit of GDP, the negative sign indicates that lower energy intensity improves efficiency and land sustainability, validating Hypothesis three and aligning with Liu et al. (2023) and Guo and Zhang (2024).

The Sobel tests (16.510 for GTI and 4.675 for RUE, both $p < 0.001$) confirm these mediation effects. Overall, the results reveal a dual parallel mediation mechanism, showing that digitalization enhances ULGUE by advancing green innovation and resource efficiency, while avoiding endogeneity concerns tied to assuming a strict causal sequence.

Table 9 presents the robustness check of mediation effects using the Bootstrap resampling method, following the recommendations of Hair et al. (2021). We conducted 1,000 bootstrap replications to generate 95% confidence intervals for the indirect effects. All intervals exclude zero and align with the Sobel test, confirming the stability of the mediation results.

TABLE 7 Balance test results for PSM.

Variable	Unmatched matched	Mean treated	Mean control	%Bias	t-value	p-value
Level of economic development	U	10.986	10.468	81.1	23.10	0.000
	M	10.826	10.801	4.0	0.79	0.431
population density	U	8.075	7.982	13.4	3.72	0.000
	M	7.979	8.000	−3.0	−0.61	0.544
Industrial Structure	U	0.452	0.464	−10.8	−3.01	0.003
	M	0.479	0.473	5.4	1.00	0.315
Environmental regulation intensity	U	0.008	0.008	−2.1	−0.58	0.562
	M	0.008	0.008	1.3	0.26	0.797
level of financial development	U	1.449	0.836	100.9	34.64	0.000
	M	1.063	1.111	−7.9	−1.78	0.075

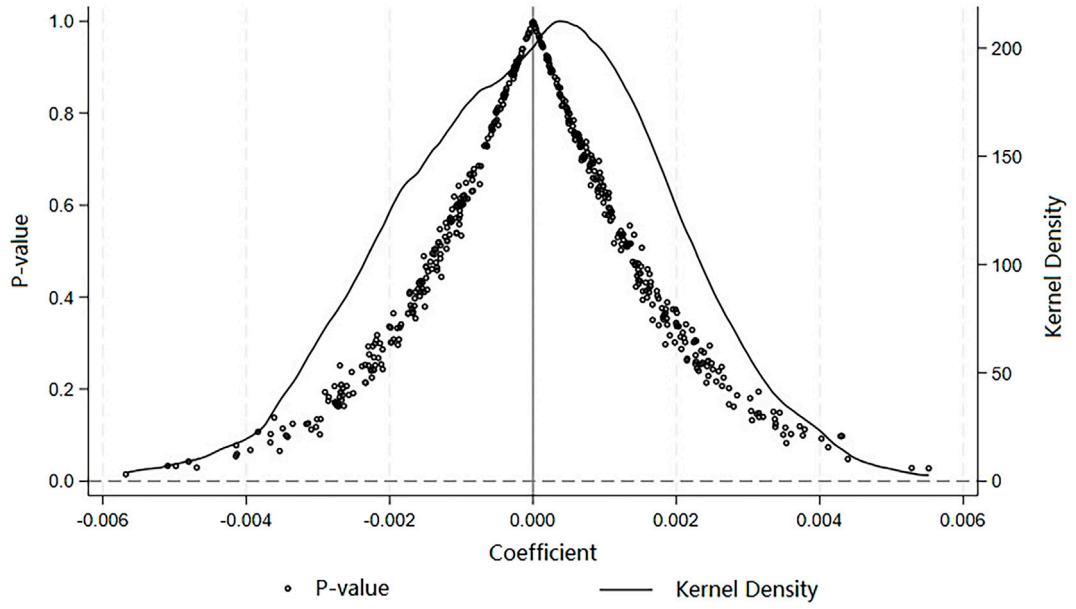


FIGURE 4
Placebo test.

4.4 Spatial spillover effects test

This study analyzes the spatial-economic effects of the NEDC policy within a spatial econometric framework following Corrado and Fingleton (2012). Three spatial weight matrices capture different inter-city relationships. The geographic distance matrix (Wd) measures spatial adjacency using inverse geographic distances between city coordinates, reflecting Tobler's First Law of Geography. The economic distance matrix (We) is constructed from the reciprocal of absolute differences in *per capita* GDP, capturing disparities in development levels and potential spillover channels. This widely used measure offers a robust proxy for economic proximity. Alternative indicators such as FDI flows were considered but excluded due to missing data and comparability issues at the prefecture level. A hybrid matrix (Wm = 0.5Wd + 0.5We) assigns equal weight to geographic and economic proximity. Following Corrado and Fingleton (2012) and Elhorst (2014), this design reflects both spatial and economic linkages.

Using these matrices, Moran's I values are calculated to test spatial correlation in ULGUE. Table 10 provides annual Moran's I statistics with Z-scores, while Figure 5 illustrates their evolution from 2007 to 2022. The figure shows a clear upward trend, indicating increasingly significant positive spatial correlation across cities. This confirms the appropriateness of spatial econometric modeling.

Model specification is further validated through diagnostics. LM-lag and LM-error tests ($p < 0.10$) identify spatial

TABLE 8 Mechanism effect test.

Variable	(1)	(2)	(3)	(4)
	Green technology innovation	Land green use efficiency	Energy utilization efficiency	Land green use efficiency
Digital Economy Development	1.539***	0.038***	−0.003***	0.057***
	(15.190)	(9.698)	(-5.101)	(14.541)
Green Technology Innovation		0.015***		
		(12.032)		
Resource Use Efficiency				−0.993***
				(-9.753)
Economic Development Level	−1.185***	−0.037***	−0.016***	−0.070***
	(-9.769)	(-7.160)	(-16.726)	(-11.561)
Population Density	0.057	0.002	0.001**	0.003**
	(1.639)	(1.053)	(2.110)	(2.040)
Industrial Structure	2.879***	0.029*	0.001	0.072***
	(7.808)	(1.683)	(0.358)	(4.008)
Environmental Regulation Intensity	−45.671***	−0.674***	0.116**	−1.224***
	(-6.450)	(-2.850)	(2.122)	(-4.904)
Financial Development Level	−0.055	−0.016***	−0.001	−0.018***
	(-0.658)	(-4.966)	(-1.312)	(-5.030)
Constant Term	11.943***	0.772***	0.195***	1.139***
	(9.250)	(14.857)	(18.530)	(18.356)
City Fixed Effects	Control	Control	Control	Control
Year Fixed Effects	Control	Control	Control	Control
Sample Size	4,512	4,512	4,512	4,512
R2	0.790	0.840	0.882	0.824
Sobel test statistic	16.510		4.675	
Sobel p-value	0.000		0.000	

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

TABLE 9 Bootstrap test.

Mediator variable	Effect type	Coefficient	Std. Error	z-value	p-value	95% confidence interval
Green Technology Innovation	Indirect Effect	0.0224	0.0025	9.01	0.000	[0.0175, 0.0273]
	Direct Effect	0.0377	0.0041	9.29	0.000	[0.0297,0.0456]
Resource Use Efficiency	Indirect Effect	0.0028	0.0007	4.18	0.000	[0.00148, 0.0041]
	Direct Effect	0.0573	0.0041	14.01	0.000	[0.0493,0.0653]

dependence; Wald and LR tests ($p < 0.01$) reject reducing the Spatial Durbin Model (SDM) to SAR or SEM; and Hausman and LR tests ($p < 0.01$) support adopting a two-way fixed effects SDM. These checks together confirm the robustness of the empirical framework.

Results in Table 11 show that across all three matrices, the "W × Digital Economy Development" coefficient is significantly positive, indicating that NEDC pilot construction enhances ULGUE. The positive "W × Land Green Use Efficiency" coefficient confirms spatial spillovers: local efficiency gains extend to surrounding areas. Decomposition of spatial effects reveals three dimensions: direct, indirect, and total effects, all significant at the 1% level. The indirect effect under Wd (1.543) is especially strong, likely due to (i)

TABLE 10 Moran's I index for land green use efficiency.

Year	Geographic distance weight matrix		Economic distance weight matrix		Nested geo-economic distance weight matrix	
	Moran's I	Z-Score	Moran's I	Z-Score	Moran's I	Z-Score
2007	0.023***	5.271	0.068**	2.386	0.046***	3.224
2008	0.034***	7.408	0.087***	3.034	0.061***	4.218
2009	0.057***	12.850	0.060**	2.252	0.059***	4.351
2010	0.038***	8.831	0.085***	3.146	0.061***	4.565
2011	0.041***	9.151	0.102***	3.681	0.072***	5.145
2012	0.044***	9.581	0.127***	4.410	0.086***	5.934
2013	0.038***	8.309	0.124***	4.335	0.081***	5.649
2014	0.038***	8.435	0.132***	4.600	0.085***	5.931
2015	0.039***	8.542	0.160***	5.536	0.100***	6.870
2016	0.039***	8.487	0.184***	6.277	0.112***	7.591
2017	0.042***	8.957	0.199***	6.722	0.120***	8.108
2018	0.047***	9.985	0.216***	7.276	0.132***	8.824
2019	0.051***	10.654	0.232***	7.796	0.142***	9.447
2020	0.056***	11.772	0.250***	8.356	0.153***	10.184
2021	0.058***	12.000	0.257***	8.599	0.158***	10.462
2022	0.059***	12.329	0.263***	8.770	0.161***	10.684

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

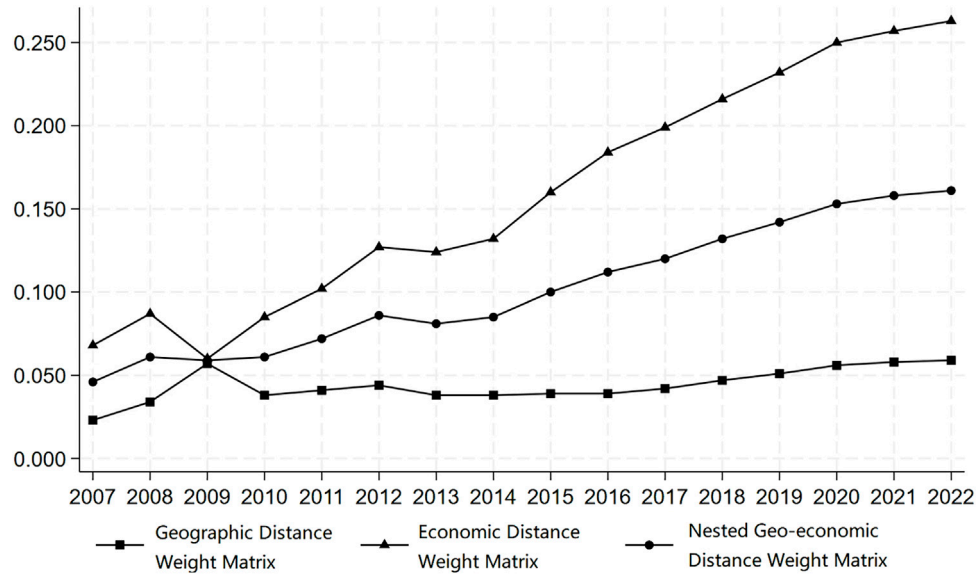


FIGURE 5
Trend of Moran's I index.

knowledge spillovers, whereby digital and green technologies developed in demonstration cities diffuse to nearby regions; (ii) labor mobility and inter-city firm linkages, which facilitate the transfer of skills, practices, and managerial know-how across urban areas; and (iii) shared infrastructure networks, such as broadband connectivity, logistics systems, and e-commerce

TABLE 11 Results of the spatial effects test.

Variable and effect type	Geographic distance weight matrix	Economic distance weight matrix	Nested geo-economic distance weight matrix
W × Digital Economy Development	0.107**	0.023***	0.039***
	(2.418)	(3.527)	(3.213)
W × Land Green Use Efficiency	0.886***	0.391***	0.788***
	(32.127)	(16.274)	(22.738)
Direct Effect	0.067***	0.048***	0.050***
	(18.029)	(17.512)	(18.259)
Indirect Effect	1.477**	0.065***	0.357***
	(2.506)	(6.392)	(4.620)
Total Effect	1.543***	0.113***	0.407***
	(2.608)	(10.400)	(5.222)
Control Variables	Control	Control	Control
Year Fixed Effects	Control	Control	Control
City Fixed Effects	Control	Control	Control
Sample Size	4,512	4,512	4,512
R2	0.088	0.176	0.133

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

platforms, which enhance inter-city integration and amplify policy diffusion Thus, the NEDC policy improves land-use efficiency not only within pilot cities but also across neighboring regions, confirming Hypothesis 4. These findings are consistent with Zheng and Chen (2024), who showed similar spatial effects for the Low-Carbon City Pilot Policy, reinforcing that green development initiatives generate significant regional spillovers.

Table 12 further reports sensitivity tests of the hybrid matrix (v = 0.3, 0.7). Results remain robust, with larger weights on economic distance amplifying indirect effects, indicating asymmetric spillovers. This supports v = 0.5 as a reasonable baseline.

4.5 Heterogeneity analysis

To examine how digital economic development affects ULGUE differently across two important aspects, this study conducts a comprehensive heterogeneity analysis: (1) geographical regions and (2) policy implementation cohorts. The multi-dimensional assessment shows significant variations in policy effectiveness based on locational characteristics and adoption timing.

4.5.1 Regional heterogeneity

Building on Zhu et al. (2023), this study divides the sample into Eastern, Central, and Western regions to test for regional variation in the digital economy's impact on urban land green use efficiency (ULGUE). Table 13 shows uniformly positive and significant coefficients, confirming that digitalization enhances ULGUE overall but with spatial gradients. The Eastern region records the strongest effect (0.068, $p < 0.01$), reflecting advantages in infrastructure, institutional support, and green innovation resources. The Central region also demonstrates a significant effect (0.049, $p < 0.01$), suggesting that digitalization contributes to greener land use even under weaker conditions. By contrast, the Western region's effect is weaker (0.039, $p < 0.05$), constrained by limited infrastructure, inefficient resource allocation, and restricted factor mobility. These findings align with Zheng and Chen (2024), who report that low-carbon city pilots deliver stronger benefits in the East due to solid economic and governance foundations.

Figure 6 further illustrates these regional disparities. Standardized coefficients are 0.217, 0.280, and 0.223 for the Eastern, Central, and Western regions, respectively, underscoring the heterogeneity of policy effects across China's economic zones.

4.5.2 Batch heterogeneity

To evaluate whether policy timing influences the green effects of digital economy development, this study incorporates batch-specific dummies within a triple difference (DDD) framework. As shown in Table 14, the estimated coefficients for the first and second batches are 0.084 and 0.058, both significant at the 1% level, while the third batch yields a coefficient of 0.010, significant only at the 10% level. These results indicate that the policy markedly enhanced ULGUE in the first two cohorts, but its impact in the third batch remains limited.

A Wald joint test is further performed on the coefficients of Digital Economy × 1st batch, 2nd batch, and 3rd batch. The joint statistic equals 17.840 and is significant at the 1% level, confirming that batch heterogeneity is statistically evident.

The weaker performance of later cohorts may stem from diminishing marginal returns, as the earlier pilots had already established critical digital infrastructure and institutional frameworks, reducing incremental benefits for subsequent cities.

TABLE 12 Sensitivity analysis of spatial effects based on the nested geo-economic weight matrix.

Variable and effect type	Nested geo-economic distance weight matrix	Nested geo-economic distance weight matrix
Weight	v = 0.3	v = 0.7
W × Digital Economy Development	0.028***	0.094***
	(3.091)	(5.137)
W × Land Green Use Efficiency	0.584***	0.896***
	(18.172)	(36.852)
Direct Effect	0.048***	0.055***
	(17.742)	(18.011)
Indirect Effect	0.129***	1.377***
	(5.923)	(3.406)
Total Effect	0.178***	1.433***
	(7.918)	(3.530)
Control Variables	Control	Control
Year Fixed Effects	Control	Control
City Fixed Effects	Control	Control
Sample Size	4,512	4,512
R^2	0.160	0.118

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

In addition, fiscal constraints, limited digital literacy, and weaker governance capacity hindered effective adoption of digital tools and enforcement of regulatory frameworks. These frictions along the chain from "digital investment → institutional embedding → green outcomes" further diluted policy effectiveness.

These findings accord with Liu et al. (2025), who show that the NEDC policy yields stronger impacts in early pilots with more advanced digital ecosystems. Similarly, Guo and Zhang (2024) reveal that initial batches facilitated efficient allocation of land and production inputs, supporting sustainable, low-carbon growth. Overall, the evidence indicates that the policy's effectiveness in enhancing ULGUE depends on timing and local readiness, while later cohorts encounter diminishing returns and uneven outcomes from weaker implementation.

5 Discussion

5.1 Key findings

This research shows that the digital economy can increase ULGUE, which is consistent with Guo and Zhang (2024) and Liu and Qiu (2023), who find that digital technology promotes resource efficiency and environmental improvement. In the context of rapid urbanization in China, digitalization is an important tool for green urban transformation. However, the effect of the digital economy may be limited by regional development levels and infrastructure, and its effectiveness differs among cities (Cheng et al., 2023; Liu et al., 2025). Our results confirm this: the digital economy has stronger effects in China's eastern regions than in western regions. Eastern areas have more advanced economic development and stronger digital infrastructure, which allow for broader technology adoption and promotion. Therefore, policies are more effective in increasing ULGUE in these regions.

In contrast, underdeveloped infrastructure in western regions limits the potential of the digital economy (Chu et al., 2023). Additionally, eastern China's superior human capital and innovation capacity amplify digital benefits, resulting in more substantial green benefits. Meanwhile, inadequate innovation endowments and underdeveloped economic foundations in western regions constrain the efficacy of the digital economy in advancing sustainable land use practices.

The digital economy indirectly improves ULGUE by stimulating green innovation and optimizing resource allocation. This finding supports Liu and Qiu's (2023) and Fan et al.'s (2024) arguments regarding the intermediary function of technological innovation in green transitions. These scholars show that innovation enhances environmental outcomes, enables efficient resource use, and facilitates greener land utilization. Because innovation effects depend on institutional environments and financial development (Berman and Bui, 1998; Beck et al., 2000), this study includes these variables as controls. This approach reinforces the robustness of our conclusion concerning the mediating role of green innovation. Nevertheless, we acknowledge that GTI and RUE may themselves be endogenously affected by digital economy development, which could bias mediation estimates. Although additional methods such as instrumental variables or dynamic panel approaches could mitigate this issue, it remains a limitation of the present study.

