frontiers | Research Topics

Urban carbon emissions and anthropogenic activities

Edited by
Ji Zheng, Mariarosaria Lombardi, Joanna Rosak-Szyrocka and Yu Li

Published in
Frontiers in Environmental Science



FRONTIERS EBOOK COPYRIGHT STATEMENT

The copyright in the text of individual articles in this ebook is the property of their respective authors or their respective institutions or funders. The copyright in graphics and images within each article may be subject to copyright of other parties. In both cases this is subject to a license granted to Frontiers.

The compilation of articles constituting this ebook is the property of Frontiers.

Each article within this ebook, and the ebook itself, are published under the most recent version of the Creative Commons CC-BY licence. The version current at the date of publication of this ebook is CC-BY 4.0. If the CC-BY licence is updated, the licence granted by Frontiers is automatically updated to the new version.

When exercising any right under the CC-BY licence, Frontiers must be attributed as the original publisher of the article or ebook, as applicable.

Authors have the responsibility of ensuring that any graphics or other materials which are the property of others may be included in the CC-BY licence, but this should be checked before relying on the CC-BY licence to reproduce those materials. Any copyright notices relating to those materials must be complied with.

Copyright and source acknowledgement notices may not be removed and must be displayed in any copy, derivative work or partial copy which includes the elements in question.

All copyright, and all rights therein, are protected by national and international copyright laws. The above represents a summary only. For further information please read Frontiers' Conditions for Website Use and Copyright Statement, and the applicable CC-BY licence.

ISSN 1664-8714
ISBN 978-2-8325-6752-4
DOI 10.3389/978-2-8325-6752-4

Generative AI statement
Any alternative text (Alt text) provided alongside figures in the articles in this ebook has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

About Frontiers

Frontiers is more than just an open access publisher of scholarly articles: it is a pioneering approach to the world of academia, radically improving the way scholarly research is managed. The grand vision of Frontiers is a world where all people have an equal opportunity to seek, share and generate knowledge. Frontiers provides immediate and permanent online open access to all its publications, but this alone is not enough to realize our grand goals.

Frontiers journal series

The Frontiers journal series is a multi-tier and interdisciplinary set of open-access, online journals, promising a paradigm shift from the current review, selection and dissemination processes in academic publishing. All Frontiers journals are driven by researchers for researchers; therefore, they constitute a service to the scholarly community. At the same time, the *Frontiers journal series* operates on a revolutionary invention, the tiered publishing system, initially addressing specific communities of scholars, and gradually climbing up to broader public understanding, thus serving the interests of the lay society, too.

Dedication to quality

Each Frontiers article is a landmark of the highest quality, thanks to genuinely collaborative interactions between authors and review editors, who include some of the world's best academicians. Research must be certified by peers before entering a stream of knowledge that may eventually reach the public - and shape society; therefore, Frontiers only applies the most rigorous and unbiased reviews. Frontiers revolutionizes research publishing by freely delivering the most outstanding research, evaluated with no bias from both the academic and social point of view. By applying the most advanced information technologies, Frontiers is catapulting scholarly publishing into a new generation.

What are Frontiers Research Topics?

Frontiers Research Topics are very popular trademarks of the *Frontiers journals series*: they are collections of at least ten articles, all centered on a particular subject. With their unique mix of varied contributions from Original Research to Review Articles, Frontiers Research Topics unify the most influential researchers, the latest key findings and historical advances in a hot research area.

Find out more on how to host your own Frontiers Research Topic or contribute to one as an author by contacting the Frontiers editorial office: frontiersin.org/about/contact

Urban carbon emissions and anthropogenic activities

Topic editors

Ji Zheng — The University of Hong Kong, Hong Kong, SAR China

Mariarosaria Lombardi — University of Foggia, Italy

Joanna Rosak-Szyrocka — Częstochowa University of Technology, Poland

Yu Li — Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (CAS), China

Citation

Zheng, J., Lombardi, M., Rosak-Szyrocka, J., Li, Y., eds. (2025). *Urban carbon emissions and anthropogenic activities*. Lausanne: Frontiers Media SA.

doi: 10.3389/978-2-8325-6752-4

Table of contents

05 Editorial: Urban carbon emissions and anthropogenic activities
Mariarosaria Lombardi

08 Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? A quasi-natural experiment from China
Mengyu Wang, Yichun Wang, Ziyi Yang and Bingnan Guo

23 Can urbanization improve carbon performance?
Zhang Jianmin, Yang Yang, Huang Jingyuan and Kao Xiaoxuan

37 All paths to the same end?—a comparative study on carbon emissions reduction effects of digital finance and green finance
Shasha Jiang and Li Wang

59 Advancing towards a low-carbon urban future in China: the role of producer services agglomeration
Shuyang Zhu

71 Does the Belt and Road Initiative reduce smog pollution in key provinces along the route?
Jingao Jiang and Maoguo Wu

91 The impact of new infrastructure development on urban total factor carbon productivity-empirical evidence based on Chinese cities
Yang Liu, Yu Wang, Bing Yan and Hengshuo Zhang

106 Impact of carbon emission trading on urban green innovation: empirical evidence from China's carbon emission trading pilot policy
Kun Tian, Duanqiang Zhai and Shuo Han

121 County-level carbon emissions in the guanzhong area of Shaanxi province: towards achieving China's dual carbon goals
Weichun Gao, Wei He, Jun Zhang, Yifei Chen and Zheng Wei

135 Digital economy, technology, and urban carbon emissions nexus: an investigation using the threshold effects and mediation effects tests
Pengsheng Sun, Ubair Nisar, Zhiyuan Qiao, Shadab Ahmad, Khyati Kathuria, Areej Al Bahir and Mahmood Ahmad

146 The evolution, characteristics, and driving forces of the rural-urban HCEs in China: based on the EIO-SDA model
Yang Yang, Meijian Yang, Jia Luo, Zhengzao Wang, Yuanying Chi and Yahui Chen

158 Carbon reduction effects of government digital attention
Rong Hu and Kaiyi Song

171 The inverted U-shaped impact of the digital economy on indirect household carbon emissions — an empirical study based on CFPS
Ying Chen, Donglin Chen, Chenfeng Gao and Xiaochao Wei

188 Analysis of the impact of the digital economy system on carbon emissions and carbon footprint from the perspective of high-quality development
Youhui Li, Beichuan Chen, Lifeng Guo and Jie Kang

203 The impact of "zero-waste city" pilot policy on corporate green transformation: a causal inference based on double machine learning
Yuren Qian, Jianfeng Jiang, Bingnan Guo and Feng Hu

217 Seeing green high-quality development: how the digital economy affects carbon emissions in the yellow river basin and yangtze river economic belt
Zhijian Lin, Hainan Liu, Lei Shi and Dongxu Cui

237 Impact of livelihood development on CO_2 emissions: empirical evidence from Yangtze River delta urban agglomeration
Zhiming Zhu and Wenxue Lin

249 The impact of digital infrastructure on the synergistic effects of urban pollution and carbon reduction: empirical evidence from China
Fanglin Li and Ziyu Diao

266 Accelerating land use carbon emissions in shrinking counties: a systematic analysis of land use dynamics in the Beijing-Tianjin-Hebei region, 2000–2020
Jianwen Zhang, Li Wang, Meichen Fu, Hongyan Wen and Sijia Li

280 Spatiotemporal analysis of decoupling urban expansion and carbon emissions in China: insights from different expansion and decoupling patterns
Xiangming Lin, Yuantao Liao and Shaojian Wang

frontiers | Frontiers in Environmental Science

TYPE Editorial
PUBLISHED 13 August 2025
DOI 10.3389/fenvs.2025.1669726

Check for updates

OPEN ACCESS

EDITED AND REVIEWED BY
Martin Siegert,
University of Exeter, United Kingdom

*CORRESPONDENCE
Mariarosaria Lombardi,
mariarosaria.lombardi@unifg.it

RECEIVED 20 July 2025
ACCEPTED 01 August 2025
PUBLISHED 13 August 2025

CITATION
Lombardi M (2025) Editorial: Urban carbon emissions and anthropogenic activities. *Front. Environ. Sci.* 13:1669726. doi: 10.3389/fenvs.2025.1669726

COPYRIGHT
© 2025 Lombardi. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Editorial: Urban carbon emissions and anthropogenic activities

Mariarosaria Lombardi*

Department of Economics, University of Foggia, Foggia, Italy

KEYWORDS

environmental policy, digitalization, low-carbon development, China, urbanization, emissions, land use, green transformation

Editorial on the Research Topic
Urban carbon emissions and anthropogenic activities

1 Introduction

The following ten scientific articles have provided robust, data-driven insights into how China can achieve its "dual carbon" goals (carbon peak and neutrality).

They highlight that:

- Digital infrastructure, green innovation, and policy experimentation are critical drivers.
- Policies must be regionally differentiated and technology-driven.
- Effective climate action depends on multi-level coordination, integrating local, regional, and national strategies.

In summary, these studies suggest that China's environmental transition must be smart, digital, inclusive, and tailored to local contexts, leveraging both market-based tools and technological advancement to build a sustainable future.

Specifically, the papers in this Research Topic can be clustered as follows.

2 Policy-driven corporate green transformation

The study by Qian et al. examines the impact of China's "Zero-Waste City" pilot policy on corporate green transformation. Using double machine learning methods on firm-level data (2016–2023), they find that the policy significantly accelerates corporate environmental upgrading. This happens through three main channels: 1) increased green technology innovation; 2) stronger government oversight; and 3) growing investor environmental awareness. Notably, the policy impact is stronger for non-state-owned firms, non-heavy-polluting sectors, and traditional industries, providing valuable evidence for targeted environmental policy effectiveness.

3 Digitalization and low-carbon governance

Digital transformation plays a central role in environmental governance, as highlighted in multiple studies.

- Hu and Song show that greater government digital attention at the city level helps reduce carbon emissions. This is achieved by improving public low-carbon awareness, enhancing governance capacity, and encouraging corporate low-carbon transitions. The effect is stronger in eastern China and in cities with more developed markets.
- Li and Diao focus on digital infrastructure, showing that it supports simultaneous reductions in pollution and carbon emissions, with a significant synergistic effect. It facilitates labor, capital, and innovation flows across cities. A nonlinear U-shaped relationship was found, suggesting that digital infrastructure must be optimized to maximize environmental gains.
- Sun et al. analyze how the digital economy influences urban carbon emissions. The effect is nonlinear: initially, digital development increases emissions, but once a certain threshold is crossed, it facilitates technological innovation, which offsets those emissions. Thus, green tech R&D is key to aligning digital growth with climate goals.

4 Land use, urban shrinkage, and emissions

Land use and demographic changes significantly affect carbon outcomes.

- Zhang et al. examine land use carbon emissions (LUCE) in shrinking counties in the Beijing- Tianjin-Hebei (BTH) region. They find that although shrinking areas emit less overall, their emissions grow faster, mainly due to inefficient urban land expansion. Severe shrinkage areas have the fastest *per capita* emission growth, stressing the need for differentiated carbon control strategies in shrinking urban regions.
- Chen et al. focus on county-level emissions in the Guanzhong region of Shaanxi. Industrial and residential sectors are the largest contributors. The spatial pattern shows a core-edge structure, with urban centers emitting more, while rural areas (like Qinling National Park) have significant carbon sink potential. This highlights the importance of localized strategies for rural low-carbon development.

5 Urbanization, agglomeration, and emissions

Urbanization and industrial agglomeration present both challenges and opportunities.

- Zhu and Lin investigates producer services agglomeration and finds it reduces local urban carbon intensity by enhancing energy efficiency and industrial structure upgrading. However, it has limited spillover effects on surrounding areas. Its benefits are stronger in non-resource-based cities and mid-sized urban areas.
- Conversely, Zhang et al. highlight a paradox: rising urbanization tends to decrease carbon emission performance per unit space. They show strong spatial autocorrelation and spillover effects, especially linked to industrial and energy structure. Therefore, urbanization without structural reforms may hinder carbon efficiency.

6 Policy innovation for pollution and carbon reduction

Innovative environmental policies are a key lever for emissions control.