TABLE 13 Regional heterogeneity analysis results.

Variables	(1)	(2)	(3)
	Eastern region	Central region	Western region
Digital Economy Development	0.068***	0.049***	0.039**
	(4.339)	(4.858)	(2.602)
Economic Development Level	−0.053**	−0.020**	0.010
	(-2.007)	(-2.451)	(0.786)
Population Density	0.018	−0.002	−0.002
	(1.459)	(-0.457)	(-0.498)
Industrial Structure	0.145	−0.039	−0.025
	(1.363)	(-1.543)	(-0.916)
Environmental Regulation Intensity	−1.157	−0.306	0.103
	(-1.418)	(-0.812)	(0.171)
Financial Development Level	−0.034**	−0.004	−0.013
	(-2.397)	(-0.511)	(-1.337)
Constant Term	0.842***	0.639***	0.311**
	(3.258)	(6.513)	(2.145)
City Fixed Effects	Control	Control	Control
Year Fixed Effects	Control	Control	Control
Sample Size	1,600	1728	1,184
R2	0.839	0.859	0.728

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

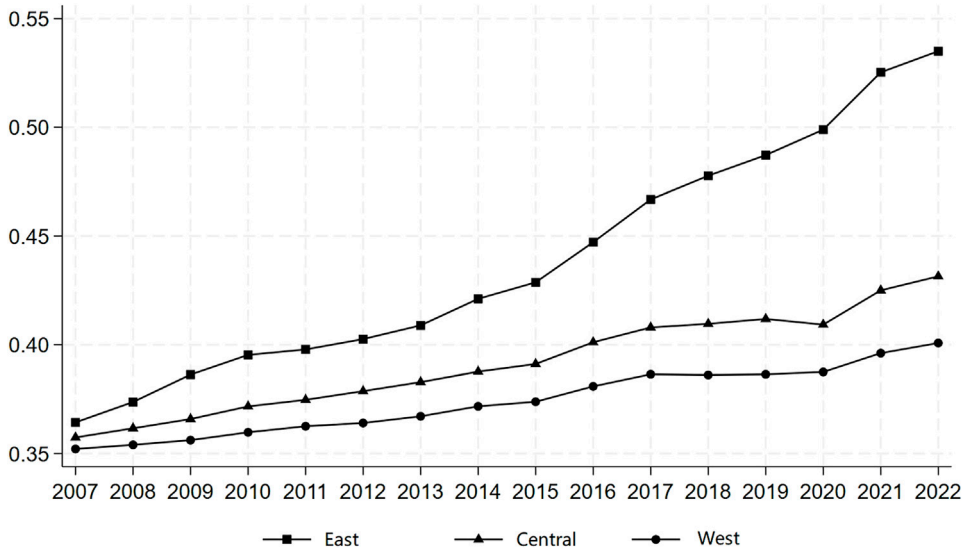


FIGURE 6
ULGUE trend from 2007 to 2022 (east vs. central vs. west).

TABLE 14 Batch heterogeneity analysis results.

Variables	(1)	(2)	(3)
	First batch	Second batch	Third batch
Digital Economy Development × 1st	0.084***		
	(9.356)		
Digital Economy Development × 2nd		0.058***	
		(10.144)	
Digital Economy Development × 3rd			0.010*
			(1.671)
Economic Development Level	−0.056***	−0.060***	−0.059***
	(-9.447)	(-10.111)	(-9.988)
Population Density	0.002	0.003**	0.002
	(1.034)	(1.968)	(1.563)
Industrial Structure	0.075***	0.069***	0.070***
	(4.123)	(3.753)	(3.773)
Environmental Regulation Intensity	−1.679***	−1.529***	−1.845***
	(-6.518)	(-5.864)	(-6.957)
Financial Development Level	−0.017***	−0.019***	−0.017***
	(-4.576)	(-4.883)	(-4.398)
Constant Term	0.971***	1.014***	1.012***
	(16.182)	(16.704)	(16.678)
City Fixed Effects	Control	Control	Control
Year Fixed Effects	Control	Control	Control
Wald joint test statistic	17.840***		
Sample Size	4,512	4,512	4,512
R^2	0.810	0.807	0.798

*, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are in parentheses.

Moreover, The digital economy yields spatial spillovers: it raises local ULGUE and improves neighbors' green performance. As Chu et al. (2023) show, digital infrastructure promotes efficiency via diffusion, information, and factor flows. Our estimate gives a spillover coefficient of 1.543. Yet, spillovers may be constrained by geography and institutions, especially where infrastructure is weak (Cheng et al., 2023), implying regionally divergent effects needing targeted policies.

5.2 Theoretical contributions

This research addresses gaps in examining the environmental effects of the digital economy across perspectives, mechanisms, and spatial dimensions. It also extends General Purpose Technology (GPT) theory.

First, we broaden the research perspective. While previous research often focuses on macro-level environmental indicators, this study examines ULGUE as a specific dimension. This approach enriches studies that link the digital economy to sustainable development.

Second, it reveals the internal mechanisms. Through empirical testing, we identify two core transmission pathways: GTI and RUE. This finding clarifies how digital technologies affect urban green transitions.

Third, we verify and quantify spatial spillover effects. This study incorporates spatial considerations into the analytical framework and uses spatial econometric techniques to empirically verify and quantify the significant positive spillover effects of the digital economy on ULGUE. This finding provides new empirical evidence for spatial economics.

Fourth, this study refines and expands the theoretical framework of GPTs. While GPT theory traditionally emphasizes the broad applicability and inter-industry complementarity of technologies (Bresnahan and Trajtenberg, 1995), it offers limited explanation of how these technologies function within ecological and sustainability transitions. To address this gap, this study introduces two specific transmission mechanisms—green technology innovation (GTI) and

resource use efficiency (RUE)—to operationalize the abstract notion of "technological complementarity" described by Helpman and Trajtenberg (1994). These mechanisms clarify how digital infrastructure drives green innovation and improves resource allocation, thereby enriching the theoretical logic of GPTs in sustainability research. Furthermore, the integration of spatial econometric techniques shows that digital infrastructure and platforms generate measurable green spillover effects across city boundaries. This spatial extension complements earlier GPT formulations by including regional interaction and cross-boundary externalities, offering new insights into how digital systems support network-based diffusion, coordinated development, and collective urban green transformation. The findings strengthen the theoretical robustness and policy relevance of GPT theory in guiding green and sustainable regional development. At the same time, we also recognize that GPTs, including digital technologies, may generate unintended environmental externalities such as electronic waste and high energy consumption in data centers, which should be incorporated into future theoretical extensions.

5.3 Policy implications

While China operates under a hierarchical and multi-tiered governance structure, the execution of NEDC policies requires coordination among multiple entities, such as governments, urban planners, and economic policymakers. Therefore, we propose targeted recommendations.

For governments, optimizing top-level design with regionally differentiated strategies is fundamental. Policies should implement tailored fiscal and industrial measures concerning uneven digital infrastructure and economic development across eastern, central, and western regions. Governments should scale up replicable models from successful E-commerce Demonstration Cities. In addition, specific policy instruments can be introduced, such as linking subsidies for 5G infrastructure to measurable improvements in green land use efficiency, or establishing cross-city digital–green innovation cooperation zones in urban clusters like the Yangtze River Delta. Governments can also lead efforts to build cross-regional digital governance and data-sharing platforms to harness spatial externalities and create green synergies.

For urban planners, integrating digital technology into spatial planning is essential. Planning departments should include digital infrastructure, such as 5G and IoT, in land-use plans. Technologies such as remote sensing and digital twins can be used to develop dynamic monitoring and simulation systems that improve land use efficiency. Land supply models should be reformed to connect land quotas and prices with firms' green technology and digital maturity. This market-oriented approach can promote ULGUE.

For economic policymakers, promoting a digital-driven green industrial ecosystem is critical. This includes establishing special funds, encouraging integration between digital platforms and manufacturing firms, and accelerating the diffusion of green technologies. Additionally, financial incentives, such as subsidies and tax breaks, can support firms in their green and digital transitions, ultimately supporting green industrial clusters and enhancing regional green competitiveness.

5.4 Limitations and future research

5.4.1 Limitations

Several limitations should be noted. First, because pollution and energy statistics are published with a lag, the dataset ends in 2022 and does not capture emerging developments such as generative AI (AIGC). Second, although the DID approach satisfies the parallel trend assumption, potential interference from concurrent initiatives (e.g., smart city or low-carbon programs) and unobservable shocks cannot be ruled out. Third, the mechanism analysis relies on proxies—patent counts for green innovation and the energy-to-GDP ratio for resource efficiency. While widely used, these indicators may not fully reflect how digital technologies affect land-use practices: patents indicate innovation potential rather than application, and energy intensity may miss structural or behavioral changes. The lack of firm-level surveys or case studies also limits explanatory depth.

In addition, comparative fit statistics (e.g., log-likelihood, AIC) for the three spatial models are not reported; although useful for robustness, they would considerably increase the analytical burden. The findings are also shaped by China's unique institutional context of state-led digital infrastructure and public land ownership, which restricts generalization to market-based or private land systems. Finally, the framework does not incorporate moderating factors such as institutional quality or urban density, nor account for feedback loops. Excluding these elements, though improving tractability, may reduce the framework's comprehensiveness.

5.4.2 Future research

Future studies can explore the following directions. First, researchers can shift the analytical focus to the micro firm level. Although this study identifies green innovation and resource efficiency as mediators at the city level, firm-level data may provide deeper insights into how digital technologies affect production processes, supply chain management, and land use decisions. Firm surveys or case studies, in particular, could help verify whether patent-based indicators and energy-intensity measures accurately reflect changes in actual land-use efficiency. Second, cross-country comparative research can be conducted. To assess the external validity and institutional contingencies of the findings, future work may compare the digital economy's effects on land-use efficiency across countries or regions with different governance structures. Third, the mechanism analysis can be refined and extended. Beyond technological and resource-based mechanisms, the digital economy may affect green land use through sociological channels, such as governance reforms, lifestyle shifts, and environmental preferences. In addition, subsequent research could integrate moderating factors such as institutional quality and urban density, as well as feedback loops within the theoretical framework, to better capture the complex interactions between digitalization and sustainable land use. Finally, future research should also pay attention to the negative externalities of digitalization, such as electronic waste and the rising energy consumption of data centers, to achieve a more balanced assessment of its role in sustainable urban transitions.

6 Conclusion

To rigorously assess the effect of digital economy expansion on ULGUE and its underlying mechanisms, this study uses panel data from 282 Chinese cities and treats the NEDC policy as a quasi-natural experiment. The main conclusions are as follows. First, the digital economy has a strong positive effect on ULGUE, which shows that digital technologies substantially contribute to urban growth and the green transformation of land use. Second, two core pathways drive this improvement: stimulating green technology innovation to upgrade land-use practices, and increasing resource allocation efficiency to direct production factors toward greener, higher-productivity sectors. Third, spatial analysis shows strong network externalities. The digital economy not only improves ULGUE locally but also positively affects neighboring cities, which emphasizes the need for regional coordination to capture digital dividends. Fourth, regional heterogeneity analysis finds an east-to-west decreasing effect, where the digital economy's benefits are greatest in eastern China, intermediate in central areas, and lowest in the west. Earlier policy adoption also produces stronger effects, which highlights the importance of policy timing and infrastructure maturity in determining effectiveness.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HJ: Conceptualization, Data curation, Investigation, Methodology, Resources, Writing – original draft. SX: Formal Analysis, Software, Validation, Writing – review and editing. Y-SS: Conceptualization, Supervision, Project administration, Funding acquisition, Visualization, Writing – review and editing.

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Conflict of interest

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EDITED BY
Shikuan Zhao,
Chongqing University, China

REVIEWED BY
Barış Kahveci,
Niğde Ömer Halisdemir University, Türkiye
Hao Dong,
Wuyi University, China

*CORRESPONDENCE
Chunyu Guo,
sufegcy@163.sufe.edu.cn

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The impact of land finance dependence on green economic efficiency: evidence from China

Chunyu Guo*

School of Finance, Shanghai University of Finance and Economics, Shanghai, China

China's reliance on land finance poses challenges to green economic efficiency. This study examines how local governments' land finance dependence affects green economic efficiency, using panel data from prefecture-level cities and a super-efficiency SBM model. Findings show that land finance dependence significantly reduces green economic efficiency, particularly in non-resource-based, environmentally protected, and urban agglomeration cities, by diverting fiscal resources to short-term development and increasing debt risks. Policy reforms are recommended to reduce land finance dependence and promote sustainable fiscal incentives.

KEYWORDS

land finance dependence, green economic efficiency, SBM model, environmentalgovernance, local government debt risk, fiscal reform

1 Introduction

Over the past few decades, China has strategically shifted its development focus to green sectors. The purpose of this transition is not merely to improve ecology, but to build a new development pattern where economic progress and ecological sustainability complement each other, while ensuring the momentum of economic growth. However, a series of reforms that centralized fiscal revenues while decentralizing expenditure responsibilities has placed fiscal pressure on local governments responsible for infrastructure, public services, and environmental governance. To bridge these gaps, local governments have increasingly relied on land finance, leveraging monopolized land supply to generate revenues, often at the expense of environmental priorities. This institutional tension raises a critical question: How does local governments' dependence on land finance shape urban green economic efficiency, and through which mechanisms do these effects manifest across diverse city types? This study investigates these dynamics, offering a novel perspective by linking fiscal incentives to resource misallocation and environmental externalities in China's decentralized system.

Behind this overarching green strategy lies a profound institutional paradox rooted in the fiscal relationship between central and local authorities. Stemming from the 1994 tax-sharing reform, which shifted revenue authority upward while devolving spending responsibilities, this paradox reshaped intergovernmental resource allocation. Local governments, charged with infrastructure provision, public services, and environmental governance, continue to face persistent fiscal shortfalls. To bridge these gaps—and to meet growth-oriented performance assessments—local officials have increasingly relied on land finance, a model that monopolizes the supply of land to generate revenues. While this reliance has reshaped local economic structures, it frequently clashes with environmental objectives. Consequently, the central government's green-development vision is constrained by local behavioral logic, generating tension between economic expansion

and ecological protection. This study seeks to analyze the environmental externalities of such fiscal dependence and to unveil the intricate landscape shaped by institutional design and local rational choice.

A pivotal question for the success of China's development transition remains unanswered: How, in quantitative terms and through which mechanisms, does local governments' dependence on land finance shape urban green economic efficiency? Existing scholarships are sharply divided. One strand highlights the positive side of land-finance revenues, arguing that they have supplied critical capital for rapid urbanization and large-scale infrastructure, some of which has improved green public facilities and thus fostered economic growth and public-goods provision. Gyourko et al. (2022) provide a comprehensive analysis of China's land finance system, emphasizing its core role in funding urban development and infrastructure projects that have been crucial for China's economic growth. Similarly, Mo (2018) finds that land finance has positively contributed to county-level economic growth by providing necessary funds for local development projects. Furthermore, Pan et al. (2015) note that land finance helps local governments manage fiscal deficits and invest in real estate markets, thereby stimulating economic activity.

The opposing strand of literature is markedly critical, asserting that overreliance on land finance distorts local officials' incentives, ensnaring them in a "growth-for-competition" prisoner's dilemma. In pursuing short-term fiscal gains and investment attraction, governments loosen environmental regulations and partake in a "race to the bottom," resulting in resource misallocation, industrial lock-in, and profound environmental damage. Van der Kamp et al. (2017) contend that decentralization and land finance prioritize economic expansion over ecological safeguards, yielding lax regulatory enforcement. Zheng et al. (2014) caution that this model jeopardizes China's sustainability by fostering "ghost cities" and social unrest. Wang et al. (2020) show empirically that land finance has escalated carbon emissions since 2003, linked to economic progress. Recent works add nuance: Chen et al. (2024) examine land finance's role in inter-city integration, noting spatiotemporal effects on sustainability; Wang D et al. (2021) assess its influence on industrial shifts, highlighting environmental and social drawbacks. This scholarly divide highlights the multifaceted effects of land finance on green economic efficiency, making resolution of the positive-negative paradox vital for evidence-based policies that harmonize growth and environmental goals in China's transition.

This study employs panel data from Chinese prefecture-level cities over the period from 2015 to 2023, utilizing a super-efficiency SBM model to assess green economic efficiency and a two-way fixed effects model for baseline regressions, which demonstrate that land finance dependence substantially hinders green economic efficiency after accounting for various controls such as *per capita* GDP and financial development; endogeneity concerns are mitigated through two-stage least squares estimation with a retail sales-to-GDP ratio as an instrumental variable, reinforcing the adverse relationship; robustness is confirmed via alternative efficiency measurement approaches like directional distance functions and global Malmquist-Luenberger indices, substitute indicators for land finance dependence, and exclusion of potentially anomalous data years; mechanism examinations reveal that land finance dependence indirectly impairs green economic efficiency by diminishing environmental regulation—evident in reduced policy emphasis and protection expenditures—and by escalating local debt risks through higher debt balances and investment bonds; heterogeneity analyses indicate more pronounced negative effects in non-resource-based cities, key environmental protection cities, and urban agglomeration cities, highlighting the institutional tensions between fiscal incentives and ecological priorities, with policy recommendations advocating for reduced reliance on land finance via sustainable reforms to harmonize economic growth and environmental sustainability in China's green development pathway.

This study makes three significant contributions to the literature. First, it extends research on resource misallocation by introducing land finance dependence as a critical institutional determinant of environmental inefficiencies. While foundational work quantified productivity losses from factor market distortions (Brandt et al., 2013), this analysis demonstrates how a specific fiscal arrangement induces misallocation in the environmental domain, resulting in measurable losses in green economic performance. Second, this study provides a critical institutional perspective—specifically focusing on local governments' land finance dependence (Porter and Claas van der, 1995; Dechezleprêtre and Sato, 2017), it reveals that fiscal pressures inherent in decentralization systematically weaken regulatory stringency, thereby explaining why the purported innovation-driving benefits of environmental policy may fail to materialize in fiscally constrained local governments. Third, the study advances the understanding of how local economic structures mediate the effects of national policies, a line of inquiry influenced by institutional analyses of innovation and reallocation (Acemoglu et al., 2018).