- Wang et al. assess the impact of Energy-Consuming Rights Trading (ECRT) as a quasi-natural experiment. Their findings show that ECRT significantly improves pollution and carbon reduction, particularly in central and western regions and in resource-based cities. The mechanism relies on green innovation and industrial upgrading. The authors recommend expanding ECRT's coverage and flexibility.
- Jiang and& Wu analyze the environmental impact of the Belt and Road Initiative (BRI). Since 2014, BRI has reduced PM2. 5 levels in key provinces along the route, mainly by fostering technological innovation and industrial restructuring. However, the effect is stronger in areas along the Silk Road Economic Belt, suggesting regional disparities. BRI also improved green total factor productivity, supporting a greener "Belt and Road."

Finally, across these ten studies, it has been possible to reveal a number of cross-cutting insights and policy implications, some of which are outlined below.

✓ Digitalization as a Double-Edged Sword Digital technologies and infrastructure support emissions reduction, but only when paired with technological innovation and regulatory adaptation. Without green innovation, digital development may initially worsen emissions.

✓ Importance of Tailored Regional Policies Geographic and economic differences matter: shrinking cities, mid-sized cities, resource-based regions, and rural counties exhibit distinct emissions patterns. As such, one-size-fits-all approaches are inadequate.

✓ Role of Structural Transformation Structural reforms—especially in industrial upgrading, energy restructuring, and land-use efficiency—are essential complements to any policy aimed at decarbonization.

✓ Synergy between Pollution Control and Carbon Goals Multiple studies confirm that policies promoting air quality improvement (e.g., PM2.5 reduction) often align with carbon reduction goals, offering co-benefits that enhance policy efficiency.

Author contributions

ML: Supervision, Validation, Writing – review and editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The author declares 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 author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 26 June 2024
DOI 10.3389/fenvs.2024.1430031

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Christian Bux,
University of Bari Aldo Moro, Italy
Muhammad Saeed Meo,
Business School, Sunway University, Malaysia

*CORRESPONDENCE
Bingnan Guo,
200600002509@just.edu.cn

†These authors have contributed equally to this work and share first authorship

RECEIVED 09 May 2024
ACCEPTED 06 June 2024
PUBLISHED 26 June 2024

CITATION
Wang M, Wang Y, Yang Z and Guo B (2024), Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? A quasi-natural experiment from China. *Front. Environ. Sci.* 12:1430031. doi: 10.3389/fenvs.2024.1430031

COPYRIGHT
© 2024 Wang, Wang, Yang and Guo. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? A quasi-natural experiment from China

Mengyu Wang†, Yichun Wang†, Ziyi Yang† and Bingnan Guo*

School of Humanities and Social Sciences, Jiangsu University of Science and Technology, Zhenjiang, China

Energy-consuming rights trading (ECRT) policy represents a critical policy instrument for China striving to achieve its "dual carbon" objectives, captivating significant attention for its potential to reduce pollution and carbon emissions. This study utilizes panel data from 290 Chinese cities spanning 2010 to 2021, leveraging the ECRT policy as a quasi-natural experiment. Employing Difference-in-Differences (DID) and Propensity Score Matching-Difference-in-Differences (PSM-DID) methodologies, we assess the effect of the ECRT policy on urban pollution and carbon reduction levels. The findings indicate: 1) Relative to non-demonstration cities, the ECRT policy significantly enhances pollution and carbon reduction levels in demonstration cities; this conclusion remains robust after rigorous testing. 2) Heterogeneity analysis indicates that the policy's effect on pollution and carbon reduction is more significant in the central and western regions, and particularly evident in key and resource-based cities. 3) Mechanism tests demonstrate that the policy facilitates urban pollution and carbon reduction by cultivating green technological innovation and industrial structure upgrading. Therefore, to further advance the ECRT policy, it is necessary to expand the breadth, depth, and flexibility of policy implementation, while also optimizing environmental regulations to fully leverage the system's potential in enhancing urban pollution and carbon emissions.

KEYWORDS

energy-consuming rights trading policy, entropy-weighted TOPSIS model, difference-in-differences model, green technological innovation, industrial structure upgrading, China

1 Introduction

With the persistent advancement of economic and social development, particularly the rapid acceleration of industrialization, the global energy demand has witnessed a surge in both its rate and magnitude. According to the BP Statistical Review of World Energy 2023, global primary energy consumption reached 604.04 exajoules, marking a 1.3% increase from the 2019 level. Specifically, fossil fuels accounted for 82% of the consumption (BP statistical review of world energy, 2023). However, such significant reliance on fossil fuels has given rise to a spectrum of environmental concerns, including air pollution and ecological degradation (Khan et al., 2020; Li and Hu, 2020). The "Climate Change 2021: The

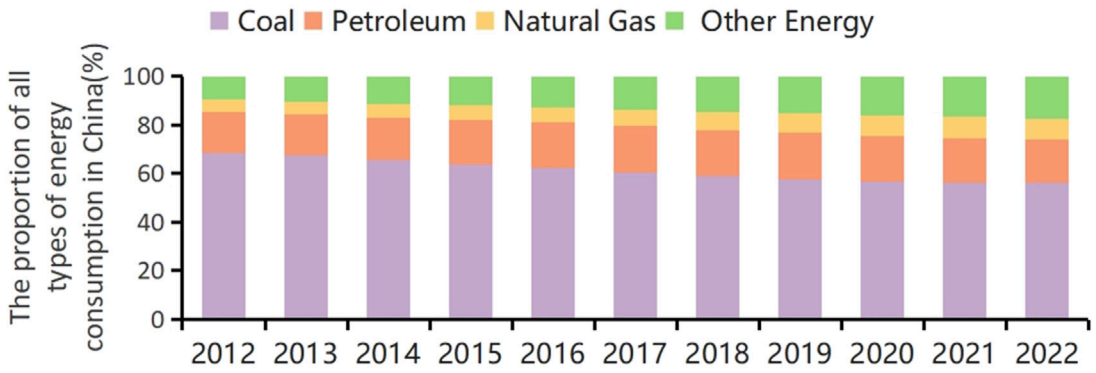


FIGURE 1
Energy consumption structure in China from 2012 to 2022.

Physical Science Basis" report compiled by the Intergovernmental Panel on Climate Change (IPCC) demonstrates that the average surface temperature from 2011 to 2020 surpassed pre-industrial levels by 1.1°C, accompanied by a continuous increase in the frequency and intensity of extreme weather events, posing significant threats to both environmental security and human health (Intergovernmental Panel on Climate C, 2023).

The majority of countries, including China, are experiencing an upward trend in carbon dioxide emissions (Shaari et al., 2021). China's role as the leading global consumer of energy has profound implications for the global environment. The nation's energy consumption and its ensuing pollution emissions issues have become a focal point for academic communities globally (Fatima et al., 2021; Bangjun et al., 2022; Meo et al., 2023; Xiao and Peng, 2023). As illustrated in Figure 1, China's energy mix relies heavily on coal, crude oil, and natural gas, supplemented by other sources such as hydropower and nuclear power.

China's characteristics of resource endowment have long been shaped by "an abundance of coal coupled with limited oil and natural gas reserves". In this light, and combined with an early economic development model characterized by high energy consumption, high emissions, and high pollution, fossil fuels are entrenched as the dominant energy source—notwithstanding their negative environmental impact. While the proportion of coal in the energy mix has steadily declined between 2012 and 2022, it remains significant (Suo et al., 2024). In 2022, China's total energy consumption reached 5.41 billion tons of standard coal equivalent, with fossil fuels—coal, petroleum, and natural gas—accounting for over 80% of this consumption. This continued reliance on fossil fuels poses a considerable challenge, contributing significantly to the country's environmental pollution problems. The "2022 China Environmental Status Report" indicates that among 339 Chinese cities, 126 (37.2%) failed to meet the environmental air quality standards. More specifically, 57 cities exceeded the limit for one pollutant, 31 for two pollutants, and 38 for three pollutants (Ministry of Ecology and Environment of China, 2022). Besides, China's overall environmental performance ranked 160th out of 180 countries in the 2022 Environmental Performance Index (EPI) report. The country also received low rankings for air quality, specifically in terms of environmental particulate matter and other related indicators (Zhong et al., 2024). As the world's largest developing nation, China faces significant gaps in environmental governance compared to developed countries and some emerging economies. Therefore, China faces immense pressure to address environmental challenges and navigate the dual constraints of resource scarcity and environmental degradation (Li et al., 2019). Therefore, a pressing imperative for achieving green and low-carbon development in China is to enhance energy efficiency and establish a development model characterized by low energy consumption, minimal pollution, and reduced emissions, thereby contributing to pollution and carbon reduction.

In response, the Chinese government has implemented a series of measures, including policies for pollutant discharge rights trading and carbon emission rights trading. During the 13th Five-Year Plan period, the "Four Revolutions and One Cooperation" energy security strategy offered guidance for China's energy development in the new era. Building on the pollutant discharge rights trading and carbon emission rights trading policies, the "Overall Plan for Ecological Civilization System Reform" introduced in 2015 first proposed the concept of energy rights. In 2016, pilot projects for energy-consuming right trading (ECRT) policy were initiated in Zhejiang, Fujian, Henan, and Sichuan provinces. The ECRT policy is based on the total energy consumption indicator (typically measured over a 1-year period). This trading occurs in a controlled region where energy-using units are allowed to trade legally obtained energy consumption quotas. The ECRT policy, similar to the European Union's white certificate trading system, emphasizes source control and utilizes the market for optimal resource allocation (Zhang et al., 2023a). Its aim is to achieve "dual control" of total energy consumption and intensity, offering a new pathway for pollution and carbon reduction.

Considering the significant theoretical and practical implications of the ECRT policy, this paper empirically evaluates and discusses several critical yet insufficiently explained issues: Firstly, how will the implementation of the ECRT policy impact the level of pollution and carbon reduction in cities? Secondly, through what mechanisms can pollution and carbon reduction be achieved? Thirdly, does the ECRT policy produce significant differences in pollution and carbon reduction effects across cities with different urban hierarchies, resource endowments, and geographical locations? Addressing these questions will enrich the

empirical research on the effects of the ECRT policy, contributing significantly to the advancement of the energy rights system, promoting harmonious coexistence between humans and nature, and thus facilitating the green transformation of the economy and society. Meanwhile, as a developing nation, China's efforts in pollution and carbon reduction offer a valuable model for other developing countries. These efforts highlight China's commitment to supporting global sustainable development through collaborative initiatives.

This study produces several marginal contributions to the existing literature. First, while most existing studies measure urban low-carbon development utilizing carbon emissions volume or carbon emission efficiency, this study innovatively employs an entropy weight-TOPSIS model. This model evaluates a city's environmental pollution index, which is then multiplied by carbon emissions to represent the city's progress in coordinated pollution and carbon reduction efforts. Second, from the policy perspective of the energy use rights trading scheme, this study utilizes data from 2011 to 2021 across prefecture-level cities to systematically examine the effect of this policy on pollution and carbon reduction. This analysis not only enriches the existing research on the ECRT policy but also provides new evidence to support the promotion of this system and the enhancement of coordinated pollution and carbon reduction efforts in cities. Finally, in terms of research content, the main contributions include three aspects: First, recognizing the common origin of carbon dioxide and other atmospheric pollutants, this paper analyzes the policy's effects on other atmospheric pollutants, thus broadening the scope of research on the environmental effects of the ECRT policy. Second, by considering the differences in geographical location, urban hierarchy, and resource endowments of cities, the study explores the heterogeneous effects of the ECRT policy on urban pollution and carbon reduction, aiding in a targeted understanding of the mechanisms through which the ECRT policy affects urban pollution and carbon reduction. Third, the paper employs a mechanism test model to analyze the role of energy intensity in the ECRT policy's effect on urban pollution and carbon reduction, contributing to a deeper understanding of the mechanisms through which the ECRT policy affects urban pollution and carbon reduction.

The rest of the paper is organized as follows. The second section contains the relevant literature review five and research hypotheses. The third section shows the model setup, data sources, variable definitions, and descriptive statistics. The fourth section reports the empirical results and robustness tests. The fifth section further tests the heterogeneity of cities from three aspects: city locations, city level, and urban resource endowment. It also explores the mechanism of ECRT policy in demonstration cities. The last one, there are conclusions and policy recommendations.

2 Literature review and research hypotheses

Environmental regulatory policies represent one of the effective means to address environmental issues, with their theoretical foundations and practical applications mutually strengthening each other. The "public good" nature of the environment means that spontaneous price mechanisms struggle to address the external diseconomies produced by environmental pollution during economic activities. Methods to address these externalities include the imposition of environmental taxes and the definition of property rights. Originating from Pigou's (Pigou, 1920) 1920 theory, which proposed the use of taxation to resolve the externalities of environmental pollution, environmental taxes represent a typical governmental control approach. The property rights theorem, introduced by Coase (Coase, 2013) in 1960, suggests that by clearly and appropriately defining initial property rights, economic value can be assigned to environmental resources, and resource allocation can be optimized through the market to achieve Pareto efficiency. Building on Coase's theorem, research on environmental regulatory policies has expanded. Dales (Dales, 1970) first applied the concept of property rights to pollution control, introducing "pollution rights trading." Montgomery (Montgomery, 1972), utilizing mathematical economic methods, demonstrated the cost-effectiveness of market-based pollution rights trading systems. In 1976, the U.S. Environmental Protection Agency (EPA) applied pollution rights trading in practice, followed by Germany, Australia, China, and other countries gradually establishing their pollution rights trading policies. Carbon emission rights trading, as an extension of pollution rights trading, was formally established as a new market-based mechanism to address greenhouse gas emissions following the signing of the Kyoto Protocol in 1997. The European Union established the Greenhouse Gas Emission Trading System (EU-ETS) in 2005, applying carbon emission rights trading on a large scale in practice (Brouwers et al., 2016), which has since enriched research in various countries. The ECRT policy is based on pollution rights trading and carbon emission rights trading policies, and it belongs to market-incentive environmental regulatory policies.

China's environmental regulatory policies primarily include command-and-control and market-incentive environmental policies (Xiong et al., 2020). Researchers have noted that China's early environmental governance was based on command-and-control environmental policies (Ren et al., 2018), where the government directly manages and controls, with "mandatory" characteristics such as market access, restrictive use, and price controls. These policies, while strict, often result in displacement effects from corporate production exceeding the benefits brought by innovation, with high implementation costs and relatively low operational efficiency. Market-incentive environmental policies, on the other hand, can internalize externalities through market transactions and economic incentives. China currently has four market-incentive environmental regulatory policies: ECRT policy, pollution rights trading, carbon emission rights trading, and water rights trading. Compared to command-and-control, market-incentive policies are less costly (Jaffe et al., 2003) and offer more significant incentives in reducing pollutant emission intensity (Kathuria, 2006). Market-based environmental regulations, represented by ECRT, pollution rights trading, and carbon emission rights trading, have become important policy tools for countries to address resource, environmental, and climate change issues. Among these, pollution rights trading and carbon emission rights trading are categorized under end-of-pipe management, while ECRT pertains to source control. Guo et al. (2024a) argued that

environmental pollution taxes leverage the advantages of tax systems in market-based resource allocation, utilizing price signals to propel the development of a green and low-carbon economy.

Regarding the effect of environmental regulatory policies on pollution and carbon reduction from an end-of-pipe management perspective, extensive theoretical and empirical research has been conducted in China. This research has explored both the macro and micro effectiveness of environmental regulatory policies in reducing pollution and carbon emissions. Effectiveness includes the effectiveness of pollution rights trading mechanisms in pilot areas for reducing pollutants and the effectiveness of carbon trading policies in reducing carbon emissions.

For instance, Dong et al. (2019), Chai et al. (2022) utilized provincial data, Yan et al. (2020), Feng. (2020), Shen et al. (2023) utilized municipal-level data, and Zhang and Zhang. (2020) utilizing industry data, have empirically demonstrated at a macro level that pollution rights trading policies or carbon emission rights trading policies significantly reduce the emissions of pollutants and carbon dioxide. At the micro level, the focus has primarily been on enterprises, with Chen et al. (2018), Zhu et al. (2022) utilizing firm-level data to prove that end-of-pipe environmental regulatory policies significantly promote emission reductions in enterprises. However, differing opinions on the effectiveness of these reductions exist, such as Shin's (Shin, 2013) view that China lacks the prerequisites for policy innovation and diffusion, with policy imitation prevailing over innovation, thus limiting the effectiveness of emission rights trading policies in reducing pollution. Guo. (2018) argued that emission permit trading policies consist of multiple policy tools, which may conflict with each other, thereby affecting the overall policy implementation, and that excessive intervention by local governments casts doubt on the efficiency of carbon emission rights trading in reducing emissions. Overall, existing research generally agrees that environmental regulatory policies from an end-of-pipe management perspective significantly promote pollution and carbon reduction, yielding environmental dividends (Song et al., 2022).

The effect of ECRT policy on pollution and carbon reduction from a source control perspective is the focal point of this paper. However, empirical studies on this subject are currently limited, with most research utilizing provincial or corporate data and treating ECRT pilot policies as quasi-natural experiments. For instance, Wang (Wang X. et al., 2023) selected panel data from 30 provinces in China from 2011 to 2020, constructing a DID model with the ECRT pilot policy as a quasi-natural experiment, and through regression analysis demonstrated that the ECRT policy can significantly reduce carbon dioxide emissions and emission intensity. Yang et al. (2024), based on provincial panel data, employed a DID model to empirically analyze the carbon mitigation effects of the ECRT policy, confirming that it could significantly reduce carbon dioxide emissions in pilot provinces. Zhang et al. (2023b) offered empirical evidence of carbon mitigation from a micro perspective, utilizing a sample of Chinese carbon-emitting companies from 2011 to 2020 and employing the DID method to study whether the ECRT policy has a dual dividend effect on corporate economic performance and carbon emissions. They found that the ECRT policy could significantly reduce corporate carbon emissions through enhancing technological innovation, thereby achieving environmental dividends. Researchers have also analyzed municipal panel data, such as Wang K. et al. (2023), who utilized the DID method combined with municipal panel data to demonstrate that implementing the ECRT policy can reduce regional carbon emission intensity by encouraging corporate green technological innovation. In their heterogeneity analysis results, the carbon mitigation effects of the ECRT policy were significant in the eastern and central regions. Han et al. (2024), utilizing panel data from 266 Chinese cities, constructed a DID model to demonstrate that the ECRT policy resulted in a reduction of 84.8% in CO_2 and 34.5% in SO_2 in pilot cities compared to non-pilot cities. Compared to studies on environmental regulatory policies from an end-of-pipe management perspective, there are fewer empirical studies on the effect of ECRT pilot policies on pollution and carbon reduction, with most originating from provincial and corporate data and fewer exploring municipal-level data, neglecting the analysis of the reduction effects on atmospheric pollutants other than carbon dioxide. Based on the common origin of carbon dioxide and other atmospheric pollutants and the policy design objectives of the ECRT policy, which aims to promote pollution and carbon reduction at all levels, this paper proposes the following hypothesis.

H1: ECRT policy can significantly enhance a city's capacity for pollution and carbon reduction.

According to Porter's hypothesis, stringent environmental regulatory policies stimulate corporate green technological innovation (Porter and Linde, 1995). Green technological innovation, which adheres to ecological and economic standards (Gao et al., 2022a), has attributes of environmental friendliness, innovativeness, and efficiency, and its importance in sustainable development continues to grow (Zhang et al., 2022). Existing research largely agrees that green technological innovation has a positive effect on pollution and carbon reduction (Chen and Lee, 2020; Shan et al., 2021; Gao et al., 2022b; Dong et al., 2022; Yi et al., 2022), often measured by the number of low-carbon technologies and green invention patents applied for or held by production units. If the cost of green technological innovation for a production unit offsets environmental costs, it will opt for green technological innovation to enhance its market profitability and competitiveness. ECRT policy, focusing on source control, is a market-incentive environmental regulatory policy that internalizes the external environmental costs caused by production units. Under the control of total energy consumption and intensity in the region, pilot area governments are responsible for the allocation of energy rights quotas, periodically granting energy units initial energy rights quotas either freely or for a fee, with differential charges applied for excess usage. In the energy market, energy units are free to trade energy rights quotas. When the cost of energy rights quotas for high-energy-consuming units exceeds the cost of innovation, to offset compliance costs and maximize profits, they will increase investment in green technological innovation, actively engaging in it to enhance input-output levels; otherwise, they will reduce output or purchase quotas to fulfill their energy-saving and consumption-reducing responsibilities (Li and Zhao, 2023). Currently, researchers have utilized empirical methods to prove that ECRT policy significantly incentivizes green technological innovation. For instance, Zhang and Chen. (2023), Shao and Liu. (2024), based

on micro-level data from Chinese enterprises, have empirically demonstrated that the ECRT policy significantly promotes green technological innovation among Chinese enterprises. At the urban level, Guo et al. (2023a), utilizing panel data from 254 Chinese cities from 2005 to 2019, combined with the DID model and Super-SBM method, verified that ECRT policy can enhance urban green development efficiency through green technological innovation. In summary, ECRT policy has an incentivizing effect on corporate green technological innovation, and green technological innovation is critical in promoting pollution and carbon reduction. Based on this, the following hypothesis is proposed.

H2: ECRT policy can promote urban pollution and carbon reduction by cultivating green technological innovation.

Advancing the upgrade of industrial structures is a crucial aspect of supply-side structural reforms (Gao et al., 2022b). Upgrading industrial structures deepens the transformation of traditional industrial sectors, optimizes their input structures, enhances resource utilization efficiency, and facilitates cleaner and more efficient production processes. The significance of industrial structure upgrading in elevating industrial development levels and accelerating pollution and carbon reduction processes is well recognized (Zhou et al., 2013; Dong et al., 2020). Regarding the effect of ECRT policy on industrial structure upgrading, empirical studies have demonstrated that ECRT policy is conducive to promoting industrial structure upgrades (Zhang and Zhou, 2024). The effect of these policies on industrial structure upgrading is twofold: firstly, ECRT policy, by classifying energy rights quotas, constrains high-energy-consuming industries, guiding them to adjust production models, optimize resource allocation, and facilitate the transfer of resources to low-energy-consuming industries, thereby compelling industrial transformation and upgrading (Xue and Zhou, 2022). Secondly, they offer significant market opportunities for emerging industries, leading to cluster effects of new industries, thus driving the development of high-tech industries and achieving the optimization and upgrading of industrial structures (Meng, 2023). In summary, ECRT policy is beneficial in promoting industrial structure upgrades, which can accelerate the process of pollution and carbon reduction. Based on this, the following hypothesis is proposed.

H3: ECRT policy can promote urban pollution and carbon reduction by cultivating the transformation and upgrading of industrial structures.

3 Research design

3.1 Model setup

3.1.1 Entropy-weighted TOPSIS model

The TOPSIS method is an optimal selection method based on the similarity to an ideal solution. Its principle involves utilizing the Euclidean distance to determine the proximity of the evaluation object to the best and worst solutions, thereby achieving a comprehensive evaluation ranking. The entropy-weighted TOPSIS method utilizes the entropy method to determine the weights of evaluation indicators, effectively overcoming the effects of subjective factors present in traditional TOPSIS methods when determining indicator weights. The entropy method allows for a more objective weighting of indicators, more reasonably reflecting the utility value of indicator data.

In environmental pollution management, the reduction of pollutants such as atmospheric pollutants, solid waste, and wastewater can bring about synergistic effects on carbon emission reduction and climate change (Chaudhry et al., 2021). Following the approach of Le et al. (Le et al., 2023), this paper adopts an enhanced entropy-weighted TOPSIS model to measure the environmental pollution index of various prefecture-level cities to represent the local ecological environment quality and degree of environmental pollution. The environmental pollution index calculation involves indicators of "three types of wastes" from 2010 to 2021 for 290 prefecture-level cities in China, specifically including the generation of general industrial solid waste (in ten thousand tons), carbon dioxide emissions from exhaust gases (in ten thousand tons), and total wastewater discharge (in ten thousand tons). The environmental pollution index is an inverse indicator; the higher its value, the more severe the city's environmental pollution and the lower the quality of its ecological environment. The calculation steps are as follows:

First, trend normalization of indicator data, $r_{ij} = \frac{x_{ij}}{min\, x_j}$, where i is the i-th evaluation indicator; j is the j-th evaluation year; x_{ij} is the judgment matrix of size $m \times n$, where $i = 1, 2, \cdots$, m; $j = 1, 2, \cdots$, n; r_{ij} is the normalized value of x_{ij}, R is represented as $(\mathrm{r_{ij}})_{\mathrm{m\times n}}$.