The paper is structured as follows: Section 2 reviews the relevant literature and presents the research hypotheses; Section 3 outlines the data sources, variable definitions, and methodology; Section 4 presents and discusses the regression results, along with robustness checks; Section 5 explores the mechanisms through which land finance dependence influences green economic efficiency; and Section 6 concludes with policy recommendations.

2 Research hypotheses

2.1 Impact of land finance dependence on urban green economic efficiency

Urban green economic efficiency represents a city's capacity to achieve economic outputs while minimizing resource inputs and environmental externalities, serving as a core metric for sustainable development under resource constraints. From a fiscal decentralization perspective, local governments in China operate within a system where revenue-sharing reforms have centralized fiscal authority while decentralizing expenditure responsibilities, creating incentives for officials to pursue short-term growth targets to secure promotions and revenues. Land finance dependence emerges as a rational adaptation to these pressures, as governments monopolize land supply to generate off-budget

revenues for infrastructure and urbanization. However, this dependence is expected to undermine green economic efficiency because it fosters a "growth-at-all-costs" logic: by prioritizing land sales and real estate-driven investments, local officials divert resources toward expansive, pollution-intensive projects that maximize immediate fiscal gains but impose long-term ecological costs, such as habitat loss and increased emissions. This relationship is theoretically rooted in the principal-agent problem, where misaligned incentives between central environmental mandates and local fiscal imperatives lead to suboptimal resource allocation, perpetuating inefficiencies in green transitions. Supporting this, Wang P et al. (2021) demonstrate that land finance reduces urban land use efficiency, leading to sprawling development that increases energy consumption and environmental degradation, while Wang et al. (2020) find that land finance significantly contributes to carbon emissions. Similarly, Gyourko et al. (2022) argue that land finance drives up land and housing prices, encouraging investment in high-pollution sectors, and (Cheng et al., 2022) highlight resource misallocation under fiscal pressures, though Zhao et al. (2024) note that green finance could mitigate volatility but is often overshadowed by land dependence.

H1: Land finance dependence negatively affects urban green economic efficiency.

2.2 Land finance dependence and environmental regulation

Environmental regulation comprises a suite of institutional tools—laws, policies, and enforcement mechanisms—designed to internalize environmental externalities and align economic activities with sustainability goals, as posited by the Porter Hypothesis, which suggests that well-crafted regulations can stimulate innovation and efficiency. In the context of China's decentralized governance, land finance dependence is theorized to weaken these regulations because it heightens fiscal vulnerabilities, compelling local governments to relax enforcement to attract investment and sustain land revenue streams. This dynamic arises from a "race to the bottom" incentive structure: under performance-based evaluations focused on GDP growth, officials face a prisoner's dilemma where competing jurisdictions undercut environmental standards to secure economic advantages, resulting in diluted regulatory stringency. Consequently, weakened regulations fail to curb pollution or promote green innovations, amplifying the negative spillover from land finance to green economic efficiency by allowing unchecked resource exploitation and environmental degradation. Empirical insights align with this, as Wang et al. (2019) find that land finance encourages relaxed regulations leading to a "race to the bottom," and Zhuge et al. (2020) highlight paradoxes where economic targets undermine efforts. Regional variations are noted by Zhao et al. (2024), while Dechezleprêtre and Sato (2017) confirm regulations' innovation potential but fiscal constraints from land dependence divert resources.

H2: Land finance dependence weakens environmental regulation, which in turn negatively affects urban green economic efficiency.

2.3 Land finance dependence and local government debt

Local government debt in China often accumulates through land-collateralized borrowing and financing platforms, reflecting a broader fiscal mismatch where decentralized spending exceeds centralized revenues. Theoretically, land finance dependence exacerbates this debt expansion by creating a leverage cycle: governments use anticipated land revenues as collateral to fund infrastructure, but volatile real estate markets and over-reliance on non-recurring income sources trap them in a debt trap, as per the soft budget constraint theory. High debt levels are expected to constrain green investments because they crowd out funding for long-term, low-return environmental projects in favor of short-term, high-yield urban developments, perpetuating a vicious cycle of fiscal risk and ecological neglect. This mediation pathway underscores how debt acts as an amplifier of land finance's negative externalities, limiting fiscal flexibility and prioritizing debt servicing over sustainable initiatives. Consistent with this framework, Cai et al. (2021) and Geng and Qian (2024) describe land as collateral driving debt risks, while Qu et al. (2023) and Tao et al. (2010) highlight regional competition and infrastructure financing limitations. Mechanisms are further explored by Zhou et al. (2023), who link debt to increased pollution, Xu (2019) tracing origins to fiscal pressures, and Wang et al. (2020) connecting to carbon emissions, with Jin et al. (2021) noting green finance's constrained mitigation potential.

H3: Land finance dependence leads to local government debt expansion, which negatively affects urban green economic efficiency.

3 Methodology

3.1 Data

To ensure data availability and completeness, this study utilizes panel data of Chinese prefecture-level cities from 2015 to 2023 for empirical analysis. The input-output indicators for green economic efficiency are primarily sourced from the China Environmental Statistical Yearbook and the China Statistical Yearbook. Data on land finance dependence are compiled from official statistics published by provincial and municipal departments of finance. Other control variables are obtained from the China City Statistical Yearbook and local statistical bulletins. Missing values are supplemented through manual searches; samples with irreparable missing data are excluded. All monetary variables are adjusted to constant 2011 prices using the GDP deflator of each city's respective province to eliminate the effects of inflation. All continuous variables have been trimmed at 1%. Ultimately, a total of 2199 valid observations are obtained.

3.2 Variable definition

3.2.1 Independent variable

The measurement of green economic efficiency (GEE) requires an analytical framework capable of simultaneously handling desirable outputs and undesirable outputs.

TABLE 1 Input-output indicators and descriptions for measuring urban green economic efficiency.

Input Indicators	Capital Input	Estimated capital stock based on the perpetual inventory method (100 million CNY)
	Labor Input	Number of employed persons at year-end (10,000 persons)
	Land Input	Built-up area (square kilometers)
	Energy Input	Total electricity consumption (100 million kWh)
	Water Resource Input	Total water consumption (100 million cubic meters)
Expected Output	Economic Output	Actual GDP (100 million CNY)
Undesirable Output	Industrial SO_2 Emissions	Industrial sulfur dioxide emissions (10,000 tons)
	Industrial Dust Emissions	Industrial smoke (dust) emissions (10,000 tons)
	Industrial Wastewater Discharge	Industrial wastewater discharge (10,000 tons)

Traditional Data Envelopment Analysis (DEA) models, such as CCR and BCC, are not suited for this task as they are typically radial, assuming proportional changes in inputs and outputs, and fail to account for non-radial slacks, which can lead to an incomplete assessment of inefficiency. To address this, we adopt the non-radial Slacks-Based Measure (SBM) model, which directly incorporates input excesses and output shortfalls into the efficiency calculation, providing a more accurate and comprehensive evaluation (Tone, 2001). The variable selection of input-output indicators is shown in Table 1. Furthermore, to overcome the limitation of standard DEA models that often assign multiple Decision-Making Units (DMUs) an identical efficiency score of '1′and thus cannot be ranked, we employ the super-efficiency SBM model. This advanced method allows efficiency scores to exceed unity, enabling the ranking of all DMUs, including those on the efficiency frontier, which offers superior discriminatory power for detailed comparative analysis.

For the dynamic analysis and robustness testing of GEE, this study selects the Directional Distance Function (DDF)-based Global Malmquist-Luenberger (GML) index model. The evolution of productivity analysis began with the Malmquist index, which, while foundational for measuring total factor productivity change, could not incorporate environmental externalities (Färe et al., 1994). A significant advancement was the development of the Malmquist-Luenberger (ML) index, which utilizes a DDF to handle undesirable outputs by simultaneously seeking to increase desirable outputs while decreasing undesirable ones (Chambers et al., 1996). However, the conventional ML index suffers from key methodological issues, including the potential for infeasibility in its linear programming and a lack of circularity, which compromises the reliability of inter-temporal comparisons. The GML index, proposed by Oh (2010), overcomes these limitations by constructing a single, global production frontier that envelops all periods. This approach ensures both the feasibility and transitivity of the results, making it a more robust and theoretically sound method for tracking the dynamics of environmental efficiency.

In essence, the dual-methodological approach employing both the super-efficiency SBM and the DDF-GML models is uniquely suited for this research because it provides a comprehensive, robust, and nuanced assessment of green economic efficiency. It has been successfully applied in similar contexts to evaluate environmental performance (Zhang and Choi, 2013). The super-efficiency SBM model offers a precise and high-resolution static analysis, capable of accurately measuring inefficiency by directly accounting for input and output slacks and providing a complete ranking of all entities, which is a critical feature that overcomes the limitations of traditional DEA models. Complementing this, the DDF-GML index provides a methodologically superior dynamic analysis. By constructing a single global frontier, it avoids the problems of infeasibility and non-transitivity that plague earlier Malmquist-Luenberger models, thus ensuring that the tracking of efficiency changes over time is both reliable and consistent. This combination allows the study to capture the robust, long-term dynamic trends, offering a far more complete and analytically rigorous evaluation than a single model could provide.

3.2.2 Dependent variable

The dependent variable in this study is local governments' land finance dependence (*LFD*), defined as the extent to which local governments rely on land-related fiscal revenues to support their public budgets. Conceptually, land finance broadly encompasses all fiscal revenues derived from land and real estate activities, including land transfer revenues (fees collected from leasing or selling state-owned land use rights) and associated taxes, such as urban land use tax, land value increment tax, and real estate-related taxes. However, due to the practical challenges of accurately and consistently capturing the full range of direct and indirect land-related taxes across jurisdictions—stemming from variations in tax reporting and data availability—this study adopts a narrower and more precise definition of LFD. Specifically, LFD is operationalized as the proportion of land transfer revenue in a local government's public budget revenue. This measure is widely used in the literature due to its reliability and availability in official fiscal data, enabling a clear and consistent assessment of local governments' reliance on land-based financing.

3.2.3 Control variables

This study selects control variables from the perspectives of urban macroeconomic characteristics and land resources, including economic development level (*PGDP*), financial development level

TABLE 2 Variable definition.

Variable type	Variable name	Variable measurement
Independent variable	*GEE*	Green economic efficiency, measured using the super-efficiency SBM model
Dependent variable	*LFD*	Land finance dependence, measured by land transfer revenue/public budget expenditure
Control variables	*PGDP*	Per capita GDP (log-transformed)
	FIR	Balance of financial institutions' deposits and loans at year-end/regional GDP
	IU	Value added of the tertiary industry/value added of the secondary industry
	FDI	Actual utilization of foreign direct investment/regional GDP
	URBAN	Non-agricultural population/registered population
	FISDEC	General government revenue/general government expenditure

TABLE 3 Descriptive statistics.

Variables	Obs	Mean	Std.Dev	Min	Median	Max
GEE	2199	0.378	0.176	0.100	0.335	1.220
LFD	2199	0.257	0.239	0.000	0.192	1.538
PGDP	2199	10.895	0.663	9.224	10.812	13.185
FIR	2199	2.808	1.252	0.910	2.492	21.301
IU	2199	1.227	0.638	0.321	1.075	5.650
FDI	2199	0.002	0.003	0.000	0.001	0.029
URBAN	2199	0.411	0.219	0.075	0.349	1.000
FISDEC	2199	0.429	0.211	0.056	0.393	1.086

(*FIR*), industrial upgrading (*IU*), openness to foreign investment (*FDI*), urbanization level (*URBAN*), and fiscal decentralization (*FISDEC*). The definitions of all variables are presented in Table 2, and their descriptive statistics are shown in Table 3.

Prior to the regression, multicollinearity in the baseline OLS model is diagnosed using the Variance Inflation Factor (VIF) method. The results show that the VIF values of all variables are below 10, suggesting that serious multicollinearity is not a concern. Since the number of cross-sectional units (N) exceeds the time span (T), Levin–Lin–Chu (LLC) and Fisher-ADF unit root tests are conducted to ensure the stationarity of the panel data and the robustness of the regression results. Both tests reject the null hypothesis of a unit root, indicating that the sample data are stationary. In addition, as shown in Table 3, there are considerable differences between the mean, maximum, and minimum values of several variables, implying potential heterogeneity across samples.

Table 3 presents the descriptive statistics of the key variables in this study. The dependent variable, *GEE*, has a mean of 0.378 and a standard deviation of 0.176, with values ranging from 0.100 to 1.220. This indicates substantial variation in green economic performance across cities. The concentration of *GEE* values in the lower range suggests that most Chinese cities still face significant challenges in achieving environmentally sustainable development, and that the overall level of green transformation remains relatively low. The independent variable, *LFD*, shows a mean of 0.257 and a relatively high standard deviation of 0.239. Its values range from 0 to a maximum of 1.538, indicating pronounced differences in the extent to which local governments rely on land-based revenues. In some cities, such reliance is remarkably high, which may incentivize local authorities to overlook environmental constraints in pursuit of fiscal expansion, thereby potentially impairing green economic efficiency. Figure 1 plots the change in green economic efficiency on lagged land fiscal dependence. The fitted line slopes downward, indicating a negative association. It should be noted that the inference relies on the panel regressions with controls and robustness checks. In addition, the distributions of other control variables appear generally normal, with no evident statistical outliers, providing a sound foundation for empirical investigation.

3.3 Model construction

This study employs a panel data model for empirical analysis. The results of the Hausman test indicate that a two-way fixed effects (FE) model with robust standard errors is more appropriate, given the significant differences across provinces. Therefore, the FE model is adopted for regression. The model is shown in Formula 1:

$$GEE_{it} = \beta_0 + \beta_1 LFD_{it} + \beta_2 \sum Control_{it} + Year_t + Province_k + \varepsilon_{it}, \quad (1)$$

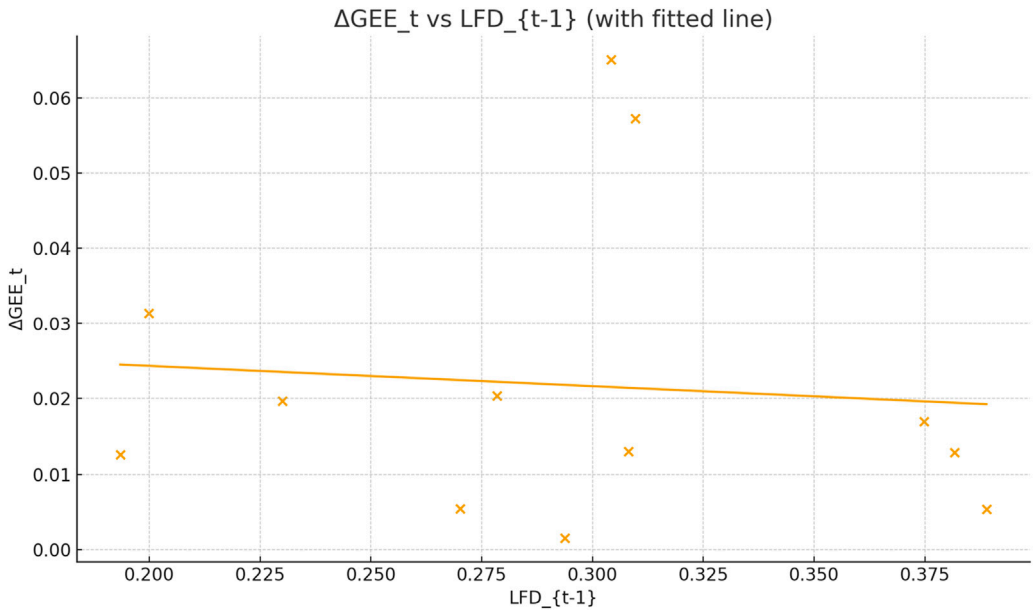


FIGURE 1
Relationship between lagged land fiscal dependence and green economic efficiency growth.

where i denotes the city, t indicates the year, and each city i belongs to a province k, which is accounted for through province fixed effects to control for inter-provincial differences in institutional settings, policy environments, and resource endowments. The term $Year_t$ captures time-fixed effects to eliminate year-specific shocks or macroeconomic trends. $Control_{it}$ is a vector of control variables. ε_{it} is the error term. The primary coefficient of interest is β_1, which reflects the impact of land finance dependence on green economic efficiency—both in terms of direction and statistical significance.

4 Basic results

4.1 Basic regression analysis

The results of the baseline regressions are presented in Table 4. All three models control for both year and province fixed effects. Column (1) shows that when land finance dependence is included as the sole explanatory variable, the estimated coefficient is statistically insignificant. This suggests that, in the absence of other key controls, the impact of land finance dependence on green economic efficiency is not clearly identifiable. A likely reason is the omission of important structural economic variables, which may weaken the explanatory power of the model.

In Columns (2) and (3), the model progressively incorporates additional control variables. After these inclusions, the coefficient on land finance dependence becomes significantly negative at the 5% level, indicating that land finance dependence has a statistically significant suppressing effect on green economic efficiency. This finding supports the negative externalities of land finance, which posits that heavy reliance on land-based revenues by local governments may erode their intrinsic motivation to pursue green transformation, thereby contributing to resource inefficiency and environmental degradation. So, Hypothesis 1 has been proven.

The theory of Fiscal Federalism explores the division of expenditure responsibilities and fiscal powers between central and local governments. While the theory emphasizes that decentralization can better meet the demand for local public goods, it also warns of the potential negative consequences of inter-jurisdictional competition. Research by scholars such as Wilson and Wildasin (2004) has provided a solid theoretical foundation for the "Race to the Bottom." To attract mobile capital and investment, local governments not only compete on taxes but may also engage in a "downward competition" on environmental, labor, and other standards. Driven by land finance, local governments have a strong incentive to maximize land transfer revenue by attracting industrial and real estate projects that can be quickly implemented. To this end, they might relax regulations in areas such as planning approval and environmental assessment, tolerating or even encouraging the entry of high-pollution, high-energy-consumption firms, thereby sacrificing environmental quality for short-term economic growth and fiscal revenue. This prevalent "race to the bottom" behavior is a significant reason for the widespread suppression of green economic efficiency at the regional level.

4.2 Endogeneity tests

In the study of green economic efficiency, land finance dependence as a core explanatory variable may suffer from endogeneity issues. On the one hand, local governments' reliance on land-based revenues can directly influence the formulation and implementation of urban green development strategies. On the other hand, changes in green economic efficiency may in turn

TABLE 4 Benchmark regression results.

Variables	(1)	(2)	(3)
	GEE	*GEE*	*GEE*
LFD	−0.0074	−0.0415**	−0.0352**
	(0.016)	(0.017)	(0.017)
PGDP		0.0725***	0.0893***
		(0.006)	(0.011)
FIR		−0.0274***	−0.0239***
		(0.004)	(0.004)
IU		0.0214***	0.0218***
		(0.008)	(0.008)
FDI			−6.6248***
			(1.669)
URBAN			−0.0538**
			(0.021)
FISDEC			−0.0013
			(0.038)
Constant	0.3798***	−0.3509***	−0.5084***
	(0.005)	(0.068)	(0.112)
Observations	2,199	2,199	2,199
Adjusted R-squared	0.372	0.415	0.420
Year FE	YES	YES	YES
Province FE	YES	YES	YES

Parentheses contain heteroscedasticity robust standard errors. *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

affect the extent to which local governments depend on land transfer income, resulting in potential bidirectional causality. Additionally, omitted variable bias and institutional differences at the city level may introduce further endogeneity concerns. To address these issues, this study adopts the two-stage least squares (2SLS) estimation method and employs an external instrumental variable to identify the causal impact of land finance dependence on green economic efficiency.

This study selects the ratio of total retail sales of consumer goods to GDP (*RETAIL*) as the instrumental variable for the endogeneity test in the baseline regression. First, in terms of relevance, retail sales of consumer goods reflect the vitality of domestic demand and the consumption structure within a city, which indirectly influences the fiscal revenue capacity of local governments. When a city exhibits strong consumption capacity and high household spending levels, the reliance of local governments on land transfer revenues tends to be lower, suggesting a strong statistical correlation between *RETAIL* and *LFD*. Second, from the perspective of exogeneity, *RETAIL* serves as an indicator of economic dynamism, and its fluctuations are primarily driven by factors such as household income, consumption preferences, and demographic structure. It does not directly intervene in the mechanisms that determine green economic efficiency, nor is it likely to affect *GEE* through channels such as green technology innovation or environmental regulation. Therefore, it satisfies the condition of exogeneity. Overall, *RETAIL* is a theoretically sound and operationally feasible instrumental variable, making it appropriate for identifying the net effect of land finance dependence on green economic efficiency.

The 2SLS regression results of Table 5 confirm the robustness of the baseline finding that "land finance dependence suppresses green economic efficiency," even after addressing endogeneity concerns. The F-value of the first-stage regression is 22.555, indicating that there is no issue of weak instruments. Specifically, a high level of reliance on land-based revenues by local governments not only affects the structure of municipal finance but may also incentivize them to overlook ecological and environmental costs in the process of urban expansion. This, in turn, undermines the effectiveness of green transition policies and significantly hampers improvements in green economic efficiency. After addressing potential reverse causality and omitted variable bias using an instrumental variable, the negative impact of land finance dependence on green economic efficiency remains statistically significant. This provides further empirical support for the theory of negative externalities of land finance. Therefore, advancing green development requires not only technological and industrial

TABLE 5 2SLS regression results.

Variables	(1)	(2)
	LFD	*GEE*
LFD		−0.3403**
		(0.169)
RETAIL	0.2070***	
	(0.040)	
PGDP	0.0136	0.0899***
	(0.014)	(0.012)
FIR	0.0353***	−0.0112
	(0.005)	(0.008)
IU	0.0121	0.0263***
	(0.010)	(0.009)
FDI	1.6342	−6.1205***
	(2.053)	(1.799)
URBAN	0.0861***	−0.0259
	(0.026)	(0.027)
FISDEC	0.3988***	0.1192
	(0.046)	(0.079)
Observations	2,199	2,199
Year FE	YES	YES
Province FE	YES	YES

Parentheses contain heteroscedasticity robust standard errors. *, **, and *** represent significance levels at 10%, 5%, and 1% respectively. Since the intercept and R-squared in the 2SLS, regression have limited statistical interpretability, they are not reported in this table.

efforts but also institutional reforms in fiscal policy and land management. Reducing dependence on land transfer revenues and restructuring a green-oriented fiscal incentive mechanism are essential steps in this process.

4.3 Robustness tests

To ensure the reliability of the baseline findings, this study conducts a series of robustness checks. First, to verify the robustness of the green economic efficiency measurement, this study recalculates green economic efficiency (*GEE1*) using the Directional Distance Function (DDF) and the Global Malmquist–Luenberger Index (GML) under the assumption of variable returns to scale (VRS). The inputs include the total number of employed persons, capital stock estimated using the perpetual inventory method with 2003 as the base year, and electricity consumption. Desired output is represented by real GDP at constant prices, while undesirable outputs are measured by the three types of industrial pollution. Second, to test the sensitivity of the results to the construction of the core independent variable, this study introduces an alternative indicator, defined as the ratio of land transfer revenue to local government comprehensive fiscal capacity (*LFD1*). Comprehensive fiscal capacity includes local revenue, tax rebates, transfer payments, government fund budget revenue, and part of the extra-budgetary income, thus providing a more comprehensive reflection of the local fiscal situation. Third, this study addresses the potential influence of anomalous events. In 2015, the National Audit Office launched a nationwide "land audit storm," conducting extensive investigations into land transfer violations. This event may have led to structural anomalies in land transfer revenue and usage behavior. To ensure the robustness of the results, this study excludes the 2015 data and re-estimates the model. Finally, to account for potential omitted variable bias, the model is re-estimated after controlling for three additional variables: green patent applications (*GPATENT*), infrastructure quality (*INFRA*), and urban river density (*RIVER*), to account for the influence of innovation capacity, physical infrastructure, and natural geographic factors.

The regression results from these tests confirm the stability of the baseline conclusions. As shown in Column (1) of Table 6, when using the alternative *GEE1* measure, the coefficient of *LFD* is −0.024, which is statistically significant at the 10% level. This indicates that the research conclusions do not depend on a specific efficiency measurement method; although the SBM and DDF-GML models differ in structure, the empirical findings consistently show that land finance dependence

TABLE 6 Robustness regression tests.

Variables	(1)	(2)	(3)	(4)
	GEE1	*GEE*	*GEE*	*GEE*
LFD	−0.0235*		−0.0427**	−0.0452***
	(0.014)		(0.019)	(0.017)
LFD1		−0.0054***		
		(0.002)		
PGDP	0.1110***	0.0882***	0.0912***	0.0794***
	(0.009)	(0.011)	(0.013)	(0.012)
FIR	−0.0022	−0.0239***	−0.0267***	−0.0298***
	(0.004)	(0.004)	(0.005)	(0.004)
IU	0.0298***	0.0211***	0.0251***	0.0197**
	(0.006)	(0.008)	(0.008)	(0.008)
FDI	−4.5964***	−6.5435***	−6.7790***	−6.6522***
	(1.363)	(1.667)	(1.842)	(1.697)
URBAN	−0.0113	−0.0551***	−0.0533**	−0.0553***
	(0.017)	(0.021)	(0.022)	(0.021)
FISDEC	−0.0810***	−0.0149	0.0152	−0.0291
	(0.031)	(0.038)	(0.044)	(0.039)
GPATENT				0.0000***
				(0.000)
INFRA				−0.0406***
				(0.009)
RIVER				0.1496***
				(0.033)
Constant	−0.8551***	−0.4839***	−0.5209***	−0.3730***
	(0.091)	(0.112)	(0.127)	(0.115)
Observations	2,199	2,199	1,925	2,121
Adjusted R-squared	0.466	0.422	0.414	0.442
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Parentheses contain heteroscedasticity robust standard errors. *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

significantly suppresses green economic efficiency under both methods. The results for the alternative land finance dependence indicator are presented in Column (2) of Table 6. The coefficient of *LFD1* is −0.005, statistically significant at the 5% level and consistent with the baseline regression. This suggests that even with a broader definition of land finance dependence, the conclusion that a higher reliance on land revenue corresponds to lower green economic efficiency remains valid. When the 2015 data is excluded, the results, presented in Column (3) of Table 6, show that the coefficient of *LFD* is −0.043, statistically significant at the 5% level. This indicates that the negative impact of land finance dependence on green economic efficiency is a persistent phenomenon and not driven by an anomalous event in a specific year. In Column (4) of Table 6, after including additional controls for innovation, infrastructure, and geography, the coefficient of land finance dependence remains significantly negative. This demonstrates that the negative relationship is not a mere artifact of a city's innovation level, infrastructure quality, or natural geography. The stability of the coefficient under this expanded set of controls confirms the robustness of the findings and provides stronger evidence for a direct link.

TABLE 7 Heterogeneity regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Resource-based	Non-resource-based	Key city	Non-key city	Urban agglomeration	Non-urban agglomeration
LFD	−0.0345	−0.0671***	−0.0701***	−0.0575*	−0.1014***	−0.0048
	(0.038)	(0.023)	(0.023)	(0.030)	(0.025)	(0.028)
PGDP	−0.0300	0.1063***	0.1419***	−0.0241	0.0875***	0.0524***
	(0.024)	(0.016)	(0.019)	(0.019)	(0.021)	(0.018)
FIR	−0.0754***	−0.0208***	−0.0250***	−0.0728***	0.0176*	−0.0445***
	(0.011)	(0.006)	(0.007)	(0.009)	(0.010)	(0.006)
IU	−0.0036	0.0380***	0.0174	0.0195*	0.0021	0.0203**
	(0.013)	(0.011)	(0.013)	(0.011)	(0.022)	(0.009)
FDI	−3.0427	−9.1559***	13.5613***	−5.5239**	−14.6857***	−3.5665
	(3.032)	(2.410)	(2.500)	(2.591)	(2.649)	(2.506)
URBAN	−0.1176***	0.0489	−0.1102***	−0.0765**	0.1677***	−0.1184***
	(0.035)	(0.032)	(0.034)	(0.030)	(0.038)	(0.028)
FISDEC	0.2949***	−0.1248**	0.1955***	0.1890***	−0.0885	0.1342**
	(0.072)	(0.057)	(0.064)	(0.061)	(0.069)	(0.056)
Constant	0.8276***	−0.6719***	−1.1346***	0.7816***	−0.5534***	−0.0911
	(0.248)	(0.161)	(0.184)	(0.200)	(0.206)	(0.174)
Observations	770	1,141	769	1,142	622	1,289
Adjusted R-squared	0.422	0.452	0.568	0.410	0.470	0.433
Year FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES

Parentheses contain heteroscedasticity robust standard errors. *, **, and *** represent significance levels at 10%, 5%, and 1% respectively.

5 Heterogeneity analysis

Heterogeneity analysis is essential for uncovering how the impacts of land finance dependence on green economic efficiency vary across city types, providing insights into underlying mechanisms and informing targeted policy interventions. Drawing on resource dependence theory and fiscal decentralization frameworks, we theorize that structural differences in fiscal bases, environmental pressures, and competitive dynamics moderate these effects. We conduct subgroup regressions based on three dimensions: resource-based vs non-resource-based cities (per the National Plan for Sustainable Development of Resource-Based Cities, 2013–2020), key vs non-key environmental protection cities (per the National Environmental Protection "11th Five-Year Plan"), and urban agglomeration vs non-agglomeration cities (focusing on five major national clusters: Beijing–Tianjin–Hebei, Yangtze River Delta, Pearl River Delta, Central Yangtze, and Chengdu–Chongqing). Results are reported in Table 7.

Resource-based cities, endowed with natural resources, often benefit from alternative fiscal revenues like resource taxes and central transfers, theoretically buffering against heavy land finance dependence and allowing more balanced environmental investments despite inherent pollution pressures from extractive industries. In contrast, non-resource-based cities lack such buffers, making them more vulnerable to LFD-driven fiscal shortfalls that crowd out green initiatives and exacerbate resource misallocation under decentralization incentives. This aligns with the "resource curse" literature, which argues that the economic impact of a dominant revenue source is conditional on institutional quality; in contexts with weaker governance or intense rent-seeking pressures, such dependence can distort incentives and crowd out investment in more sustainable, productive sectors (Mehlum et al., 2006). The results in Columns (1) and (2) support this: the *LFD* coefficient is insignificant in resource-based cities but significantly negative in non-resource-based ones. Mechanistically, this links to weakened regulation in non-resource cities, where land finance dependence intensifies a "race to the bottom" to attract non-extractive investments, impairing green economic efficiency.

Key environmental protection cities are designated with stricter mandates and enhanced central support, theoretically fostering stronger regulatory frameworks and green awareness to mitigate

harms to land finance dependence. Counterintuitively, however, fiscal pressures from land finance dependence may amplify negative effects here: heightened environmental standards increase compliance costs, but LFD-induced revenue volatility forces trade-offs, diluting enforcement and crowding out investments, as central mandates clash with local fiscal imperatives. This reflects the inherent tensions in fiscal federalism, where local governments are caught between central mandates and local economic pressures. The intense competition for capital can discipline governments to adopt pro-business policies, sometimes at the expense of regulatory stringency (Cai and Treisman, 2005). Columns (3) and (4) show the coefficients of *LFD* is significantly negative in key cities while milder and less significant in non-key ones. This mechanism ties to debt escalation, where land finance dependence in mandated cities leads to leveraged borrowing for compliance, paradoxically undermining long-term green economic efficiency.

Urban agglomerations feature intense intercity competition, regional integration, and infrastructure demands, theorized to exacerbate the effects of land finance dependence via amplified "growth-for-competition" dilemmas. The high density and close proximity within urban agglomerations intensify inter-jurisdictional competition (Duranton and Diego, 2020), pressuring local governments to use land finance as a tool for rapid, large-scale development to attract mobile capital and talent. Clustered governments face heightened pressures to leverage land for coordinated development, often at ecological costs, while non-agglomeration cities operate with less rivalry and more localized strategies. Columns (5) and (6) confirm this: *LFD*'s coefficient is significantly negative in agglomeration cities while it is insignificant in non-agglomeration ones. Mechanistically, this reflects regulatory weakening and debt risks in agglomerations, where competition drives relaxed standards and collective borrowing, intensifying environmental inefficiencies.

6 Influence mechanisms

6.1 The intensity of environmental regulation

Theoretically, the fiscal structure of local governments not only determines the direction of fiscal resource allocation but also shapes their policy implementation preferences. When local governments heavily rely on land transfer revenues, they tend to prioritize land supply and infrastructure investment to attract investment and boost GDP growth. This, in turn, reduces their fiscal attention and political commitment to environmental protection and ecological governance. Therefore, the intensity of environmental regulation may serve as a key mediating variable through which land finance dependence affects green economic efficiency. This paper selects "environmental regulation intensity" as one of the transmission channels in the mechanism analysis. By examining whether land finance dependence significantly influences local governments' willingness and capacity to engage in environmental governance, the study further explores how it constrains green development.

Columns (1) and (2) of Table 8 present the regression results for the environmental regulation mechanism. Drawing on the text-based policy indices constructed by Baker et al. (2016), Caldara and Iacoviello (2022), and Li et al. (2024), we calculated the government attention index on environmental issues; this rigorous measurement method has been applied to the analysis of a broader range of government reports. Specifically, in Column (1), the dependent variable is the frequency and proportion of environmental terms appearing in local government work reports (*DEC*), which serves as a proxy for government environmental governance following (Chen et al., 2018). Government work reports are official, programmatic policy documents that outline administrative agendas and implement decisions of legislative bodies. As such, the frequency and relative weight of environmental language in these reports offer a comprehensive reflection of the government's regulatory emphasis and environmental policy stance. The regression result shows that the coefficient of land finance dependence is −5.8328, statistically significant at the 5% level, indicating that higher land finance dependence is associated with fewer environmental expressions in formal policy documents—reflecting a reduced emphasis on environmental concerns.

Column (2) uses the share of energy conservation and environmental protection expenditure in total fiscal expenditure (*PEE*) as the dependent variable. The coefficient of *LFD* is −0.0040, statistically significant at the 10% level, suggesting that as local governments become more dependent on land finance, they allocate a smaller proportion of their fiscal resources to environmental protection.

These findings demonstrate that land finance dependence indirectly affects urban green economic efficiency by weakening the intensity of environmental regulation. Both mechanism variables are significantly and negatively impacted by land finance dependence, providing further empirical support for the theory of negative externalities of land finance, Hypothesis 2 has been verified. This mechanism highlights that to effectively enhance green economic efficiency, it is necessary to reduce reliance on land-based revenues at the source, strengthen the political incentives and fiscal support for environmental policy, and enhance the capacity and willingness of local governments to engage in effective environmental governance.

6.2 Local government debt risk

In addition to the intensity of environmental regulation, local government debt risk may also serve as a crucial mechanism through which land finance dependence affects green economic efficiency. Under the current fiscal system, local governments face an imbalance between revenue and expenditure responsibilities, often resorting to borrowing to fill fiscal gaps. Especially as land transfer revenues become a key source of fiscal income, governments may engage in large-scale borrowing by leveraging land assets or anticipated revenues to sustain intensive infrastructure investment and urban expansion, thereby escalating debt risk. More critically, excessive reliance on land finance and implicit debt instruments reinforces short-term growth preferences, crowding out fiscal support for environmental governance and green industries. Therefore, if land finance dependence significantly increases government debt risk, it provides indirect evidence that its negative effect on green economic efficiency may operate through a "leveraged expansion" pathway.

TABLE 8 Mechanism regression tests.