Second, calculate the information entropy e_j, $e_j = -k\sum_{i=1}^{m} f_{ij}\, ln\, f_{ij}$, $f_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$ ($\mathrm{k} = \frac{1}{ln\, m}$ is the Boltzmann constant).

Third, determine the weight values W_j, $W_j = \frac{1-e_j}{n-\sum_{j=1}^{n} e_j}$, $W_j \in [0, 1]$, and $\sum_{j=1}^{n} W_j = 1$.

Fourth, construct the weighted normalized decision matrix $Z = (z_{ij})_{m\times n} z_{ij} = W_j \times r_{ij}$.

Fifth, calculate the positive and negative ideal solutions and perform weighted processing on the normalized indicator values to construct the trend-normalized weighted normalized matrix Z, where Z^+ represents the positive ideal solution, and Z^- represents the negative ideal solution.

$$Z^+ = \left\{ \max_{1\le i\le m} z_{ij} \middle| i = 1, 2, \cdots, m \right\} = \{z_1^+, z_2^+, \cdots, z_n^+\} \tag{1}$$

$$Z^- = \left\{ \min_{1\le i\le m} z_{ij} \middle| i = 1, 2, \cdots, m \right\} = \{z_1^-, z_2^-, \cdots, z_n^-\} \tag{2}$$

Sixth, calculate the Euclidean distances to the positive and negative ideal solutions, denoted as S^+ and S^-, respectively, representing the distances of each evaluation scheme to the positive and negative ideal solutions.

$$S^+ = \sqrt{\sum_{j=1}^{n} \left(Z_{ij} - Z_j^+\right)^2} \, (i = 1, 2, \cdots, m) \tag{3}$$

$$S^- = \sqrt{\sum_{j=1}^{n} \left(Z_{ij} - Z_j^-\right)^2} \, (i = 1, 2, \cdots, n) \tag{4}$$

Finally, calculate the proximity to the ideal solution ($\mathrm{C_i}$), where $(\mathrm{C_i}) = \frac{S_i^-}{S_i^+ + S_i^-}$. The proximity ($\mathrm{C_i}$) indicates the distance of the evaluation object to the positive ideal solution, i.e., the closeness

of the evaluation target to the optimal solution, with $C_i \in [0, 1]$. Since all selected calculation indicators are inverse indicators, a C_i closer to one indicates that the city's ecological environment quality is closer to the worst level, while a C_i closer to 0 indicates that the city's ecological environment quality is closer to the optimal level.

3.1.2 DID model

Based on the Environmental Stress Model (IPAT), experimental and control groups are constructed from demonstration cities and policy implementation timings to test the policy effect of the carbon emission trading mechanism on pollution and carbon reduction. Drawing on the research method of Guo et al. (2024b), by introducing time dummy variables (*Time*) and city dummy variables (*Treat*), a Difference-in-Differences model is constructed as follows:

$$emission_{it} = \alpha_0 + \alpha_1 did_{it} + \alpha_c X_{it} + \sigma_t + \delta_i + \varepsilon_{it} \quad (5)$$

where $emission_{it}$ represents the pollution and carbon reduction level of city i in year t. The level of pollution and carbon reduction is characterized by the interaction term of carbon emissions and the environmental pollution index, both of which are inverse indicators. Constructing an interaction term reflects the overall reduction level and exhibits common source characteristics, aligning with the "common source of carbon and pollution" theory and fitting the holistic and systemic nature of pollution and carbon mitigation governance. did_{it} is a dummy variable for the ECRT policy; α_1 represents the policy effect of ECRT; X_{it} includes control variables; σ_t denotes fixed effects by year; δ_i represents city fixed effects; ε_{it} is the random disturbance term. This model effectively controls for characteristic differences and time trends between the experimental and control groups to some extent.

3.1.3 Variable description

3.1.3.1 Explained variable

Pollution and carbon reduction level (*emission*). Based on the availability of city level pollution and carbon reduction data and existing literature practices, this paper applies the Eqs 1–4 and characterizes the city's pollution and carbon reduction level utilizing the interaction term of carbon emissions and the environmental pollution index.

3.1.3.2 Explanatory variable

ECRT policy (*DID*). This variable is a dummy variable, taking a value of one in the year and following years when an ECRT policy is implemented in a city or its province, and 0 otherwise.

3.1.3.3 Control variables

In order to more accurately assess the effect of the ECRT policy on the city's pollution and carbon reduction levels, this paper controls for other factors that may affect city pollution and carbon emissions. These include city population size (*lnpop*), represented by the logarithm of the city's permanent population; economic development level (*lngdp*), represented by the logarithm of *per capita* GDP; education level (*lnedu*), represented by the logarithm of local government education spending; fiscal expenditure (*lnpfe*), represented by the logarithm of general budgetary expenditures of local finances; and foreign direct investment (*fin*), represented by the ratio of actual foreign direct investment to GDP.

TABLE 1 Descriptive statistics of the variables.

Variable	Obs	Mean	Std	Min	Max
Emission	3,480	0.097	0.061	0.004	0.621
DID	3,480	0.065	0.243	0	1
Lnpop	3,480	2.548	0.305	1.306	3.532
Lngdp	3,480	7.190	0.410	6.017	8.635
Lnedu	3,480	5.689	0.349	4.181	7.060
Lnfep	3,480	6.454	0.336	5.086	7.930
Fin	3,480	1.007	0.714	0.462	7.450
Ris	3,480	0.960	0.631	0.047	5.584
Patent	3,480	7.476	19.070	0.011	307.110

3.1.3.4 Mechanism variables

The transmission mechanism involves two variables: industrial structure upgrading (*ris*), indicated by the ratio of the value added of the tertiary sector to the secondary sector; and green technological innovation (*patent*), represented by *per capita* patent grants.

This study utilizes panel data from 290 prefecture-level and above cities in China from 2010 to 2021 to appraise the effect of the ECRT policy on urban pollution and carbon reduction. The data are derived from the "China City Statistical Yearbook," "China Environmental Statistical Yearbook," and various prefecture-level statistical yearbooks. Descriptive statistics of the variables are demonstrated in Table 1.

4 Empirical results and robustness tests

4.1 Baseline regression

The baseline regression results based on Eq. 5, as displayed in Table 2, assess the effect of the ECRT policy on pollution and carbon reduction. Column (1), controlling only for individual and year-fixed effects, demonstrates an interaction coefficient of −0.026, significant at the 1% level. Columns (2) to (7) add control variables sequentially to Column (1)'s model. After accounting for other factors, the core explanatory variable *DID* consistently demonstrates a significant negative coefficient, indicating a robust incentivizing effect of the ECRT policy on local pollution and carbon reduction, thereby enhancing environmental welfare for local residents. Therefore, Hypothesis H1 is confirmed.

Moreover, coefficients for permanent population and economic development level are significantly positive, suggesting that higher economic levels and larger populations increase carbon dioxide emissions. Conversely, coefficients for educational financial support, local fiscal support, and openness are significantly negative, indicating that increased educational and fiscal expenditures, along with greater openness, contribute to reducing carbon emissions and enhancing environmental conditions.

TABLE 2 Baseline regression results.

Variable	(1)	(2)	(4)	(5)	(6)	(7)
DID	−0.026*** (0.004)	−0.034*** (0.004)	−0.036*** (0.004)	−0.031*** (0.003)	−0.033*** (0.003)	−0.034*** (0.003)
Lnpop		0.069*** (0.003)	0.071*** (0.005)	0.072*** (0.005)	0.077*** (0.005)	0.071*** (0.005)
Lngdp			−0.058*** (0.004)	−0.074*** (0.004)	−0.119*** (0.005)	−0.117*** (0.005)
Lnedu				−0.038*** (0.003)	−0.025*** (0.003)	−0.026*** (0.003)
Lnfep					−0.106*** (0.007)	−0.099*** (0.007)
Fin						−0.006*** (0.001)
Con	0.099*** (0.001)	−0.076*** (0.008)	−0.227*** (0.017)	−0.108*** (0.019)	0.005 (0.020)	−0.017 (0.020)
Obs	3,480	3,480	3,480	3,480	3,480	3,480
R^2	0.014	0.132	0.186	0.225	0.279	0.282
Id-fixed	YES	YES	YES	YES	YES	YES
Year-fixed	YES	YES	YES	YES	YES	YES

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

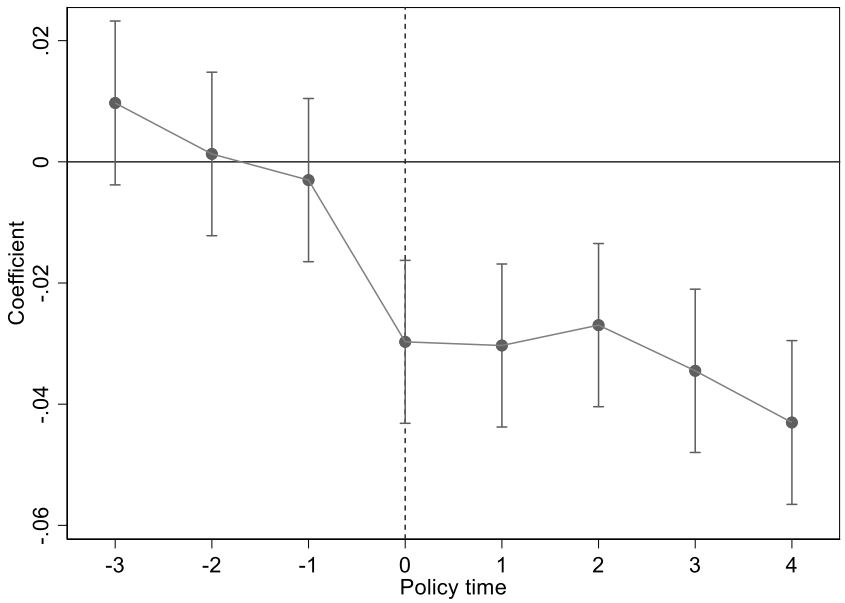


FIGURE 2
Parallel trend test graph.

4.2 Parallel trend test

A fundamental prerequisite for employing the Difference-in-Differences approach is satisfying the parallel trends assumption. This involves that, prior to the implementation of the ECRT policy, the experimental and control groups' urban pollution and carbon reduction levels must follow the same temporal trends. Following the methodology of Bi et al. (2019), an event study model is constructed as follows:

$$emission_{it} = \alpha_0 + \sum_{k=-3,k\neq-1}^{4} \alpha_k did_{it}^k + \alpha_c X_{it} + \sigma_t + \delta_i + \varepsilon_{it} \quad (6)$$

where i represents the city, and t denotes the year; did_{it}^k expresses a dummy variable representing the "event" of implementing the ECRT policy. The assignment rule for did_{it}^k is as follows: let u_i denote the policy implementation time point of the ECRT policy. If $t - u_i = k$, then $did_{it}^k = 1$; otherwise, $did_{it}^k = 0$. The setting of k is as follows: since the year of implementation is the 0th period, and the first batch was established in 2017, 2021 marks the fourth year of the pilot area's establishment, hence the maximum value of k in Eq. 6 is four; periods prior to the implementation of the ECRT policy extend back seven periods, but due to graphical limitations, this paper consolidates the 5th, 6th, and 7th years before the pilot into the

TABLE 3 PSM—DID regression results.