Variables	(1)	(2)	(3)	(4)
	Environmental regulation		Government debt risk	
	DEC	*PEE*	*LGB*	*UIB*
LFD	−5.8328**	−0.0040*	0.5333***	1.0265***
	(2.306)	(0.002)	(0.069)	(0.119)
PGDP	3.7326**	0.0024*	0.0549	0.4374***
	(1.578)	(0.001)	(0.048)	(0.082)
FIR	−0.6885	0.0006	0.1667***	0.3592***
	(0.585)	(0.001)	(0.017)	(0.031)
IU	3.5736***	−0.0005	0.1245***	0.0181
	(1.042)	(0.001)	(0.031)	(0.056)
FDI	436.5522*	−0.1288	31.2347***	56.1805***
	(225.785)	(0.204)	(6.865)	(11.686)
URBAN	2.3857	0.0085***	−0.2875***	−0.4833***
	(2.756)	(0.002)	(0.082)	(0.144)
FISDEC	−16.4313***	−0.0024	1.2999***	1.3141***
	(5.334)	(0.005)	(0.162)	(0.278)
Constant	14.4557	0.0016	13.4155***	8.4011***
	(15.562)	(0.014)	(0.469)	(0.811)
Observations	1,925	1,925	1,844	1,876
Adjusted R-squared	0.224	0.250	0.703	0.717
Year FE	YES	YES	YES	YES
Province FE	YES	YES	YES	YES

Parentheses contain heteroscedasticity robust standard errors. *, **, and *** represent significance levels at 10%, 5%, and 1% respectively. For the convenience of reporting, we have implemented order of magnitude control.

Columns (3) and (4) of Table 8 present the regression results for the debt risk mechanism. In Column (3), where the dependent variable is the outstanding balance of local government debt (*LGB*), the coefficient of land finance dependence is significantly positive at the 1% level, indicating that greater dependence on land finance is associated with higher government debt levels. Column (4) uses the scale of urban investment bonds (*UIB*) issued by local government financing platforms as the dependent variable. The *LFD* coefficient is again significantly positive at the 1% level, suggesting that land finance dependence significantly promotes the expansion of urban investment bonds, further reflecting the accumulation of government debt risk.

These results indicate that land finance dependence suppresses green economic efficiency indirectly by increasing the debt burden of local governments. Hypothesis 3 has been verified. The volatility of land revenue, combined with aggressive fiscal behavior, encourages local governments to maintain urban expansion through a land–debt–investment cycle. This not only exacerbates fiscal unsustainability but also undermines strategic investment in green transformation. Faced with mounting debt pressure, local governments are more likely to prioritize projects with short-term fiscal returns over those with long-term environmental benefits. This mechanism confirms that the "leveraged expansion logic" inherent in land finance dependence is a critical cause of inefficient and unsustainable green development. Therefore, curbing the expansion of local government debt and regulating land finance behavior are institutional prerequisites for improving green economic efficiency.

7 Conclusions and implications

This paper empirically investigates the impact of land finance dependence on green economic efficiency. The results indicate that a high dependence on land finance significantly suppresses green economic efficiency. Using the super-efficiency SBM model to measure green economic efficiency and conducting heterogeneity tests to examine differences across various city types, the study finds that the negative impact of land finance dependence is more pronounced in non-resource-based cities, key environmental protection cities, and urban agglomerations. This supports the theory of negative externalities of land finance, which suggests that local governments, in pursuit of short-term economic

growth and fiscal revenue, often overlook environmental protection and green development, leading to a decline in green economic efficiency. The study also explores the mediating mechanisms of environmental regulation intensity and local government debt risk, revealing the pathways through which land finance dependence affects green economic efficiency and highlighting the importance of fiscal and land policy reforms.

These findings carry significant implications for the literature on environmental economics and public finance. By demonstrating how a specific fiscal institution, land finance dependence, induces environmental inefficiency, this study contributes a crucial institutional perspective to the resource misallocation literature. The results suggest that the growth-at-all-costs driven by fiscal pressures, systematically undermines the effectiveness of environmental governance. The identified mechanism of weakened environmental regulation challenges the universal applicability of the Porter Hypothesis, which posits that stringent regulation can foster innovation. Our findings indicate that in contexts of high fiscal stress, local governments may lack the political will or financial capacity to enforce such regulations, leading to environmental standards becoming more lenient rather than stricter. Similarly, the link between land finance and escalating local debt reveals a critical trade-off between short-term urban expansion and long-term sustainable development. This pressure on fiscal revenue growth crowds out necessary green investments, suggesting that achieving environmental goals is intrinsically linked to fiscal reform and the management of systemic financial risks. Therefore, the very mechanism designed to fund urbanization through land finance simultaneously erects barriers to a sustainable green transition.

While this study contributes to understanding land finance dependence's impact on green economic efficiency, limitations exist. First, panel data from prefecture-level cities may miss regional variations, especially in counties. Second, other fiscal sources like external inflows were not fully considered. Future research can expand by exploring dynamic relationships across city types, introducing variables like governance capacity and green innovation as moderators, and using natural experiments with longer data for robustness.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The datasets contained in the article are from the publicly available documents of various departments and have been manually organized. We are willing to provide them when readers need them. Requests to access these datasets should be directed to CG, chen_fu@sjtu.edu.cn.

Author contributions

CG: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review and editing.

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EDITED BY
Cunyi Yang,
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Liang Li,
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Mohammad Fazle Rabbi,
University of Debrecen, Hungary
Sonia Sattar,
Punjab Group of Colleges, Pakistan
Lei Zhuang,
Nanjing Tech University, China

*CORRESPONDENCE
Shanshan Ye,
mthichau50@gmail.com

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Spatiotemporal evolution characteristics and influencing factors of China's interprovincial industrial green efficiency based on the super-efficiency SBM model

Jinyu Wang[1], Rongqiang Xu[2] and Shanshan Ye[3]*

[1]School of Economics, Beijing Technology and Business University, Beijing, China, [2]Information Center of Ministry of Natural Resources, Beijing, China, [3]Shaoguan University, Shaoguan, Guangdong, China

With the rapid development of the economy and excessive resource consumption, improving industrial green efficiency is a crucial pathway to achieving sustainable industrial development. Based on the super-efficiency SBM model and using provincial panel data from 2005 to 2022, this study measures China's industrial green efficiency index. It constructs an indicator system with 36 specific indicators selected from seven dimensions: industrial governance, economic foundation, factor input, technological efficiency, environmental governance, natural factors, and pollutant emissions. The study employs the geographical detector method to conduct an in-depth analysis of the driving effects of industrial green efficiency. The key findings are as follows: (1) Since 2005, China's industrial green efficiency index has exhibited an initial increase followed by a slight decline, dropping from 0.668 to 0.623. (2) The pace of China's green transition has been gradually accelerating, yet significant disparities in green efficiency indices remain among provinces, with particularly pronounced gaps between the developed eastern regions and the underdeveloped western regions. (3) The Moran's Index indicates that 77.4% of China's provinces show a positive spatial correlation between their industrial green efficiency and that of neighboring provinces, with this proportion on the rise. Strong spatial clustering is observed in Shanghai, Zhejiang, and Fujian, while spatial dispersion is noted in Hebei and Guangdong. (4) Industrial governance has the most significant driving effect on industrial green efficiency, followed by economic foundation (1.153), factor input (0.772), technological efficiency (0.637), environmental governance (0.567), natural factors (0.338), and pollutant emissions (0.239). (5) At present, economic development, industrial upgrading, capital investment, and green finance are the key driving forces behind industrial green efficiency. The negative impact of pollutant emissions has been gradually decreasing, while the role of technological innovation, though important, has shown a marginal diminishing trend in the later stages. Additionally, the digital economy's contribution to industrial green efficiency has been steadily increasing.

KEYWORDS

super-efficiency SBM model, industrial green efficiency, digital economy, spatial pattern, industrial governance, sustainable development

1 Introduction

In recent years, as the global ecological crisis has intensified, green, low-carbon, and sustainable development has become a global consensus. As the world's second-largest economy, China bears the responsibility of leading the global transition toward green development and has elevated green development to a national strategy (Yang et al., 2025). Against this backdrop, China has incorporated the construction of an "ecological civilization" into its overall development agenda. Since 2018, the Chinese government has issued a series of policy documents—such as the Evaluation Measures for Ecological Civilization Construction Goals and the Opinions on Accelerating the Promotion of Ecological Civilization Construction—explicitly calling for the acceleration of green and low-carbon technological innovation, the optimization of industrial structure, and the advancement of high-quality development. In particular, China's 14th Five-Year Plan identifies green development as a key pathway for promoting high-quality development and emphasizes the need to achieve a harmonious balance between economic growth and environmental protection. The industrial sector consumes about 70% of China's total energy (Zhang A. et al., 2022) and emits 62% of its carbon dioxide (Fang et al., 2022). Therefore, promoting the green transformation of industry, improving energy efficiency, and reducing carbon emissions are critical for achieving China's dual carbon targets of peaking CO_2 emissions by 2030 and reaching carbon neutrality by 2060. In February 2024, the Ministry of Industry and Information Technology, together with six other ministries, issued new guidelines on accelerating the greening of the manufacturing sector, highlighting the importance of advancing green industrial development. Industrial green efficiency (INGE)—a key indicator reflecting both ecological and economic performance of the industrial sector—has thus become a central policy target in China's green transition (Zhang et al., 2025; Sun and Zhou, 2024).

Since the reform and opening-up, China's economy has grown at an average annual rate of 9.2%. However, rapid industrialization has placed enormous pressure on resources and the environment. In 2022, the industrial sector contributed 40% of China's GDP but accounted for 60% of CO_2 emissions. This growth model is approaching ecological limits. According to the Ministry of Ecology and Environment, in 2022 approximately 19.4% of arable land was polluted, and 80.6% of groundwater was classified as poor or very poor in quality (Xiu et al., 2023). Confronted with these challenges, the 19th National Congress of the Communist Party of China elevated ecological civilization construction to a "millennium plan," and committed to achieving carbon peaking by 2030 and carbon neutrality by 2060. As the backbone of China's economy, the green transformation of the industrial sector is pivotal to the success of this national strategy. Yet, China's INGE faces multiple challenges: regional disparities are significant—for example, in 2022, energy consumption per unit of industrial value added in eastern provinces was only 60% of that in the western region; structurally, heavy industry still accounts for over 60% of total industrial output, but its carbon intensity is four times that of light industry (Liu et al., 2023). Existing studies have not sufficiently revealed the driving mechanisms underlying these issues. Improvements in INGE rely not only on technological innovation and policy support but are also shaped by regional economic foundations, industrial structures, and environmental governance. Therefore, analyzing the spatial distribution, driving forces, and transformation pathways of China's interprovincial INGE is of great importance for advancing the national green development strategy and promoting balanced regional development.

This study uses panel data from 31 Chinese provinces between 2005 and 2022 to construct a comprehensive indicator system covering seven dimensions: industrial governance, economic foundations, factor inputs, technological efficiency, environmental governance, natural conditions, and pollutant emissions. Employing the super-efficiency SBM model, Moran's I, and the Geodetector method, the study examines spatial disparities in provincial INGE and explores the mechanisms driving these patterns. The findings are intended to provide policymakers with targeted recommendations, support China's industrial green transformation, and contribute to the realization of a green, low-carbon, and sustainable economy and society.

Building on existing literature, this paper contributes in several ways. First, it integrates the super-efficiency SBM model with the Geodetector method to quantify INGE across provinces and explain its driving factors. Second, it develops a detailed system of 36 indicators across seven dimensions, enhancing the scientific robustness and explanatory power of the results. Third, it applies Moran's I to capture spatial correlation, revealing agglomeration effects and regional imbalances in INGE, thereby offering theoretical insights for regional collaborative governance. Fourth, it analyzes the effects of industrial governance, economic foundations, factor inputs, technological efficiency, environmental governance, natural conditions, and pollutant emissions on INGE, broadening the policy perspective on green industrial transformation.

The remainder of this paper is organized as follows. Section 2 reviews the literature and outlines the contributions of this study. Section 3 introduces the models, methodologies, and data sources. Section 4 analyzes the spatiotemporal evolution of INGE in China. Section 5 examines the influencing factors of INGE. Section 6 concludes with key findings and policy implications.

2 Literature review

2.1 International research focus on INGE

The concept of eco-efficiency was first introduced by German scholar Schaltegger, who measured economic development's environmental performance using the ratio of value increment to environmental impact increment. This concept has since been widely applied across various fields (Wang et al., 2016). Current research on industrial efficiency mainly focuses on the following aspects. (1) Measurement Methods of Industrial Efficiency. The primary methods used for measuring industrial efficiency include Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) (Wang and Lin, 2024; Yu, 2023). Scholars have used DEA-based methods to calculate input-output efficiency while considering environmental pollution as an undesirable output (Shuai and Fan, 2020). Additionally, the SBM model and DDF model have been employed to estimate industrial green total factor productivity (TFP) and its growth rate (Zhu et al., 2021; Zhu et al., 2019; Dong et al., 2021). Compared to the traditional SBM model, the super-efficiency SBM model offers greater flexibility and can quantify the impact of different factors on green efficiency, making it suitable for cross-regional and cross-temporal comparative studies (Zhong et al., 2023; Xu et al., 2022; Ding et al., 2022). (2) Regional Differences in Industrial Efficiency. Research on regional industrial

efficiency differences can be categorized into macro-level and micro-level studies based on the geographical scope of analysis (Ding et al., 2022; Gu et al., 2021; Bai et al., 2018; Xie et al., 2019). Macro-level studies focus on national, provincial, and municipal scales, primarily analyzing temporal changes in eco-efficiency and spatial correlation patterns. Micro-level studies mainly examine firms, investigating variations in eco-efficiency across different types of enterprises and regions (Uche et al., 2024). (3) Influencing Factors of Industrial Eco-Efficiency. Industrial eco-efficiency is influenced by multiple factors, including economic development, technological innovation, industrial structure, resource endowments, and environmental governance (Miao et al., 2021; Jin et al., 2019; Wang et al., 2024). Many scholars incorporate energy consumption, pollutant emissions, resources, and environmental factors into total factor productivity (TFP) analysis frameworks to estimate industrial green TFP (Yuan et al., 2020; Jiang et al., 2024; Lin and Wang, 2024). With the growing emphasis on green development in both policy and academic research, scholars have increasingly focused on the roles of environmental regulation, institutional innovation, and technological progress (Hameed et al., 2024; Xuan et al., 2024). However, the impact of environmental regulation on eco-efficiency remains controversial. Sun et al. (2024) argues that strict environmental regulations facilitate the adoption of energy-saving and emission-reduction technologies, thereby enhancing green efficiency. Ouyang et al. (2022) suggests that overly stringent environmental regulations may increase compliance costs for enterprises, hinder technological innovation, and ultimately reduce green efficiency.

2.2 Research progress on INGE in China

In recent years, domestic scholars have focused on the impact of regional, policy, and technological factors on INGE (Yao et al., 2018; Wang and Wang, 2021). Li and Zeng (2020) used the super-efficiency SBM model to study the INGE of 31 provinces in China, and the results showed that the green efficiency of coastal areas and developed provinces was significantly higher than that of inland areas. Li G. et al. (2023) and Liu et al. (2024) pointed out that technological innovation and green investment have become key factors in improving China's INGE. Guo et al. (2020) measured the green development efficiency of 34 cities in Northeast China, and the results showed that industrial agglomeration hindered the improvement of green development efficiency, and there was a U-shaped relationship between industrial agglomeration and green development. Lu et al. (2024) used the Super SBM-ML model to analyze the INGE of the middle and lower reaches of the Yangtze River Economic Belt from 2011 to 2020, finding that the INGE in these areas showed an upward trend, with an average annual growth rate of 1.48%. The regions with high INGE were mainly concentrated in eastern coastal cities, while regions with low INGE were mainly located in central and western China. Gu et al. (2023) constructed fixed effects models, spatial Durbin models (SDM), moderating effect models, and threshold models using panel data from the Beijing-Tianjin-Hebei urban agglomeration from 2011 to 2020. The empirical results showed that industrial digitalization significantly improved urban green development efficiency (GDE), but there were significant spatial differences and imbalances.

2.3 Research methodology for INGE

In the measurement and analysis of INGE, the most commonly applied approaches are Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA is a non-parametric method that constructs an efficiency frontier through linear programming and evaluates relative efficiency in a multi-input–multi-output framework. Since DEA does not rely on a specific functional form of the production function, it offers flexibility and transparency in handling nonlinear and multidimensional input–output structures (Coelli, 1998; Nazarko and Šaparauskas, 2014; Krmac and Mansouri Kaleibar, 2023). By contrast, SFA is a parametric approach that requires the assumption of a specific production function, allowing random noise to be separated from inefficiency effects, which makes it particularly suitable for efficiency analyses where stochastic disturbances are significant (Hjalmarsson et al., 1996; Fall et al., 2018). Consequently, DEA has been more widely applied in policy analysis and composite performance evaluations, while SFA is better suited to contexts where random shocks must be explicitly accounted for. Within DEA, several extended models have been developed. The early CCR (Charnes–Cooper–Rhodes) model assumes constant returns to scale (CRS) and is appropriate for evaluating overall efficiency levels (Koziarski and Woźniak, 2017; Lotfi et al., 2010). The BCC (Banker–Charnes–Cooper) model, by allowing variable returns to scale (VRS), separates pure technical efficiency from scale efficiency (Dellnitz et al., 2018). The Slacks-Based Measure (SBM) model further incorporates slack variables in inputs and outputs, enabling direct treatment of resource waste and output shortfalls. This makes the SBM model particularly suitable for INGE studies, especially in multi-input–multi-output settings involving undesirable outputs such as environmental pollution (Li and Shi, 2014; Zhang et al., 2017). In recent years, the super-efficiency SBM model has been widely employed in interprovincial and firm-level studies of green efficiency. This approach can capture marginal differences in relative efficiency, thereby providing robust evidence for policy evaluation (Huang et al., 2021; Zhong et al., 2021).

In summary, DEA and SFA each have distinct advantages and limitations. DEA is more suitable for green efficiency measurement in multidimensional, multi-output contexts, while the SBM model and its super-efficiency extension offer a more nuanced framework that accommodates environmental constraints and resource inefficiency, yielding intuitive and operational results. Building upon this, the present study employs the super-efficiency SBM model in combination with spatiotemporal analysis of interprovincial INGE and the Geodetector method. This integrated framework systematically reveals the driving forces of INGE and their spatial heterogeneity, thereby providing theoretical and methodological support for China's industrial green transformation policies.

2.4 Innovations of this study

Existing research on INGE still has several limitations. Most studies lack a long-term, dynamic perspective for comparative analysis, and the mechanisms driving INGE remain insufficiently explored. To address these gaps, this study integrates the perspectives of national low-carbon policies, INGE, and its spatiotemporal evolution, employing the super-efficiency SBM

model, Moran's I, and the Geodetector method to analyze the spatiotemporal evolution of interprovincial INGE in China and its driving factors.

The main innovations of this study are as follows: It investigates the spatial clustering and dispersion patterns of China's INGE, analyzing the evolution of green efficiency over a long-term temporal scale. It systematically examines the effects of industrial governance, economic foundations, factor inputs, technological efficiency, environmental governance, natural conditions, and pollutant emissions on INGE, thereby clarifying the underlying driving mechanisms.

3 Research methodology and data sources

3.1 Ecological efficiency evaluation system

Based on the Cobb-Douglas production function and drawing on the research approaches of Tao et al. (2016), Garrett-Peltier (2017), Li and Zeng (2020), Zhang and Choi (2013), Zhang L. et al. (2022), Wang (2023), and Hou et al. (2018), this study constructs a model for measuring China's INGE, focusing on input indicators, desired output indicators, and undesired output indicators (as shown in Table 1). The input factors include labor, measured by the number of industrial employees; capital, estimated using the perpetual inventory method to obtain industrial capital stock; energy, represented by total industrial energy consumption; and water resources, measured by industrial water consumption. The output factors consist of desired output, represented by deflated industrial added value, and undesired output, measured using three indicators: total industrial wastewater discharge, industrial solid waste emissions, and sulfur dioxide (SO_2) emissions in industrial exhaust gas. This study employs MATLAB software and applies the super-efficiency SBM model to calculate China's INGE index.

3.2 Research methodology

3.2.1 Super efficiency SBM model

The super-efficiency SBM (Super-SBM) model directly accounts for input redundancy and output shortfalls, making it suitable for efficiency measurement that includes undesired outputs such as pollutants (Li et al., 2013; Zh et al., 2018). It has been widely applied in the fields of green efficiency, environmental governance, and energy efficiency (Jiang et al., 2020; Yu et al., 2019). The formula is as follows:

$$min\rho^{\star} = \frac{1+\frac{1}{m}\sum_{m=1}^{M}\left(S_m^x/X_m^t\right)}{1-\frac{1}{l+h}\left(\sum_{l=1}^{L}S_l^y/y_{jl}^t+\sum_{h=1}^{H}S_n^b/b_{jh}^t\right)} \tag{1}$$

$$\begin{cases} x_{jm}^t \geq \sum_{j=1,j\neq 0}^{n}\lambda_j^t x_{jm}^t + s_m^x, \\ y_{jl}^t \geq \sum_{j=1,j\neq 0}^{n}\lambda_j^t y_{jl}^t - s_l^y, \\ b_{jh}^t \geq \sum_{j=1,j\neq 0}^{n}\lambda_j^t b_{jh}^t + s_h^b, \\ \lambda_j \geq 0, s_m^x \geq 0, s_y^y \geq 0, j = 1,2,3,\ldots,n, \end{cases} \tag{2}$$

In the formula, $\rho^{\star}$ represents the INGE index; S_m^x, S_l^y, and S_h^b correspond to the respective input, expected output, and non-expected output slack variables; n denotes the number of decision-making units (DMUs); and λ is the weight vector of the decision-making units.

3.2.2 Spatial autocorrelation analysis

The Moran's I index is a commonly used spatial autocorrelation analysis method for measuring the degree of clustering or dispersion of a variable in geographic space (Moran et al., 2008). It can reveal whether there is a spatial agglomeration effect in INGE across regions, as well as its scope and intensity. The calculation formula is as follows:

$$I = \frac{\sum_{i=1}^{n}\sum_{j}^{n}\omega_{ij}\left(x_i-\bar{x}\right)/\left(x_j-\bar{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_j} \tag{3}$$

$$I' = \frac{x_i-\bar{x}}{S^2}\sum_{j}^{n}\omega_{ij}\left(x_i-\bar{x}\right) \tag{4}$$

In the formula, I represents the global Moran's index, I' represents the local Moran's index, n is the number of provinces, i and j are different spatial units, x refers to the proximity of INGE, $\bar{x}$, S^2 is the mean and variance of INGE, and ω_{ij} is the spatial weight matrix. In this study, if the spatial units are adjacent, ω_{ij} as takes the value of 1; otherwise, it takes the value of 0.

TABLE 1 INGE evaluation indicator system.

Variable category	Variable name	Variable description	Unit
Input variables	Labor Input	Average number of industrial workers	Ten thousand people
	Capital Input	Actual capital stock	100 million RMB
	Energy Input	Total industrial energy consumption	Ten thousand tons of standard coal
	Resource Input	Industrial water consumption	100 million cubic meters
Expected output variables	Industrial Added Value	Deflated by the price index	100 million RMB
Unexpected output variables	Industrial Wastewater Discharge	Chemical Oxygen Demand (COD) in wastewater	Ten thousand tons
	Industrial Solid Waste Discharge	Hazardous waste generation	Ten thousand tons
	Industrial Air Emission	Sulfur dioxide emission in waste gases	Ten thousand tons



FIGURE 1
Overview of the study area.

3.2.3 Geodetector

Geodetector is an emerging spatial statistical analysis method that detects the impact of different spatial factors on the spatial heterogeneity of a target variable, thereby revealing its spatial relationships (Zhao et al., 2020; Zhu et al., 2020). The formula is as follows:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} Nh\sigma_h^2 \tag{5}$$

3.3 Study area and data sources

This study focuses on 31 Chinese provinces (excluding Hong Kong and Macau) as the research area, as illustrated in Figure 1, and involves a total of 43 indicators. Economic and social data, including *per capita* GDP, urbanization rate, and total resident population, were obtained from the China Statistical Yearbook and the respective provincial statistical yearbooks. Environmental indicators, such as the proportion of nature reserves, forest coverage, industrial wastewater discharge, generation of general industrial solid waste, and sulfur dioxide emissions from industrial exhaust, were sourced from the China Environmental Statistical Yearbook. Industrial indicators, including the number of industrial employees and total assets of industrial enterprises, were derived from the China Industrial Statistical Yearbook, while data on wastewater treatment capacity were obtained from the China Urban Statistical Yearbook. Additional data were supplemented from official Chinese sources and other reliable authoritative institutions.

4 Temporal and spatial changes in China's INGE

4.1 Temporal changes in China's INGE

Based on panel data from 31 provinces in China from 2005 to 2022, the INGE index of China was calculated using the Super-SBM model (Equations 1, 2). The results are shown in Figure 2.

The national INGE index exhibited a general upward trend followed by a slight decline. Specifically, from 2005 to 2009, the INGE index increased from 0.668 to 0.736, showing a steady growth of approximately 10.16%. From 2010 to 2015, the index declined from 0.767 to 0.623, a decrease of 18.75%. This decline may have been influenced by factors such as industrial overcapacity, high resource consumption, and the failure to fully implement environmental protection requirements. From 2016 to 2022, the INGE index slightly declined from 0.644 to 0.634, showing minor

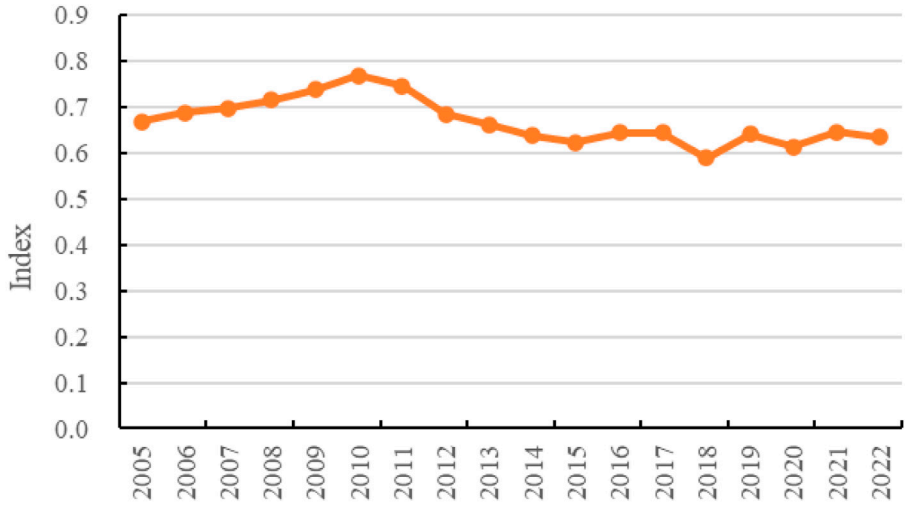


FIGURE 2
Trend of changes in China's INGE index from 2005 to 2022.

fluctuations. In 2022, China's INGE index was 0.634, a 4.2% decrease compared to 2005. Throughout the period from 2005 to 2022, the INGE index in China exhibited certain volatility. Although there were periods of growth, the overall increase was limited, especially after 2015, when a downward trend emerged. During the period from 2005 to 2015, China's economic growth was relatively fast, and there was a positive correlation with the growth of the INGE index. However, after 2016, with the slowdown of economic growth, the improvement in green efficiency did not keep pace, reflecting the lagging effect of industrial structural transformation.

Table 2 shows the INGE indices of China's 31 provinces for selected years.

Overall, there are still significant disparities in the green efficiency indices among provinces in China, with a particularly prominent gap between the developed eastern regions and the underdeveloped western regions. In 2022, only 12 provinces had an INGE index greater than 1.000, and 61.3% of the provinces had an INGE index still below 1.000. Eastern and coastal provinces such as Beijing, Shanghai, Guangdong, and Fujian have consistently maintained a leading position in green efficiency, with most showing a stable upward trend. The green efficiency index in Beijing increased steadily from 1.204 in 2005 to 1.270 in 2022. Shanghai and Guangdong's indices have remained high, consistently exceeding 1.000 since 2005, indicating that these regions have achieved a more mature green transformation driven by green industries, technological innovation, and environmental policies.

Meanwhile, some resource-dependent, heavy industrial provinces such as Hebei, Shanxi, and Heilongjiang generally have green efficiency indices lower than 1.000, and some even show a long-term declining trend. For example, the green efficiency index in Hebei decreased from 0.533 in 2005 to 0.422 in 2022, demonstrating a continuous downward trend. The province's heavy reliance on traditional industries has increased pressure on its green transformation. Heilongjiang's green efficiency index dropped sharply from 1.060 in 2005 to 0.252 in 2022, posing significant challenges in promoting green industrial transformation.

Although central and western provinces such as Hubei, Sichuan, and Shaanxi started later, they showed significant improvements in certain years. For instance, Hubei's green efficiency index reached 0.510 in 2020 and 1.003 in 2022, reflecting the province's initial achievements in green transformation driven by policy initiatives and the application of green technologies. Provinces like Shaanxi and Sichuan also showed some recovery from 2020 to 2022, primarily due to the gradual introduction of green industries and economic restructuring.

Western provinces such as Qinghai, Tibet, and Xinjiang have maintained relatively low green efficiency indices with considerable fluctuations. For example, Tibet's green efficiency index declined from 1.086 in 2005 to 0.183 in 2022, almost reaching its lowest point. Xinjiang's INGE index in 2022 was 0.330, which remains relatively low compared to other provinces.

To examine the robustness of the green efficiency index calculated using the super-efficiency SBM model, this study employs the Malmquist productivity index for comparative analysis. The results show a Pearson correlation coefficient of 0.323 ($p < 0.001$), indicating a significant positive correlation between the annual national average green efficiency index and the Malmquist total factor index, with consistent overall trends. Further examination reveals that efficiency change (EC) remains relatively stable, with annual national averages ranging from 0.94 to 1.06, whereas technological change (TC) exhibits larger fluctuations, with averages ranging from 0.93 to 1.19, making it the primary driver of variations in the Malmquist total index. These findings suggest that the green efficiency index calculated in this study reliably captures the spatiotemporal evolution of interprovincial INGE and demonstrates robust performance.

Furthermore, we calculated the SFA index, and the results show that Super-SBM and the SFA index are significantly positively correlated, with a Pearson correlation of 0.437 and a Spearman correlation of 0.449 ($p < 0.001$). Regression analysis

TABLE 2 Interprovincial INGE indices in key years of China.

Serial number	Country	The INGE index				
		2005	2010	2015	2020	2022
1	Beijing	1.204	1.206	1.230	1.258	1.270
2	Tianjin	1.037	1.045	1.039	1.059	1.055
3	Hebei	0.533	0.553	0.502	0.460	0.422
4	Shanxi	0.570	1.016	0.366	0.449	1.030
5	Inner Mongolia	0.437	0.315	0.293	0.370	0.492
6	Liaoning	0.596	1.002	0.451	0.394	0.354
7	Jilin	0.318	0.332	0.369	0.402	0.327
8	Heilongjiang	1.060	0.598	0.359	0.220	0.252
9	Shanghai	1.119	1.112	1.081	1.130	1.080
10	Jiangsu	0.745	1.003	1.004	1.000	1.023
11	Zhejiang	1.024	1.040	1.058	1.024	1.021
12	Anhui	0.320	0.408	0.397	0.363	0.373
13	Fujian	0.719	1.037	1.043	1.135	1.129
14	Jiangxi	1.011	1.040	0.552	0.421	0.424
15	Shandong	1.087	1.056	1.050	0.673	0.465
16	Henan	1.044	1.058	0.547	1.024	1.024
17	Hubei	0.364	0.606	1.005	0.510	1.003
18	Hunan	0.464	1.004	1.043	1.014	1.015
19	Guangdong	1.087	1.070	1.073	1.064	1.057
20	Guangxi	0.344	0.453	0.336	0.256	0.243
21	Hainan	0.483	0.444	0.323	0.261	0.331
22	Chongqing	0.589	1.017	0.686	0.771	0.651
23	Sichuan	0.353	0.477	0.494	0.622	0.504
24	Guizhou	0.299	0.335	0.343	0.445	0.429
25	Yunnan	0.465	0.452	0.365	0.343	0.333
26	Tibet (Xizang)	1.086	1.073	0.183	0.174	0.183
27	Shaanxi	0.545	1.029	1.081	1.022	1.040
28	Gansu	0.320	0.424	0.298	0.316	0.303
29	Qinghai	0.184	0.215	0.180	0.273	0.221
30	Ningxia	0.250	0.361	0.236	0.249	0.276
31	Xinjiang	1.035	1.009	0.316	0.284	0.330

also indicates that SFA has a significant positive explanatory effect on Super-SBM (regression coefficient = 1.0419, $p < 0.001$). These results suggest that the two methods are consistent in measurement direction and overall trend, indicating that the efficiency evaluation results based on the Super-SBM model are robust and reliable.

To further test the robustness of the green industrial efficiency index calculated using the Super-efficiency SBM model, we computed the Super-SBM index using both industrial exhaust emissions and CO_2 emissions (Super_SBMco2, where CO_2 replaces industrial exhaust). The results show a Pearson correlation of 0.495 ($p < 0.001$) and a Spearman correlation of 0.696 ($p < 0.001$) between the two indices, indicating a significant positive correlation in both overall trend and ranking. This demonstrates that substituting CO_2 emissions for industrial exhaust does not change the overall conclusions of the efficiency evaluation, further confirming the robustness of the Super-SBM results.

TABLE 3 Classification of INGE levels.

I	II	III	IV	V
(0.110, 0.358]	(0.358, 0.527]	(0.527, 0.823]	(0.823, 1.080]	(1.080, 1.273]

4.2 Spatial changes in INGE in China

As revealed in the previous analysis, there are significant spatial differences in China's INGE. To more intuitively observe these spatial disparities, we utilized ArcGIS 17.0 for further visualization. Firstly, the INGE index was categorized into five levels using the natural breaks method. The classification criteria are presented in Table 3.

Overall, the INGE index in China exhibits two peaks, concentrated around the levels of 0.408 and 0.990. Statistical analysis reveals that approximately 35.3% of provinces fall into Level 2, while about 31.0% of provinces are also at Level 2 (Figure 3). Between 2005 and 2014, provinces with relatively low green efficiency (Levels 4 and 5) represented a larger proportion. Starting from 2015, the number of provinces at Level 1 gradually increased, while the number of provinces at Levels 4 and 2 decreased, indicating that some provinces have made progress in improving green efficiency. Notably, between 2020 and 2022, the number of provinces at Level 1 significantly increased to 11, suggesting that China's green transformation has expanded to more provinces. The number of provinces at Levels 2 and 3 has decreased, indicating that most provinces are progressively improving INGE and advancing toward efficient and sustainable green development.

Figure 4 displays the INGE levels of Chinese provinces from 2005 to 2022, with values ranging from 1 to 5, where higher values represent higher INGE. By comparing the changes in levels across different provinces, the long-term trends of green industrial development and regional disparities can be analyzed. Beijing, Shanghai, and Tibet have consistently maintained the highest level (Level 5), with their INGE leading the country and remaining at a high level for an extended period. Coastal economically developed provinces such as Guangdong, Jiangsu, Zhejiang, and Fujian are generally at Levels 4 or 5, indicating strong industrial green development and widespread application of green technologies. In contrast, western provinces like Qinghai, Ningxia, Gansu, and Xinjiang have consistently remained at Levels 1 or 2, reflecting lower INGE and relatively slow green transformation.

As noted earlier, the period from 2016 to 2022 witnessed an acceleration in China's green transformation. Economic provinces like Beijing, Shanghai, Fujian, and Guangdong continued to maintain high levels of INGE. Simultaneously, provinces such as Shaanxi, Yunnan, and Tibet, which had previously been at low-efficiency levels, have gradually moved into the middle-to-high levels, indicating the initial success of industrial transformation. However, resource-dependent and heavy industry-reliant provinces like Heilongjiang, Xinjiang, and Hebei continue to face significant challenges, with little improvement in their green efficiency.

4.3 Spatial correlation analysis of INGE across Chinese provinces

4.3.1 Global spatial autocorrelation analysis

To analyze the spatial clustering of the INGE indices across provinces, a critical spatial matrix was first constructed based on the actual locations of the provinces. Using Equations 2, 3, the Moran's I index for the period 2005–2022 was calculated for China's INGE indices, with the results shown in Table 4.