Variable	(1)	(2)
DID	−0.026*** (0.004)	−0.035*** (0.003)
Obs	3,480	3,480
R^2	0.014	0.278
Controls	No	YES
Id-fixed	YES	YES
Year-fixed	YES	YES

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

fourth year prior, and the 2nd year before the pilot is utilized as the base period to avoid multicollinearity, thus Eq. 6 does not include the dummy variable for $k = -1$. The coefficient α_k reflects the effect of the energy rights system before and after its implementation on the city's pollution and carbon reduction levels. If $k < 0$, the parameter α_k is not significantly different from 0, indicating that it has passed the parallel trend test, as depicted in Figure 2.

In Figure 2, the horizontal axis represents the number of years before and after the establishment of the ECRT policy, and the vertical axis represents the level of urban pollution and carbon reduction. It is evident that before the implementation of the energy rights system, the estimated values of α_k do not reject the null hypothesis of being zero, satisfying the parallel trends test. The regression coefficients after the implementation of the energy rights system indicate that cities implementing this policy experienced an immediate improvement in pollution and carbon reduction levels.

4.3 Analysis based on the PSM-DID method

Another prerequisite for utilizing the Difference-in-Differences approach is that the selection of experimental and control groups must satisfy the randomness assumption. This paper uses control variables as covariates and employs the Mahalanobis distance matching method to match samples of the experimental and control groups, thus reducing selection bias. Specifically, a Logit regression of the policy dummy variable on control variables is conducted to obtain propensity score matching values, with cities having similar scores as the control group. After obtaining matched experimental and control groups, it is necessary to test whether they satisfy the common support assumption, i.e., whether there are significant differences between the groups post-matching. The absence of significant differences in the test results post-matching confirms the effectiveness of the PSM-DID method employed in this study.

Meanwhile, the study evaluates the matching effect of the experimental and control groups through the probability density function graph of the propensity scores. The probability density distributions of the propensity scores for the matched experimental and control groups are closer post-matching compared to pre-matching, indicating a good matching effect.

After verifying the reliability of the PSM-DID method, further regression analysis is conducted, with results demonstrated in Table 3. Similar to the baseline regression results, the mean regression coefficients of the policy dummy variable are significantly negative, indicating that the implementation of the ECRT policy has a reducing effect on urban pollution and carbon emissions, thereby confirming the robustness of the baseline regression results.

4.4 Robustness tests

4.4.1 Placebo test

This study adopts the analytical approach of Yang et al. (2019) by conducting a placebo test as follows: Firstly, 55 cities are randomly selected from a total of 290 as a "pseudo-experimental group," assuming these cities have implemented the ECRT policy, with the remaining cities as the control group. Then, a random year is selected for the "pseudo-experimental group" as the policy year (pseudo policy time), and a "pseudo policy dummy variable" (interaction term) is created for regression analysis. This process is repeated 500 times, yielding 500 regression results, including regression coefficients, standard errors, and p-values for the "pseudo policy dummy variable." The distribution of the estimated coefficients is then plotted to appraise whether factors other than the ECRT policy significantly affect the cities' pollution and carbon reduction levels. As illustrated in Figure 3, the estimated coefficients from random grouping are primarily distributed around zero, significantly differing from the true coefficients, with most p-values exceeding 0.1. This indicates that the implementation of the ECRT policy has no significant effect on the randomly selected experimental group, further confirming the robustness and reliability of the research findings.

4.4.2 Exclusion of other policies' effects

The introduction of other policies may also affect urban pollution and carbon reduction levels. Specifically, the low-carbon city pilot policy and the carbon trading policy, implemented around the same period, could potentially affect pollution and carbon reduction. The low-carbon city pilot policy was officially implemented starting July 2010, with following phases launched in November 2012 and January 2017. This policy advocates for industrial restructuring and energy consumption reduction to achieve "dual carbon" objectives and control total carbon emissions. Accordingly, a corresponding policy dummy variable, *DID1*, is established: for demonstration cities, the year of the pilot and following years are set to 1, while other years are set to 0. Besides, in 2011, China initiated the construction of a carbon emissions trading market, designating Shenzhen, Beijing, Shanghai, Tianjin, Guangdong, Hubei, Chongqing, and Fujian as carbon trading pilot regions. Enterprises can buy and sell additional carbon emission rights based on production and operational needs, offering a new pathway for corporate carbon reduction. The policy implementation nodes for this are set in 2011 and 2017, with a corresponding dummy variable, *DID2*, established. The energy-saving and emission reduction measures adopted by the low-carbon city pilot policy and the carbon trading policy have a certain effect on pollution and carbon reduction, suggesting that

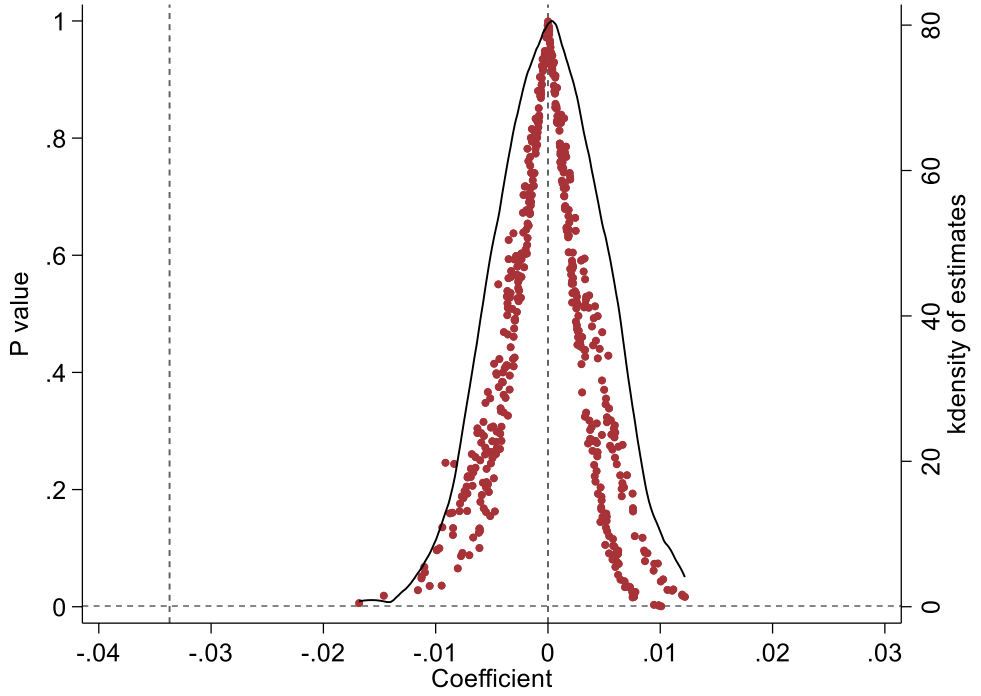


FIGURE 3
Placebo test.

TABLE 4 Robustness test excluding other policies' interference.

Variable	(1)	(2)	(3)
DID	−0.038*** (0.003)	−0.035*** (0.003)	−0.038*** (0.003)
DID1	−0.016*** (0.002)		−0.013*** (0.002)
DID2		−0.016*** (0.003)	−0.007** (0.003)
Con	−0.051** (0.021)	−0.041** (0.021)	−0.057*** (0.021)
Obs	3,480	3,480	3,480
R^2	0.291	0.285	0.292
Controls	YES	YES	YES
Id-fixed	YES	YES	YES
Year-fixed	YES	YES	YES

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

the effect of the ECRT policy on pollution and carbon reduction levels in pilot areas may have been overestimated.

To eliminate interference from two other policies, dummy variables *DID1* and *DID2* are incorporated into the baseline regression model. The regression results, as presented in Table 4, indicate that both the low-carbon city pilot policy and the carbon trading policy significantly affect urban pollution and carbon reduction levels. Even under these conditions, the regression coefficient of the policy dummy variable for the establishment of the ECRT policy remains significantly negative and virtually unchanged. This finding suggests that the pollution reduction attributed to the ECRT policy has not been overestimated.

4.4.3 Policy exogeneity

The multi-period Difference-in-Differences model requires that the experimental and control groups could not have formed effective expectations prior to the policy implementation, necessitating the assurance of policy exogeneity. Therefore, the regression equation includes a dummy variable for the 3 years prior to the implementation of the ECRT policy (i.e., 2014), with results presented in Table 6. The regression results, after including control variables and controlling for city-fixed effects and year-fixed effects, exhibit that the core explanatory variable's coefficient remains significantly negative, while the coefficient for 2014 is not significant, indicating the absence of anticipatory effects.

4.4.4 Substitution of the explained variable

Following existing literature practices, the baseline regression previously utilized an interaction term of carbon emissions and the environmental pollution index to measure the city's pollution and carbon reduction levels. Industrial sulfur dioxide is also a significant contributor to urban pollution. This paper substitutes industrial sulfur dioxide (*lnso2*) as the dependent variable in the baseline regression for a robustness test, with results demonstrated in Table 5. The inclusion of control variables results in a significantly negative coefficient for the policy dummy variable, further demonstrating the relative robustness of the previous findings.

4.4.5 Exclusion of central cities

The sample data in this study includes 290 cities, including ordinary prefecture-level cities as well as provincial capitals, sub-provincial cities, and municipalities directly under the central government. The behavioral patterns of local governments in

TABLE 5 Other robustness tests.

Variable	Anticipatory Effects Test	Substitution of the Explained Variable	Exclusion of Central Cities
DID	−0.031*** (0.005)	−0.017*** (0.001)	−0.029*** (0.003)
Con	−0.012 (0.020)	0.446*** (0.007)	0.174*** (0.022)
Obs	3,480	3,480	3,480
R^2	0.278	0.087	0.313
Id-fixed	YES	YES	YES
Year-fixed	YES	YES	YES

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

TABLE 6 Regional heterogeneity test.

Variable	Eastern	Central-Western
DID	0.002 (0.004)	−0.021*** (0.003)
Con	0.022 (0.072)	0.010 (0.117)
Obs	3,480	3,480
R^2	0.870	0.696
Controls	YES	YES
Id-fixed	YES	YES
Year-fixed	YES	YES

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

TABLE 7 City Level heterogeneity test.

Variable	Core	Ordinary
DID	−0.010*** (0.002)	0.015 (0.015)
Con	−0.043 (0.071)	−0.078 (0.117)
Obs	3,480	3,480
R^2	0.869	0.868
Controls	YES	YES
Id-fixed	YES	YES
Year-fixed	YES	YES

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

cities of different administrative levels may vary significantly, and higher-level cities control more resources than ordinary cities, potentially leading to biases when regressing all cities together. Therefore, this paper excludes samples from provincial capitals, sub-provincial cities, and municipalities directly under the central government, retaining only ordinary prefecture-level cities for regression. The results, also demonstrated in Table 5, indicate that after excluding central cities, the implementation of the ECRT policy continues to significantly reduce urban pollution intensity and carbon emissions, further verifying the robustness of the aforementioned conclusions.

5 Further tests

5.1 Heterogeneity tests

5.1.1 Regional heterogeneity test

Given the geographical diversity and economic disparities across provinces in China, this study divides the 30 provinces into two sub-samples: Eastern and Central-Western regions. It then conducts regression analyses to assess the effect of the ECRT policy on urban pollution and carbon reduction levels in these regions. The heterogeneity test results, as presented in Table 6, indicate that the policy dummy variable's coefficient is positive and not significant in column 1), but significantly negative in column 2). This indicates that the ECRT policy has a significant effect on reducing carbon dioxide emissions and improving environmental pollution in the Central-Western regions of China, but not in the Eastern regions. This discrepancy can be attributed to the more advanced industrial transformation and ecological management systems in the Eastern regions, which have already achieved success, rendering the effect of the ECRT policy less significant there. In contrast, the Central and Western regions are still in the early stages of industrial transformation, with heavy industry playing a dominant role in their industrial structures. The ongoing severe resource depletion and environmental pollution in these regions make enhancing the ecological environment a pressing issue, hence the more significant policy effects of the ECRT policy.