From the table, it can be observed that from 2005 to 2011, the Moran's I index for China's INGE indices had p-values greater than 0.100, and Z-values were lower than the critical value of 1.65, indicating that the Moran's I index did not pass the test and the

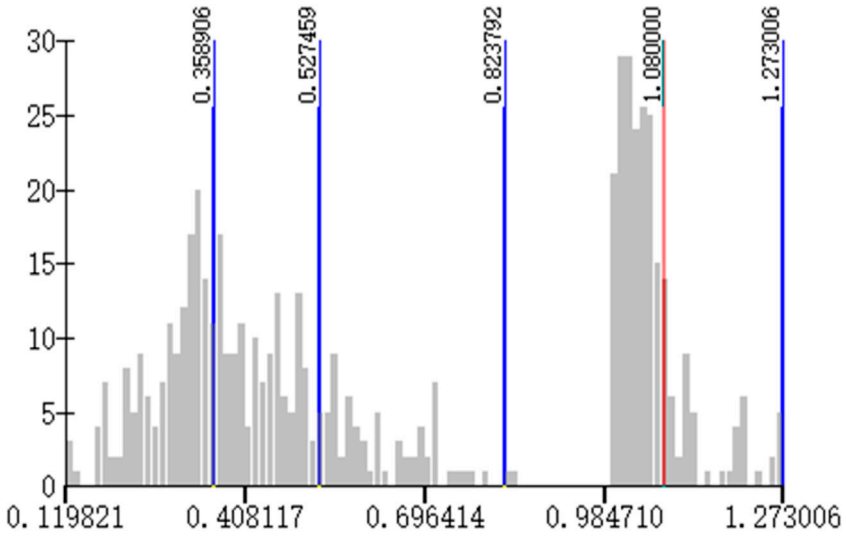


FIGURE 3
Statistical distribution of inter-provincial INGE in China.

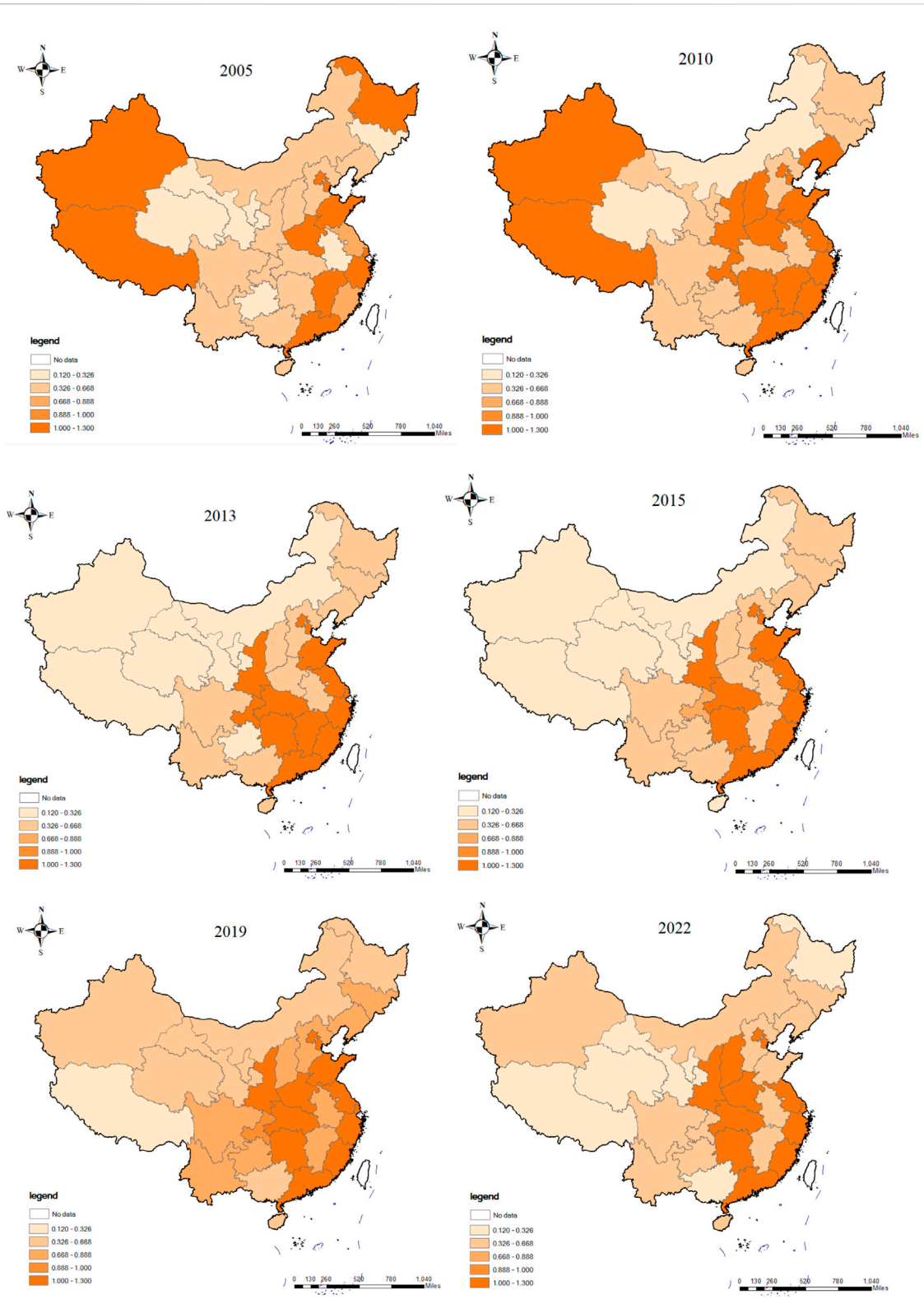


FIGURE 4
Spatial pattern of INGE index in China.

spatial correlation was weak. From 2012 to 2022, the Moran's I index generally increased, and for most years, the p-values were significant at the 5% level, indicating a significant positive spatial correlation in INGE across provinces. This suggests that neighboring provinces exhibited similar trends in green efficiency. Notably, during 2012–2014, the Moran's I index peaked (above 0.3), and the p-values were all less than 0.01, suggesting strong spatial autocorrelation and a gradual reduction in regional disparities in

TABLE 4 Global Moran's I index of INGE from 2005 to 2022.

Year	Moran's I	*p* value	Z value
2005	0.097	1.176	0.120
2006	0.108	1.274	0.101
2007	0.033	0.600	0.274
2008	0.012	0.407	0.342
2009	0.024	0.516	0.303
2010	0.079	1.010	0.156
2011	0.211	2.203	0.014
2012	0.385	3.769	0.000
2013	0.36	3.548	0.000
2014	0.332	3.300	0.000
2015	0.266	2.708	0.003
2016	0.312	3.114	0.001
2017	0.314	3.139	0.001
2018	0.232	2.416	0.008
2019	0.262	2.666	0.004
2020	0.181	1.945	0.026
2021	0.225	2.337	0.010
2022	0.233	2.404	0.008

green efficiency. In 2020–2022, the Moran's I index showed slight fluctuations but remained at a high level, and in most years, the p-values were below 0.05, indicating that the spatial autocorrelation of green efficiency remained evident.

Overall, after 2012, the spatial autocorrelation of INGE across China's provinces gradually increased, demonstrating an enhanced spatial agglomeration. The following factors summarize the reasons for this development, in conjunction with national policy changes. First, policy guidance: since 2010, China has successively implemented three batches of low-carbon city pilot projects. In October 2011, the government officially approved seven provinces and cities, including Beijing, Shanghai, Tianjin, and Shenzhen, to initiate carbon trading pilot projects. Green policies, environmental protection regulations, and related incentive measures have gradually been promoted nationwide, encouraging coordinated development and mutual influence among provinces. Second, technological dissemination: beginning in 2011, the Yangtze River Delta integration facilitated the mutual integration and technology transfer of green industries across provinces. For instance, the experiences of Jiangsu and Zhejiang in green manufacturing and environmental protection industries have been widely adopted by other provinces and cities. The dissemination of green technologies and environmental protection equipment has reduced regional disparities. Third, regional coordination: inter-regional cooperation has strengthened, such as in areas like green energy, environmental protection industries, and the circular economy, promoting collective progress in green development across provinces.

4.3.2 Local spatial autocorrelation analysis

This section utilizes the local Moran's I index to examine the spatial clustering of INGE between the 31 provinces and their neighboring provinces, and to determine whether spatial clustering or spatial dispersion exists in different periods. The results are shown in Figure 5.

Upon observing the Moran's I index, it is evident that the majority of provinces in China exhibit positive values of the INGE Moran's I index, indicating a positive correlation with the clustering of neighboring provinces. Specifically, in 2022, 24 provinces (77.4% of all provinces) had a positive Moran's I index, an increase of 16.1 percentage points compared to 2005. From a spatial distribution perspective, regions such as Shanghai, Zhejiang, and Fujian in the eastern coastal area exhibit significantly positive Moran's I indices, indicating strong spatial clustering. These regions generally have higher green efficiency, primarily due to advanced green industry policies, technological innovations, and strong market competitiveness. In contrast, provinces in central and western regions, such as Hebei, Guangdong, and Hainan, display stronger spatial dispersion, with notable differences in INGE compared to neighboring provinces. This is mainly due to differences in industrial structures, imbalances in resource allocation, and regional variations in policy implementation.

5 Analysis of the influencing factors of provincial INGE in China

As noted above, interprovincial differences in INGE in China are substantial. Existing literature indicates that the formation of INGE is influenced by multiple factors, drawing on theories from environmental and development economics. First, the Environmental Kuznets Curve (EKC) suggests that early stages of economic development are often accompanied by high pollution levels, whereas environmental efficiency gradually improves with industrial upgrading and the adoption of green technologies (Kaika and Zervas, 2013; Dogan and Inglesi-Lotz, 2020). Second, Porter's hypothesis posits that appropriate environmental regulation can stimulate technological innovation in firms, thereby enhancing green efficiency (Lanoie et al., 2011; Rubashkina et al., 2015). Third, based on factor endowment and resource-based theories, inputs such as capital, labor, and energy constitute fundamental sources of efficiency differences (Sokoloff and Engerman, 2000; Quang Dao, 2013). In addition, regional innovation system theory emphasizes the critical role of technological efficiency and innovation diffusion in promoting green transformation (Li X. et al., 2023). It can be seen that, according to the theory of green growth, green efficiency is influenced not only by the level of economic development but also constrained by multiple factors such as resource input, technological innovation, industrial structure, and environmental governance. Therefore, this study constructs an analytical framework for INGE (Figure 6), proposing that seven dimensions—industrial governance, economic foundation, factor input, technological efficiency, environmental governance, natural factors, and pollution emissions—comprising 36 specific indicators (Table 5), collectively influence the spatiotemporal

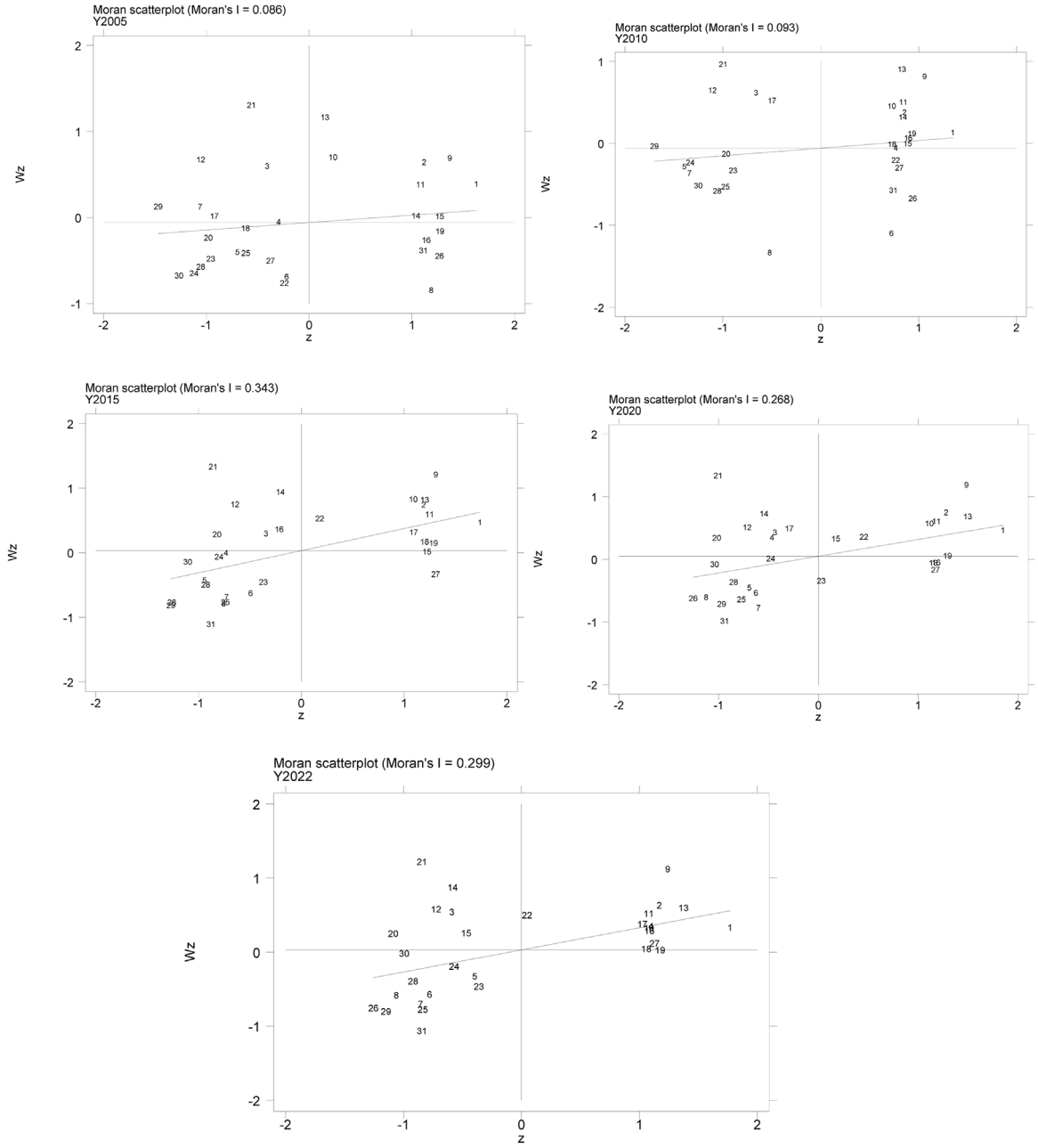


FIGURE 5
Spatial distribution of provincial INGE local autocorrelation in China. The numbers in this figure represent provinces, and their corresponding codes are shown in Table 2.

evolution of INGE through mechanisms such as institutional constraints, development conditions, resource endowments, and innovation diffusion.

To quantitatively identify the impact of these drivers on interprovincial INGE, this study employs the Geodetector method. To reduce the potential bias arising from single-year observations, the period 2005–2022 is divided into six subperiods: 2005–2007, 2008–2010, 2011–2013, 2014–2016, 2017–2019, and 2020–2022. First, each set of indicators is classified using the natural breaks method in ArcGIS. Then, combined with provincial INGE indices, the explanatory power (q-value) of each indicator is calculated based on Equation 5. The results are presented in Figure 5.

Based on the Geodetector analysis (Table 6), the correlation between each dimension and INGE, as well as its temporal evolution, can be quantitatively assessed. Overall, during 2020–2022, industrial governance exhibited the strongest correlation with INGE (q = 1.612), followed by economic foundations (q = 1.153), factor inputs (q = 0.772), technological efficiency (q = 0.637), environmental governance

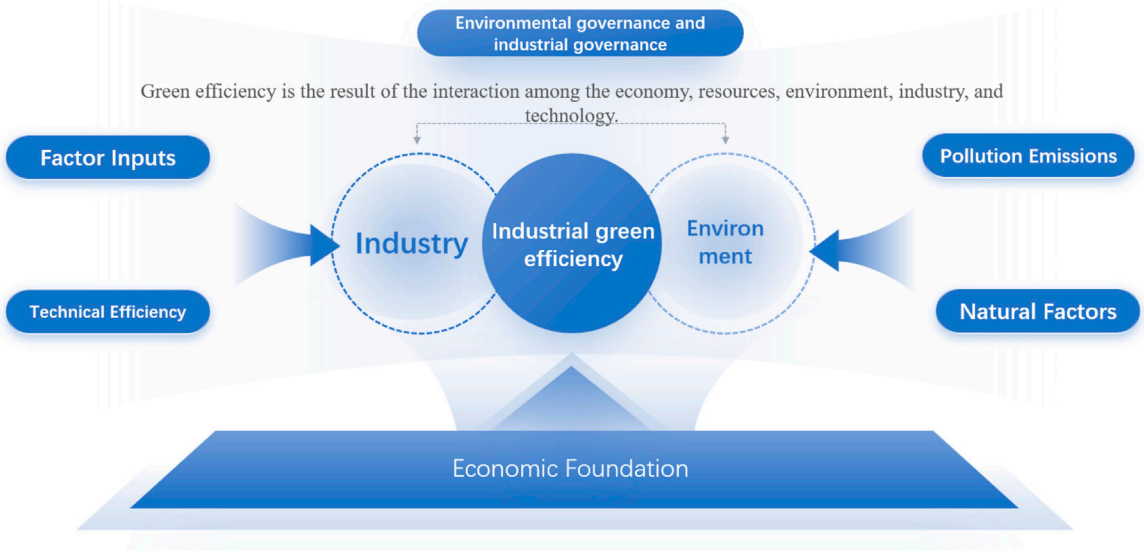


FIGURE 6
Logical framework of factors influencing INGE.

(q = 0.567), natural conditions (q = 0.338), and pollutant emissions (q = 0.239). Since 2005, the correlation of industrial governance has increased by 0.589, representing the largest growth, followed by pollutant emissions (0.125). Industrial governance has consistently ranked first in correlation since 2008, while economic foundations and factor inputs have remained highly correlated, indicating stable associations between these factors and INGE.

Specifically, the correlation of economic foundations has consistently been among the highest across all subperiods, reaching 1.245 in 2017–2019 and ranking second, suggesting a close relationship between the level of economic development and INGE. Factor input correlation was 0.784 in 2005–2007 and gradually increased, peaking at 1.358 during 2014–2016, indicating that labor and capital inputs have increasingly influenced green efficiency. Technological efficiency exhibited relatively stable correlations (medium ranking), suggesting a certain linkage between technological progress and green efficiency, although its strength is lower than that of economic foundations and industrial governance, potentially due to variations in technology maturity and diffusion.