5.1.2 City level heterogeneity test

The scale and classification of cities might also influence the pollution reduction effects observed in the experimental groups. On one hand, compared to ordinary cities, core cities have significant advantages in terms of industrial structure, government financial input, and transportation levels. These advantages enable core cities to effectively allocate resources through economic agglomeration effects, thereby better addressing environmental pollution issues. On the other hand, core cities carry more functions and have a stronger demand for energy consumption, necessitating the use of significant land resources, which can lead to congestion effects and exacerbate environmental pollution. Therefore, based on the "Notice on Adjusting Urban Scale Division Standards" issued by the Chinese government in 2014, this study categorizes the experimental and control groups into

TABLE 8 Urban resource endowment heterogeneity test.

Variable	Non-Resource-Based	Resource-Based
DID	0.008 (0.007)	−0.039*** (0.002)
Con	0.005 (0.119)	−0.266*** (0.008)
Obs	3,480	3,480
R^2	0.867	0.307
Controls	YES	YES
Id-fixed	YES	YES
Year-fixed	YES	YES

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

core cities and ordinary cities. Core cities include municipalities directly under the central government, provincial capitals, separately planned cities, and special economic zone cities, while ordinary cities comprise all other cities. The regression results in Table 7 indicate that, compared to ordinary cities, core cities experience a stronger pollution and carbon reduction effect under the ECRT policy. This conclusion suggests that as China continues to establish and optimize its environmental regulatory policies, the governance models of core cities are transforming, which is expected to further alleviate the congestion effects faced during their development.

5.1.3 Urban resource endowment heterogeneity

To explore the differential effects of the ECRT policy on resource-based and non-resource-based cities under varying resource endowments, this study refers to the "National Sustainable Development Plan for Resource-based Cities (2013–2020)" issued by the Chinese government in 2013. Based on the resource endowments of the cities, the 290 cities selected for this study are categorized into 114 resource-based cities and 176 non-resource-based cities. The regression results in Table 8 indicate that the ECRT policy's pilot in resource-based cities has a more significant effect on pollution and carbon reduction. This may be attributed to the relatively homogenous industrial structure of resource-based cities, primarily characterized by labor-intensive and capital-intensive industries with high carbon emissions and pollution levels. The ECRT policy facilitates the flow of innovative elements in resource-based cities, accelerating the transformation and upgrading of industrial structures through the spillover of low-carbon production technologies, thereby promoting industrial low-carbon development and enhancing the capacity for pollution and carbon reduction in these cities.

5.2 Mechanism analysis

Previous results indicate that the ECRT policy significantly reduces urban pollution levels and carbon emissions. The development of the ECRT policy can impact urban pollution and carbon reduction through two channels: upgrading industrial structures and cultivating green technological innovation. Therefore, a transmission effect model is constructed as follows.

Step One: appraise the effect of the implementation of the ECRT policy on the mechanism variables:

$$mech_{it} = \alpha_0 + \alpha_1 did_{it} + \alpha_c X_{it} + \sigma_t + \delta_i + \varepsilon_{it} \quad (7)$$

Step Two: Assess the effect of the mechanism variables on urban pollution and carbon reduction levels:

$$emission_{it} = \beta_0 + \beta_1 mech_{it} + \beta_c X_{it} + \sigma_t + \delta_i + \varepsilon_{it} \quad (8)$$

where $mech_{it}$ represents the mechanism variables, with other variables defined as in Eq. 5. The implementation of the ECRT policy primarily enhances the city's capacity for pollution and carbon reduction by promoting industrial structure upgrading and green technology innovation.

The paper conducts mechanism analysis according to Eqs 7, 8. Table 9 reports the results of the influencing mechanisms of the ECRT policy on urban pollution and carbon reduction levels: The ECRT policy reduces urban pollution levels by promoting industrial structure upgrading and cultivating green technological innovation, thereby optimizing the capacity for pollution and carbon reduction. Hypothesis H2 and H3 are confirmed.

TABLE 9 Mechanism analysis.

Variable	Industrial Structure Upgrading		Green Technology Innovation	
	Ris (1)	Emission (2)	Patent (3)	Emission (4)
DID	0.040*** (0.003)		0.174*** (0.046)	
Ris		−0.050*** (0.012)		
Patent				−0.005*** (0.002)
Obs	3,456	3,456	3,456	3,456
R^2	0.817	0.862	0.799	0.835
Controls	Yes	Yes	Yes	Yes
Id-fixed	Yes	Yes	Yes	Yes
Year-fixed	Yes	Yes	Yes	Yes

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; robust standard errors are in parentheses.

6 Discussion

The implementation of the energy use rights trading scheme in China stands as a significant measure taken towards ecological advancement and green development, carrying substantial weight in curtailing energy consumption and emissions, cultivating clean energy development, and propelling economic transformation and upgrading. Studies have demonstrated a significant improvement in pollution and carbon reduction in pilot cities as a direct result of this system, confirming its positive environmental impact. However, research indicates that the improvement in pollution and carbon reduction in these pilot cities only saw a modest increase of 0.034 units, suggesting that the energy use rights trading scheme has not comprehensively enhanced pollution and carbon reduction at the individual prefecture-level city, and its efficacy may not be universally applicable. Several factors could contribute to this limited impact. 1) While China's adoption of an energy use rights trading scheme signals a clear commitment to ecological progress, the system remains in its early stages and has not benefited from the full force of policy and financial backing thus far, which has limited its effectiveness. 2) There appear significant gaps in the supplementary measures and policy support across different pilot regions. For instance, Fujian province has, since 2017, continuously introduced implementation documents for the ECRT policy. These documents have outlined quota allocation plans, providing a legal framework for the scheme. In contrast, the current design of the ECRT policy in Henan province primarily focuses on enterprise compliance, aiming to achieve the province's total energy consumption control targets through market mechanisms, resulting in insufficient market vibrancy. 3) Variations in geographical location, city level, and resource endowment across cities have led to discrepancies in the effectiveness of the energy use rights trading scheme. These gaps could lead to significant differences in the environmental benefits the system brings to different prefecture-level cities.

A mechanistic analysis reveals that cities primarily enhance their level of pollution and carbon reduction through industrial structures upgrading and green technological innovation. Enhanced green technology innovation enables enterprises to implement cleaner production practices, thereby improving urban environmental performance. Moreover, technological innovation represents a fundamental driving force for optimizing and upgrading industrial structures. By optimizing the allocation of energy and resources, industrial structural upgrading can effectively reduce energy consumption.

Heterogeneity analysis reveals that the pollution and carbon reduction levels of cities in central and western China, core cities, and resource-based cities are more significantly influenced by the energy rights trading system. This could be attributed to the fact that eastern regions have relatively mature industrial transformation, upgrading, and ecological environment governance systems, leading to certain achievements. In contrast, central and western regions remain in early phases of industrial transformation and upgrading. The development model dominated by heavy industries still holds a prominent position in their industrial structure, and resource depletion and environmental pollution remain serious concerns. Therefore, the policy effects are more significant in central and western regions. Compared to ordinary cities, core cities possess more comprehensive infrastructure, a more rational industrial layout, and abundant government financial support, providing fertile ground for developing the ECRT policy. On the other hand, ordinary cities have relatively insufficient policy support, and their high-energy-consuming industries are not sensitive to market incentives. Therefore, the impact of the ECRT policy is less significant in ordinary cities compared to core cities. In comparison to non-resource-based cities, resource-based cities in China have richer natural resource endowments but face long-term challenges such as a single industrial structure and high dependence on fossil fuels. The economic development of resource-based cities relies more on resource development and utilization, and related industries often exhibit characteristics of high energy consumption and high emissions, resulting in relatively high energy conservation and emission reduction potential. This renders the ECRT policy more effective in enhancing carbon emission efficiency. The economic development of non-resource-based cities relies more on service industries, manufacturing, and technological innovation. These industries have higher energy utilization efficiency and relatively lower energy conservation and emission reduction potential. However, the ECRT policy can still significantly enhance urban carbon emission efficiency by upgrading industrial structures, cultivating green technology innovation, and facilitating industrial structure upgrading.

In contrast to previous studies (Guo et al., 2023b; Guo et al., 2024c; Feng et al., 2024) that relied on traditional statistical methods, this study leverages panel data from pilot regions to shed lights on the relationship between energy rights trading schemes and urban pollution and carbon reduction initiatives. Addressing the limitations of existing literature (Yang et al., 2023; Hu et al., 2024; Jia et al., 2024; Qiu et al., 2024), this research optimizes the evaluation index system for pollution and carbon reduction at the prefecture-level city. This comprehensive system consists of four key aspects of pollutant emissions: general industrial solid waste generation, carbon dioxide emissions from exhaust gases, total wastewater discharge, and overall carbon emissions.

7 Conclusion and recommendations

This study utilizes panel data including 290 Chinese cities from 2010 to 2021, employing an advanced entropy weight-TOPSIS model to quantify environmental pollution indices. The implementation of the ECRT policy represents a "quasi-natural experiment," with the DID model facilitating empirical analysis. Findings demonstrate that the ECRT policy effectively mitigates urban environmental pollution and carbon emissions. While low-carbon city pilot policies and carbon trading policies also contribute to pollution reduction and decarbonization, robustness tests confirm that the effect of the ECRT policy is not overstated. Heterogeneity studies indicate a more significant effect of the ECRT policy on pollution reduction and emission control in central and western regions compared to the eastern regions. Besides, core cities can leverage the ECRT policy to reduce congestion effects, significantly alleviating pollution emissions. Resource-rich cities, specifically, can enhance the pollution reduction effects of the ECRT policy. Mechanism tests illustrate that the ECRT policy reduces energy intensity, thereby effectively

enhancing urban pollution reduction and decarbonization capabilities.

Based on these conclusions, the following policy recommendations are proposed:

Firstly, accelerate the advancement and optimization of China's ECRT market infrastructure. Observations from demonstration cities indicate a synergistic effect of market-incentive-based ECRT policy in reducing carbon emissions and environmental pollutants, achieving coordinated enhancement in pollution reduction and decarbonization. These experiences could be disseminated to other industries and fields, exploring and establishing markets for energy rights, emission rights, and other resource-environmental rights, thereby realizing coordinated governance levels and maximizing environmental management objectives.

Secondly, promote the transformation and upgrading of the energy consumption structure. Mechanism action tests demonstrate that the synergistic effect of the ECRT policy on pollution reduction and decarbonization is driven by cultivating green technological innovation and industrial structure upgrading. Therefore, it is crucial to widely promote green energy-saving emission reduction technologies, clean and efficient processes, and accelerate the transition from traditional to emerging, zero-carbon energies in industrial development. Besides, China needs to expedite the transformation and upgrading of industrial structures, transform traditional high-energy-consuming industries, continuously promote the efficient operation of green industrial projects, and consistently enhance regional green development levels.

Thirdly, coordinated governance of pollution reduction and decarbonization necessitates localization. Empirical results and heterogeneity analysis indicate regional imbalances in China's coordinated governance level of pollution reduction and decarbonization. Environmental pollution management should be tailored to regional economic levels and developmental disparities, exploring locally suitable economic development policies and measures, thereby achieving regional environmental management goals while enhancing coordinated efficiency in pollution reduction and decarbonization.

8 Limitations and future prospects

This study is not without several limitations attributable to data availability and methodological limitations. 1) The findings of this study are based on a Chinese dataset. Future research should explore data sources from other emerging economies to assess the validity and generalizability of these conclusions. 2) This study primarily focuses on the mediating effects of green technology innovation and industrial structure upgrading on the pollution and carbon reduction at the prefecture-level city. However, other potential influencing factors, such as government support and corporate environmental performance, were not included. This might impact the comprehensiveness of the analysis. Future studies should consider incorporating these factors to enrich the current findings. 3) The emissions trading scheme remains in its early phrases of development, resulting in a scarcity of relevant indicators. The effectiveness of emissions trading systems is significantly influenced by market maturity. Future research should study how market forces affect corporate environmental performance and evaluate the impact of the emissions trading market size on urban pollution and carbon reduction efforts.

Data availability statement

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

Author contributions

MW: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Visualization, Writing–original draft, Writing–review and editing. YW: Data curation, Formal Analysis, Investigation, Methodology, Project administration, Resources, Writing–original draft, Writing–review and editing. Ziyi Yang: Data curation, Formal Analysis, Funding acquisition, Methodology, Project administration, Resources, Writing–review and editing. Bingnan Guo: Writing–review and editing, Conceptualization, Project administration, Supervision.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Bangjun, W., Linyu, C., Feng, J., and Yue, W. (2022). Research on club convergence effect and its influencing factors of *per capita* energy consumption: evidence from the data of 243 prefecture-level cities in China. *Energy* 263, 125657. doi:10.1016/j.energy.2022.125657

Bi, C., Jia, M., and Zeng, J. (2019). Nonlinear effect of public infrastructure on energy intensity in China: a panel smooth transition regression approach. *Sustainability* 11, 629. doi:10.3390/SU11030629

BP statistical review of world energy (2023). *Insights by source and country | statistical review of world energy*. energyinst.org).

Brouwers, R., Schoubben, F., Van Hulle, C., and Van Uytbergen, S. (2016). The initial impact of EU ETS verification events on stock prices. *Energy Policy* 94, 138–149. doi:10.1016/j.enpol.2016.04.006

Chai, S., Sun, R., Zhang, K., Ding, Y., and Wei, W. (2022). Is emissions trading scheme (ETS) an effective market-incentivized environmental regulation policy? Evidence from China's eight ETS pilots. *Int. J. Environ. Res. Public Health* 19 (6), 3177. doi:10.3390/ijerph19063177

Chaudhry, I. S., Nazar, R., Ali, S., Meo, M. S., and Faheem, M. (2021). Impact of environmental quality, real exchange rate and institutional performance on tourism receipts in East-Asia and Pacific region. *Curr. Issues Tour.* 25, 611–631. doi:10.1080/13683500.2021.1894101

Chen, Y., and Lee, C.-C. (2020). Does technological innovation reduce CO2 emissions? Cross-country evidence. *J. Clean. Prod.* 263, 121550. doi:10.1016/j.jclepro.2020.121550

Chen, Y., Sun, Y., and Wang, C. (2018). Influencing factors of companies' behavior for mitigation: a discussion within the context of emission trading scheme. *Sustainability* 10 (2), 414. doi:10.3390/su10020414

Coase, R. H. (2013). The problem of social cost. *J. Law Econ.* 56 (4), 837–877. doi:10.1086/674872

Dales, J. H. (1970). *Pollution, property and prices;: an essay in policy-making and economics, F.*

Dong, B., Xu, Y., and Fan, X. (2020). How to achieve a win-win situation between economic growth and carbon emission reduction: empirical evidence from the perspective of industrial structure upgrading. *Environ. Sci. Pollut. Res. Int.* 27 (35), 43829–43844. doi:10.1007/s11356-020-09883-x

Dong, F., Dai, Y., Zhang, S., Zhang, X., and Long, R. (2019). Can a carbon emission trading scheme generate the Porter effect? Evidence from pilot areas in China. *Sci. Total Environ.* 653, 565–577. doi:10.1016/j.scitotenv.2018.10.395

Dong, F., Zhu, J., Li, Y., Chen, Y., Gao, Y., Hu, M., et al. (2022). How green technology innovation affects carbon emission efficiency: evidence from developed countries proposing carbon neutrality targets. *Environ. Sci. Pollut. Res.* 29 (24), 35780–35799. doi:10.1007/s11356-022-18581-9

Fatima, T., Karim, M. Z. A., and Meo, M. S. (2021). Sectoral CO2 emissions in China: asymmetric and time-varying analysis. *J. Environ. Plan. Manag.* 64 (4), 581–610. doi:10.1080/09640568.2020.1776691

Feng, Y. (2020). Does China's carbon emission trading policy alleviate urban carbon emissions? *IOP Conf. Ser. Earth Environ. Sci.* 508 (1), 012044. doi:10.1088/1755-1315/508/1/012044

Feng, Y., Guo, B., Wang, X., and Hu, F. (2024). Facilitating or inhibiting? The impact of environmental information disclosure on enterprise investment value. *Environ. Sci. Pollut. Res.* 31 (5), 7793–7805. doi:10.1007/s11356-023-31583-5

Gao, P., Wang, Y., Zou, Y., Su, X., Che, X., and Yang, X. (2022a). Green technology innovation and carbon emissions nexus in China: does industrial structure upgrading matter? *Front. Psychol.* 13, 951172. doi:10.3389/fpsyg.2022.951172

Gao, P., Wang, Y., Zou, Y., Su, X., Che, X., and Yang, X. (2022b). Green technology innovation and carbon emissions nexus in China: does industrial structure upgrading matter? *Front. Psychol.* 13, 951172. doi:10.3389/fpsyg.2022.951172

Guo, B., Feng, W., and Lin, J. (2024a). Does market-based environmental regulation improve the residents' health: quasi-natural experiment based on DID. *Inq. J. Health Care Organ. Provis. Financing* 61, 469580241237095. doi:10.1177/00469580241237095

Guo, B., Feng, Y., and Hu, F. (2024b). Have carbon emission trading pilot policy improved urban innovation capacity? Evidence from a quasi-natural experiment in China. *Environ. Sci. Pollut. Res.* 31 (7), 10119–10132. doi:10.1007/s11356-023-25699-x

Guo, B., Feng, Y., Lin, J., and Wang, X. (2024c). New energy demonstration city and urban pollutant emissions: an analysis based on a spatial difference-in-differences model. *Int. Rev. Econ. Finance* 91, 287–298. doi:10.1016/j.iref.2024.01.048

Guo, B., Feng, Y., and Wang, X. (2023b). The effect of environmental information disclosure on carbon emission. *Pol. J. Environ. Stud.* doi:10.15244/pjoes/173106

Guo, B., Hu, P., Zhang, H., Weng, X., and Hu, F. (2023a). The improvement of energy-consuming right trading policy on the efficiency of urban green development. *Front. Environ. Sci.* 11, 11. doi:10.3389/fenvs.2023.1123608

Guo, H. (2018). China's experiment of emission permits trading. *Environ. Dev.* 26, 112–122. doi:10.1016/j.envdev.2018.02.001

Han, D., Bi, C., Wu, H., and Hao, P. (2024). Energy and environment: how could energy-consuming transition promote the synergy of pollution reduction and carbon emission reduction in China? *Urban Clim.* 55, 101931. doi:10.1016/j.uclim.2024.101931

Hu, F., Ma, Q., Hu, H., Zhou, K. H., and Wei, S. (2024). A study of the spatial network structure of ethnic regions in Northwest China based on multiple factor flows in the context of COVID-19: evidence from Ningxia. *Heliyon* 10 (2), e24653. doi:10.1016/j.heliyon.2024.e24653

Intergovernmental Panel on Climate C (2023). *Climate change 2021 – the physical science Basis: working group I contribution to the sixth assessment report of the intergovernmental panel on climate change*. Cambridge: Cambridge University Press.

Jaffe, A. B., Newell, R. G., Stavins, R. N., Mäler, K.-G., and Vincent, J. R. (2003). *Chapter 11 - technological change and the environment handbook of environmental economics*. Germany: Elsevier, 461–516. doi:10.1016/S1574-0099(03)01016-7

Jia, S., Zhu, X., Gao, X., and Yang, X. (2024). The influence of carbon emission trading on the optimization of regional energy structure. *Heliyon* 10 (11), e31706. doi:10.1016/j.heliyon.2024.e31706

Kathuria, V. (2006). Controlling water pollution in developing and transition countries—lessons from three successful cases. *J. Environ. Manag.* 78 (4), 405–426. doi:10.1016/j.jenvman.2005.05.007

Khan, H., Khan, I., and Binh, T. T. (2020). The heterogeneity of renewable energy consumption, carbon emission and financial development in the globe: a panel quantile regression approach. *Energy Rep.* 6 (6), 859–867. doi:10.1016/j.egyr.2020.04.002

Le, D., Ren, F., and Li, Y. (2023). The effect of energy use rights trading policy on environmental performance: evidence from Chinese 262 cities. *Int. J. Environ. Res. Public Health* 20 (4), 3570. doi:10.3390/ijerph20043570

Li, S., and Zhao, C. (2023). Driving effects of energy-consuming right transaction system on corporate low-carbon technological innovation. *China Popul. Resour. Environ.* 33 (10), 124–134. doi:10.12062/cpre.2023061

Li, X., and Hu, Z. (2020). Interaction between economic growth energy consumption and environmental pollution. *Int. J. Environ. Pollut.* 68, 162. doi:10.1504/IJEP.2020.120159

Li, Z., Shao, S., Shi, X., Sun, Y., and Zhang, X. (2019). Structural transformation of manufacturing, natural resource dependence, and carbon emissions reduction: evidence of a threshold effect from China. *J. Clean. Prod.* 206, 920–927. doi:10.1016/j.jclepro.2018.09.241

Meng, Z. (2023). Whether the Pilot Policy of "Trading with Energy Rights" can promote regional industrial transformation and upgrading: evidence from 282 prefecture-level cities in China. *Sci. Technol. Industry* 23 (18), 40–46.

Meo, M. S., Nathaniel, S. P., Khan, M. M., Nisar, Q. A., and Fatima, T. (2023). Does temperature contribute to environment degradation? Pakistani experience based on nonlinear bounds testing approach. *Glob. Bus. Rev.* 24 (3), 535–549. doi:10.1177/0972150920916653

Ministry of Ecology and Environment of China (2022). *China environmental Status bulletin 2022*. Available at: https://www.mee.gov.cn/hjzl/sthjzk/zghjzkgb/202305/P020230529570623593284.pdf.

Montgomery, W. D. (1972). Markets in licenses and efficient pollution control programs. *J. Econ. Theory* 5 (3), 395–418. doi:10.1016/0022-0531(72)90049-X

Pigou, A. C. (1920). Co-Operative societies and income tax. *Econ. J.* 30, 156. doi:10.2307/2223009

Porter, M. E., and Linde, C. V. D. (1995). *Green and competitive: ending the stalemate*.

Qiu, L., Hu, F., Zhang, S., Gao, J., Tang, Z., Chen, X., et al. (2024). DIGITALIZATION EMPOWERMENT FOR GREEN ECONOMIC GROWTH: THE IMPACT OF GREEN COMPLEXITY. *Environ. Eng. Manag. J.* 23, 519–536. doi:10.30638/eemj.2024.040

Ren, S., Li, X., Yuan, B., and Chen, X. (2018). The effects of three types of environmental regulation on eco-efficiency: a cross-region analysis in China. *J. Clean. Prod.* 173, 245–255. doi:10.1016/j.jclepro.2016.08.113

Shaari, M., Zainol Abidin, N., Ridzuan, A. R., and Meo, M. S. (2021). The impacts of rural population growth, energy use and economic growth on CO2 emissions. *Int. J. Energy Econ. Policy* 11, 553–561. doi:10.32479/ijeep.11566

Shan, S., Genç, S. Y., Kamran, H. W., and Dinca, G. (2021). Role of green technology innovation and renewable energy in carbon neutrality: a sustainable investigation from Turkey. *J. Environ. Manag.* 294, 113004. doi:10.1016/j.jenvman.2021.113004

Shao, W., and Liu, J. (2024). Does the energy-consuming right trading system promote green technology innovation of enterprises? *Heliyon* 10, e26458. doi:10.1016/j.heliyon.2024.e26458

Shen, J., Tang, P., Zeng, H., Cheng, J., and Liu, X. (2023). Does emission trading system reduce mining cities' pollution emissions? A quasi-natural experiment based on Chinese prefecture-level cities. *Resour. Policy* 81, 103293. doi:10.1016/j.resourpol.2023.103293

Shin, S. (2013). China's failure of policy innovation: the case of sulphur dioxide emission trading. *Environ. Polit.* 22, 918–934. doi:10.1080/09644016.2012.712792

Song, D., Chen, M., and Zhu, W. (2022). Has the energy-consuming right trading system achieved win-win development for China's environment and economy? *China Popul. Resour. Environ.* 32, 134–145. doi:10.12062/cpre.20220614

Suo, R., Wang, Q., Tan, Y., and Han, Q. (2024). An innovative MGM–BPNN–ARIMA model for China's energy consumption structure forecasting from the perspective of compositional data. *Sci. Rep.* 14 (1), 8494. doi:10.1038/s41598-024-58966-z