Natural factors showed relatively low and stable correlations (q = 0.184 during 2008–2010, ranked sixth), implying that natural conditions, such as water resources and forest coverage, exert limited short-term influence on INGE. Environmental governance correlations increased markedly from 2008 to 2013, reaching 1.122 during 2011–2013 and ranking second, reflecting the gradual influence of environmental policies and green industrial guidance on INGE. By 2017–2019, environmental governance correlation remained high at 1.110, ranking third, indicating a stable association between governance measures and green efficiency.

Overall, industrial governance, economic foundations, and factor inputs consistently exhibited high correlations across all periods. In 2020–2022, the contribution of industrial governance to INGE correlation reached 30.3%, an increase of 7.3 percentage points compared with 2005. Factors such as industrial agglomeration, industrial upgrading, green finance, and government intervention have become increasingly prominent in their influence on INGE.

Based on the analysis of 36 indicators (Figure 7), the main characteristics and dynamic trends of factors influencing INGE can be summarized.

First, from a dynamic perspective, the correlation between economic foundation factors and INGE shows a continuously increasing trend. The correlation of *per capita* GDP (X1) increased from 0.352 to 0.532, indicating that with economic development, the role of digital economy and green technology investment in promoting INGE has gradually become more prominent. The correlation of industrial structure (X2) fluctuates but shows an overall upward trend, reflecting a certain positive association between the increasing share of the service sector and INGE. The correlation of urbanization rate (X3) varies between 0.259 and 0.343, suggesting that infrastructure development and improvements in energy efficiency during urbanization may have a stable link with green efficiency.

Second, the importance of capital and technological inputs has gradually increased. The correlation of capital investment (X6) rose from 0.206 to 0.293, indicating that capital investment in industrial green development is increasingly associated with green technology upgrading and equipment renewal. R&D investment (X10) peaked at 0.296 during 2011–2013 and then declined to 0.130, reflecting a possible lag effect between technological innovation and INGE, with diminishing marginal correlation.

Third, the negative association of pollutant emissions has gradually weakened. Correlations for wastewater (X11), waste gas (X12), and solid waste (X14) emissions are relatively low and show a

TABLE 5 Selection of influencing factors for provincial INGE in China.

Influencing factors	Impact factor	Impact indicator
Economic foundation	X1: Economic Development Level	GDP *per capita*
	X2: Industrial Structure Proportion	Tertiary Industry Proportion
	X3: Urbanization Level	Urbanization Rate
	X4: Population Size	Total Permanent Population
Factor inputs	X5: Labor Input	Industrial Employment
	X6: Capital Input	Total Industrial Enterprise Assets
	X7: Water Resource Input	Industrial Water Consumption
	X8: Power Input	Electricity Consumption
	X9: Energy Input	Industrial Energy Consumption
	X10: R&D Investment	R&D Expenditure
Pollution emissions	X11: Wastewater Discharge	Chemical Oxygen Demand (COD) in Wastewater
	X12: Exhaust Gas Emissions	Sulfur Dioxide Emissions in Exhaust Gas
	X13: Hazardous Waste	Hazardous Waste Generation
	X14: Solid Waste	General Industrial Solid Waste
Technical efficiency	X15: Economic Cleanliness	Water Usage per 10,000 GDP
	X16: Industrial Water Efficiency	Water Usage per 10,000 Industrial Added Value
	X17: Agricultural Water Efficiency	Water Usage per Unit of Arable Land
	X18: Residential Water Efficiency	Per Capita Domestic Water Usage
Natural factors	X19: Water Resource Quantity	Water Resources per Unit Area
	X20: Water Resource Richness	Per Capita Water Resources
	X21: Water Resource Source	Urban Water Supply Comprehensive Production Capacity
	X22: Water Resource Tension	Water Resource Development Utilization Rate
	X23: Forest Coverage Rate	Forest Coverage Rate
Environmental governance	X24: Water Supply Facilities Construction	Water Supply Coverage Rate (County-level)
	X25: Urban Greening Level	Green Coverage Rate in Built-up Areas
	X26: Ecological Protection Efforts	Proportion of Protected Natural Area
	X27: Ecological Environmental Management Efforts	Per Capita Environmental Water Usage
	X28: Industrial Pollution Control Efforts	Completed Investment in Industrial Pollution Control
	X29: Wastewater Treatment Rate	Wastewater Treatment Rate
	X30: Wastewater Treatment Capacity	Wastewater Treatment Capacity
Industrial governance	X31: Industrial Cluster Index	Industrial Cluster Index
	X32: Industry Digitization	Digital Economy Index
	X33: Industry Advancement Index	Industry Advancement Index
	X34: Financial Inclusion Index	Financial Inclusion Index
	X35: Green Finance Index	Green Finance Index
	X36: Government Intervention	General Budget Expenditure/GDP

decreasing trend, indicating that pollution control measures have partially reduced the negative association between pollutant emissions and INGE.

Fourth, the correlations of industrial agglomeration and green finance have become increasingly significant. The correlation of the industrial agglomeration index (X31) remained relatively stable,

TABLE 6 Driving intensity and ranking of factors influencing interprovincial INGE in China.

Factor	2005–2007		2008–2010		2011–2013		2014–2016		2017–2019		2020–2022	
	Impact effect	Ranking	Impact effect	Ranking	Impact effect	Ranking	Impact effect	Ranking	Impact effect	Ranking	Impact effect	Ranking
Economic foundation	1.093	1	0.871	2	0.869	4	1.069	3	1.245	2	1.153	2
Factor input	0.784	3	0.684	4	0.887	3	1.358	2	0.974	4	0.772	3
Pollution emissions	0.114	7	0.124	7	0.146	7	0.250	7	0.246	7	0.239	7
Technical efficiency	0.632	4	0.509	5	0.615	5	0.594	5	0.719	5	0.637	4
Natural factors	0.269	6	0.184	6	0.437	6	0.517	6	0.548	6	0.338	6
Environmental governance	0.541	5	0.749	3	1.122	2	0.985	4	1.110	3	0.567	5
Industrial governance	1.023	2	0.887	1	1.406	1	1.746	1	1.768	1	1.612	1

reaching 0.219 in 2020–2022, suggesting that resource optimization and regional clustering may have a long-term association with INGE. The correlation of the green finance index (X35) increased from 0.050 to 0.261, reflecting the growing role of green finance in supporting energy-saving projects and green technology development.

Regarding indicator categories: Economic development and industrial structure: Per capita GDP (X1), industrial structure (X2), and urbanization rate (X3) show a stable positive correlation with green efficiency over the long term, particularly in later periods. However, economic growth may have a "threshold effect," whereby the growth in correlation slows after reaching a certain level. Factor inputs and technological innovation: Capital investment (X6) and R&D investment (X10) are significantly correlated with green efficiency, although the marginal correlation of R&D investment decreases, suggesting that the efficiency of technology commercialization still has potential to improve in the green transition. Labor input (X5) shows a relatively low correlation, indicating a limited association between traditional labor-intensive inputs and green efficiency. Resources and environmental governance: Correlations of water resources (X7) and energy inputs (X9) are relatively low, implying that improving resource use efficiency may have a stronger association with green efficiency than merely increasing resource inputs. The negative correlation of pollutant emissions (X11–X14) is weakening, reflecting the increasingly significant role of environmental governance policies in promoting green efficiency. Institutional and policy factors: The correlations of industrial agglomeration (X32) and green finance (X35) have steadily increased, indicating that financial and institutional policies are gradually becoming more influential in industrial green development. Moreover, indicators related to the digital economy show gradually strengthened positive correlations with INGE, suggesting that digital transformation may be one of the key drivers of industrial green development.

To further verify the driving effects of various factors on interprovincial INGE identified by the Geodetector analysis, this study employs the Spatial Durbin Model (SDM) for empirical testing using panel data. The regression results show that the coefficients of most key factors in the SDM align with the directions indicated by the Geodetector analysis, confirming the robustness of their explanatory power. For example, economic foundation indicators (X1: *per capita* GDP; X2: tertiary industry share), R&D investment (X10), and industrial governance-related indicators (X31: industrial agglomeration; X35: green finance) all exhibit significant positive effects, indicating a stable promoting influence on INGE. Some spatial lag variables are also significant, suggesting the presence of notable spatial spillover effects in INGE. This implies that economic development, industrial upgrading, and green finance investment in surrounding regions can impact local green efficiency through regional linkages. In contrast, coefficients for pollutant emissions (X11–X14) and natural factors (X19–X23) are relatively small or insignificant, consistent with the lower q-values observed in the Geodetector analysis. Overall, the main driving factors identified by the Geodetector are confirmed to be robust in the SDM verification.

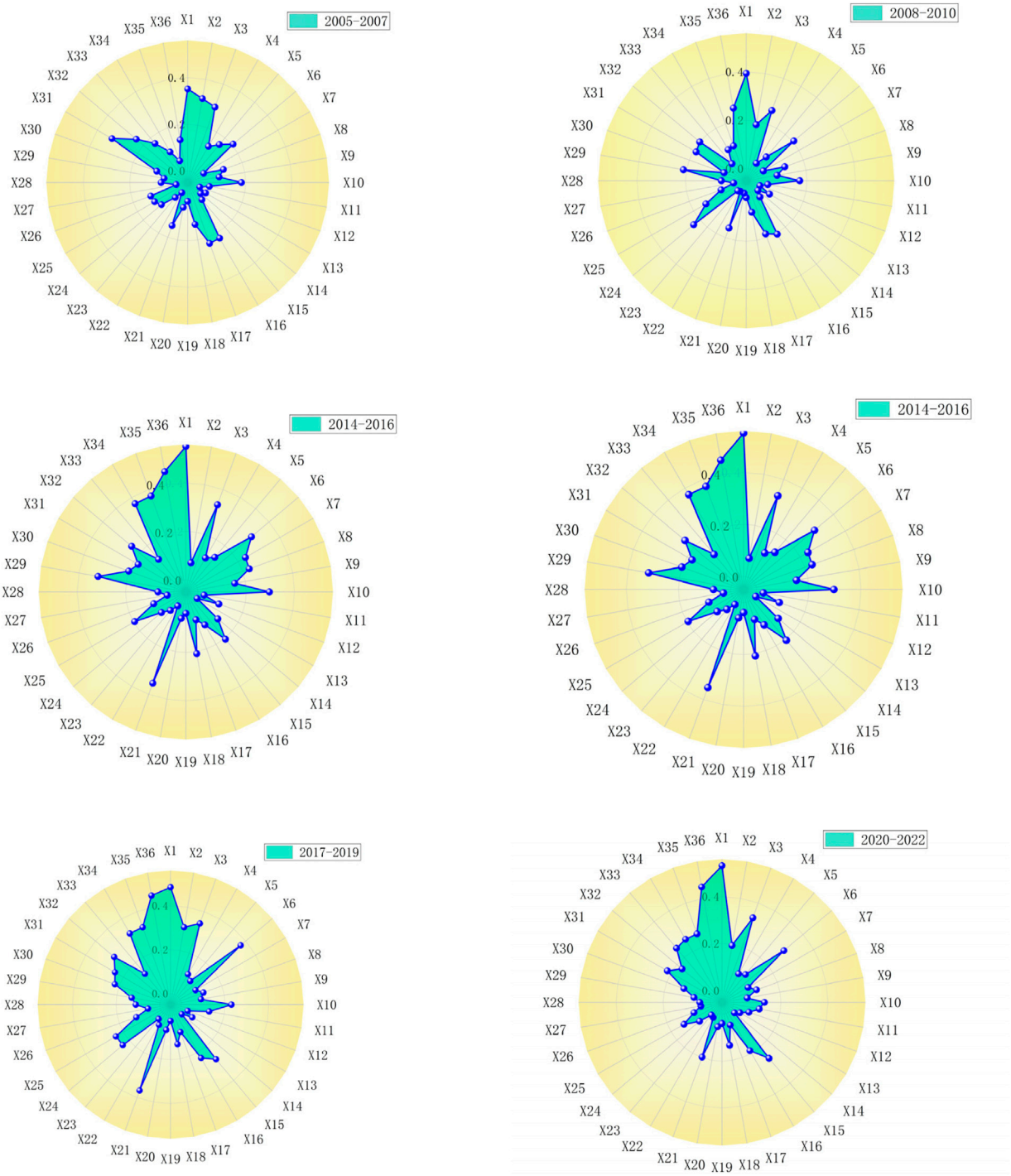


FIGURE 7
Impact effects of 36 indicators on interprovincial INGE in China.

6 Main conclusions and outlook

This study is based on panel data from 31 provinces in China from 2005 to 2022. The provincial INGE index is calculated using the super-efficiency SBM model. This section, with the aid of Moran's index, determines the spatial agglomeration or spatial dispersion phenomenon of provinces during different periods. A total of 36 specific indicators are selected from seven aspects: economic foundation, factor input, pollution emissions, technical efficiency, natural factors, environmental governance, and industrial governance. The geographic detector is used to quantitatively identify the impact effects of each driving factor on the interprovincial INGE in China.

6.1 Main findings

1. Since 2005, China's interprovincial INGE has generally exhibited a trend of initial increase followed by a slight decline. The efficiency index rose from 0.668 in 2005–2009 to 0.736, then decreased to 0.623 during 2010–2015, and slightly increased to 0.634 in 2016–2022. The improvement in efficiency did not fully align with economic growth, reflecting a lag effect in industrial structural transformation.
2. Significant regional disparities in green efficiency were observed. Eastern coastal provinces (e.g., Beijing, Shanghai, Guangdong, Fujian) consistently ranked at the forefront, whereas resource-dependent and heavy-industrial provinces (e.g., Hebei, Shanxi, Heilongjiang) showed limited improvement. Moran's I analysis indicates that approximately 77.4% of provinces exhibited positive spatial correlation with neighboring provinces, suggesting gradually increasing spatial clustering. The eastern coastal regions show pronounced spatial agglomeration, whereas some central and western provinces remain spatially dispersed.
3. Industrial governance has the greatest impact on INGE, followed by economic foundation (q = 1.153), factor inputs (q = 0.772), technological efficiency (q = 0.637), environmental governance (q = 0.567), natural factors (q = 0.338), and pollutant emissions (q = 0.239). The effect of economic foundation on green efficiency has continuously strengthened, while the importance of capital and technological investment has notably increased. The negative effects of pollutant emissions have relatively weakened, whereas the positive impacts of industrial agglomeration and green finance have become increasingly significant.

6.2 Policy recommendations

1. Optimize industrial structure and promote green upgrading. Implement green transformation and industrial upgrading in high-pollution sectors based on regional characteristics to narrow the East-Central-West gap and promote coordinated regional development.
2. Strengthen capital and technological investment. Enhance the conversion of scientific research achievements and technological innovation capabilities to increase the endogenous driving force of INGE.
3. Enhance pollution control and environmental regulation. Continue reducing industrial pollutant emissions, improve environmental governance, and further alleviate constraints on green efficiency.
4. Promote industrial agglomeration and green finance. Leverage the effects of industrial clustering and financial instruments to support green technology innovation, achieving coordinated development of regional industrial chains.

6.3 Limitations and future research

This study employed the Geodetector method to examine the spatial heterogeneity and driving factors of China's interprovincial INGE, revealing the significant roles of industrial governance, economic foundation, and other factors. However, several limitations should be noted:

First, this study adopts the Super-efficiency SBM model, but its inherent limitations are not fully resolved. The super-efficiency SBM may produce efficiency scores that are excessively high and lack comparability; some decision-making units (DMUs) may encounter infeasible solutions in small samples, and the results are sensitive to extreme values. Future studies could cross-validate the results using traditional DEA or SFA methods.

In addition, the geographic detector method itself has certain limitations. On one hand, the results are sensitive to the discretization of variables, and different grouping schemes may lead to variations in explanatory power; on the other hand, multicollinearity among factors may cause overestimation or underestimation of some variables' explanatory effects. Future research is recommended to employ panel threshold models or machine learning approaches to explore complex nonlinear relationships and interaction effects among factors.

Moreover, although this study has tested the robustness of efficiency evaluation results using CO_2 emissions, limitations remain in terms of data availability and coverage, and the selection of input-output indicators still has certain constraints. In the context of carbon neutrality, future research could further incorporate more comprehensive carbon emission data, environmental constraint indicators, and other relevant variables to enhance the scientific rigor and policy relevance of the analysis.

Future research can further expand on this study by analyzing the differentiated effects of various environmental policies on INGE, exploring the mechanisms and nonlinear effects of technological innovation, R&D investment, and green finance on green efficiency, and combining case studies or survey data to conduct more detailed analyses of regional industrial governance and policy implementation effectiveness.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JW: Formal Analysis, Data curation, Writing – original draft, Writing – review and editing, Supervision, Project administration. RX: Formal Analysis, Data curation, Writing – original draft, Writing – review and editing. SY: Supervision, Project administration, Writing – review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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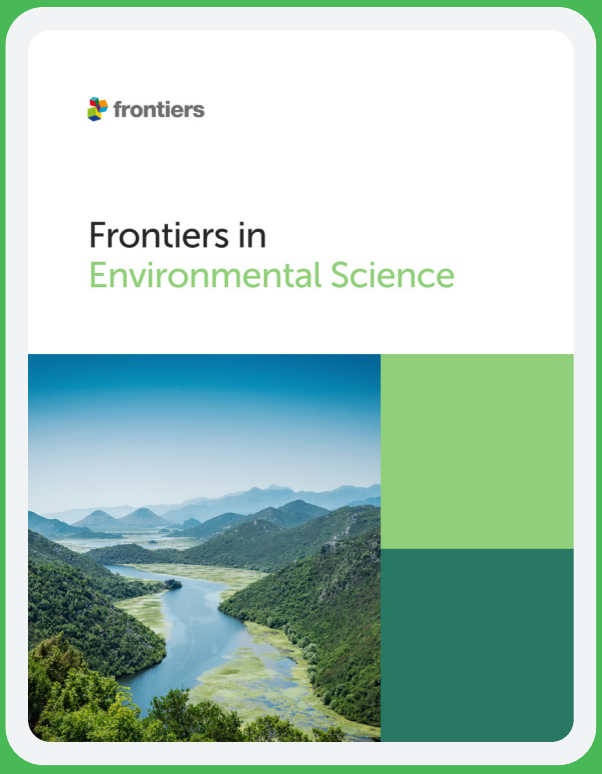
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