Wang, K., Su, X., and Wang, S. (2023b). How does the energy-consuming rights trading policy affect China's carbon emission intensity? *Energy* 276, 127579. doi:10.1016/j.energy.2023.127579

Wang, X., Li, Q., and Scheiner, S. (2023a). Search for osme bonds with π systems as electron donors. *Econ. Problems* 29 (04), 79–85. doi:10.3390/molecules29010079

Xiao, M., and Peng, X. (2023). Decomposition of carbon emission influencing factors and research on emission reduction performance of energy consumption in China. *Front. Environ. Sci.* 10, 10. doi:10.3389/fenvs.2022.1096650

Xiong, H., Jing, Z., and Zhan, J. (2020). Impact of different environmental regulatory tools on technological innovation of Chinese industrial enterprises above designated size. *Resour. Sci.* 42 (7), 1348–1360. doi:10.18402/resci.2020.07.11

Xue, F., and Zhou, M. (2022). Can the energy-consuming right transaction system improve energy utilization efficiency? *China Popul. Resour. Environ.* 32 (1), 54–66. doi:10.12062/cpre.20210616

Yan, Y., Zhang, X., Zhang, J., and Li, K. (2020). Emissions trading system (ETS) implementation and its collaborative governance effects on air pollution: the China story. *Energy Policy* 138, 111282. doi:10.1016/j.enpol.2020.111282

Yang, D., Guo, R., O'connor, P., Zhou, T., Zhang, S., Meng, H., et al. (2023). Embodied carbon transfers and employment-economic spillover effects in China's inter-provincial trade. *Front. Environ. Sci.* 11, 11. doi:10.3389/fenvs.2023.1088997

Yang, W., Yuan, G., and Han, J. (2019). Is China's air pollution control policy effective? Evidence from Yangtze River Delta cities. *J. Clean. Prod.* 220, 110–133. doi:10.1016/j.jclepro.2019.01.287

Yang, X., Long, J., Lin, H., Cai, Z., and Jiang, P. (2024). Enhancing efficiency or optimizing industrial structure? A comprehensive assessment of China's energy consumption rights trading system. *Energy Sustain. Dev.* 78, 101380. doi:10.1016/j.esd.2024.101380

Yi, M., Lu, Y., Wen, L., Luo, Y., Xu, S., and Zhang, T. (2022). Whether green technology innovation is conducive to haze emission reduction: empirical evidence from China. *Environ. Sci. Pollut. Res.* 29 (8), 12115–12127. doi:10.1007/s11356-021-16467-w

Zhang, A., and Chen, Q. (2023). Research on the effect and transmission mechanism of energy-consuming right trading system on green technological innovation. *Sci. Technol. Prog. Policy* 40 (3), 93–103. doi:10.6049/kjjbydc.2021070534

Zhang, H., and Zhang, B. (2020). The unintended impact of carbon trading of China's power sector. *Energy Policy* 147, 111876. doi:10.1016/j.enpol.2020.111876

Zhang, Q., Li, J., and Wang, J. (2023a). Does energy-consuming right trading have double dividend effect on firm's economic performance and carbon emission? *Environ. Sci. Pollut. Res.* 30 (48), 105595–105613. doi:10.1007/s11356-023-29864-0

Zhang, Q., Li, J., and Wang, J. (2023b). Does energy-consuming right trading have double dividend effect on firm's economic performance and carbon emission? *Environ. Sci. Pollut. Res. Int.* 30 (48), 105595–105613. doi:10.1007/s11356-023-29864-0

Zhang, T.-J., Zhou, J.-Y., Wang, M., Ren, K., Imran, M., and Wang, R. (2022). Cultivation mechanism of green technology innovation in manufacturing enterprises under environmental regulations in China. *Front. Environ. Sci.* 10, 10. doi:10.3389/fenvs.2022.926896

Zhang, Y., and Zhou, L. (2024). Impact of energy-consuming right trading policy on the optimization and upgrading of regional industrial structure. *China Popul. Resour. Environ.* 34 (1), 71–83. doi:10.12062/cpre20230340

Zhong, S., Fang, Y. A., and Jing, H. (2024). Evaluation the impact of electricity consumption on China's air pollution at the provincial level. *PLOS ONE* 19 (4), e0301537. doi:10.1371/journal.pone.0301537

Zhou, X., Zhang, J., and Li, J. (2013). Industrial structural transformation and carbon dioxide emissions in China. *Energy Policy* 57, 43–51. doi:10.1016/j.enpol.2012.07.017

Zhu, D., Liu, C., Dong, Y., and Hua, J. (2022). The effect of environmental regulation on corporate environmental governance behavior and its mechanisms. *Sustainability* 14 (15), 9050. doi:10.3390/su14159050

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 15 July 2024
DOI 10.3389/fenvs.2024.1431324

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Gianluigi De Pascale,
University of Foggia, Italy
Vera Amicarelli,
University of Bari Aldo Moro, Italy

*CORRESPONDENCE
Yang Yang,
bwu_yangyang@126.com

RECEIVED 11 May 2024
ACCEPTED 24 June 2024
PUBLISHED 15 July 2024

CITATION
Jianmin Z, Yang Y, Jingyuan H and Xiaoxuan K (2024), Can urbanization improve carbon performance?
Front. Environ. Sci. 12:1431324.
doi: 10.3389/fenvs.2024.1431324

COPYRIGHT
© 2024 Jianmin, Yang, Jingyuan and Xiaoxuan. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Can urbanization improve carbon performance?

Zhang Jianmin, Yang Yang*, Huang Jingyuan and Kao Xiaoxuan

China University of Mining and Technology, Beijing, China

Cities are the core carriers and key positions to achieve the dual carbon goals. It is of great significance to explore whether promoting urbanization can improve carbon emission performance, which is of great significance to comprehensively promote the goal of carbon neutrality. Based on the panel data from 2006 to 2021, this paper analyzes the spatial autocorrelation of carbon emission performance per unit space and the impact mechanism of urbanization process on it. The fixed-effect model was further used to identify the influencing factors of spatial carbon emission performance. The results show that: 1) China's carbon emission performance per unit space is declining year by year. 2) There is a strong positive spatial correlation and stable path dependence on the performance of carbon emissions per unit space in each region. 3) To a certain extent, increasing the level of urbanization will reduce the carbon emission performance per unit space. 4) The urbanization process has a spatial spillover effect on the carbon emission performance per unit space of surrounding provinces, and the spatial spillover effect of industrial structure and energy consumption structure is more obvious than that of economic level, population density and urbanization rate. Based on the conclusions, this paper puts forward specific policy suggestions to reduce the carbon emission performance per unit space to help the low-carbon development of cities.

KEYWORDS

urbanization, carbon emissions, carbon performance, spatial Dubin model, spatial spillover environment performance

1 Introduction

With the acceleration of urbanization and the increasing population on a global scale, regional development is facing more and more challenges, one of which is environmental problems. Studies have shown that cities are the main source of the highest energy consumption and greenhouse gas emissions. The process of urbanization is directly related to environmental indicators such as urban land use efficiency, traffic congestion, energy consumption and carbon emissions (Ishii et al., 2009). In 2020, China put forward the goal of carbon peak and carbon neutrality, that is, China is committed to achieving carbon emission peak before 2030 and carbon neutrality before 2060 (Zhuang, 2021). As an important indicator of urban planning and management, urbanization plays an important role in the sustainable development and environmental protection of cities and regions. Therefore, building low-carbon cities has become an inevitable choice for China to embrace climate change and promote the development of a low-carbon economy.

At present, the discussion on carbon emissions mainly focuses on the influencing factors of carbon emissions (Song and Lu, 2009; Lin and Liu, 2010; Chen et al., 2014), characteristics (Hu et al., 2008), and estimation methods (Feng, 2011; Wang, 2012; Jing et al., 2019), among which carbon emission performance has become the focus of the

discussion. Liu Guoping (Liu and Zhu, 2013) proposed that carbon emission welfare performance is the economic and social welfare output per unit of carbon emissions based on the ecological welfare performance theory and the steady-state economic theory of Herman Daly (Daly, 1974). Yan Wentao et al. further expanded carbon performance into energy utilization performance, air environment performance, water environment performance, biodiversity performance, and soil environmental performance. It is also applied to the study of environmental performance, root causes of environmental problems, and optimal spatial structure (Yan et al., 2012). Hua Jian et al. define carbon emission performance as two meanings based on reality and expectation. Reality: Carbon performance refers to the ratio between the actual expected output per unit of carbon emissions and the expected output of the optimal production technology. Expectation: Carbon emission performance is the ratio of the theoretical carbon emission boundary to the actual carbon emission (Hua et al., 2013).

Studies have shown that about 50% of CO_2 emissions from residential transportation can be attributed to urban morphological factors such as urban form, land structure, building type, and transportation network, and urbanization has a non-negligible impact on carbon emissions (Zuo et al., 2022). Based on the quantitative relationship between urban spatial form and carbon emissions, Ewing pointed out that urban spatial structure indirectly affects residents' emissions through intermediate factors (Ewing and Rong, 2008). Ou et al. analyzed the relationship between carbon emissions and spatial structure and morphology, and showed that single-center cities have higher LPIs and are more prone to congestion and high carbon emissions (Ou et al., 2013). Zahabi, et al. showed that improving the urbanization process and land use mix can reduce greenhouse gas emissions (Zahabi et al., 2012). Hilber et al. pointed out that increasing population density and increasing the number of automobiles can lead to a proportional decrease in CO_2 emissions (Hilber and Palmer, 2014). In fact, carbon emissions are not only affected by the local urbanization process, but also by the spatial spillover effects brought by the surrounding areas. Du Huibin pointed out that China's regional carbon emission performance shows an obvious regional cluster phenomenon, and there is a strong spatial positive correlation (Du et al., 2013).

The above studies focus on the impact and mechanism of local urbanization on carbon emissions, but lack of in-depth discussion on spatial externalities. There is still insufficient research on the positive and negative effects of regional spillover on carbon emissions. The central problem of Spatial Economics is to explain the agglomeration of economic activities in geographic space (Liang, 2005). Ecological Geography the laws and mechanisms of the relationship between various components of the ecosystem and the geospatial distribution pattern of ecological processes (Fu and Fu, 2019). In order to introduce the land scale factor, this paper proposes the carbon emission performance per unit space from the perspective of Spatial Economics and Ecological Geography, and defines it as the ratio of carbon emissions or environmental load to GDP within a certain spatial range. At the same time, the positive effects of economic and welfare output per unit of carbon emissions and the negative effects of environmental load per unit space are considered, and the relationship between land resource input and environmental impact targets is studied. It includes the control of the scale of carbon emissions in a certain space, as well as the restrictions on resource input and emission output intensity targets, which more comprehensively reflects the dimensions and complexity of carbon emission performance. Based on the theory of ecological economics and the perspective of spatial interaction, the Spatial Dubin Model is constructed by using econometric methods to study the logical relationship between urbanization process and carbon emission performance per unit space. At the same time, this paper explores the impact mechanism of spatial spillover effects between regions on the carbon emission performance per unit space, aiming to put forward spatial planning and policy suggestions for regional environmental constraint indicators, help China achieve the dual carbon goals in an orderly and efficient manner, promote the coordination of economy, society and environment, and achieve sustainable development.

2 Research hypothesis

2.1 Hypothesis 1: The impact of urbanization on spatial carbon emission performance

The impact of urbanization on the performance of carbon emissions per unit space mainly comes from the changes and fluctuations in economy, population, energy, and industrial structure (Li and Zhou, 2012; Sun et al., 2013; Shen et al., 2023). Both the theory of ecological modernization and the theory of urban environmental transformation believe that with the evolution of urban development, the quality of urban environment will deteriorate first and then improve (Zhang et al., 2016). The growth of GDP is usually accompanied by an increase in energy consumption, including an increase in energy demand for industrial production, transportation, and residential life. The consumption of these energy sources is often accompanied by large amounts of greenhouse gas emissions, especially carbon dioxide. However, when the level of economic agglomeration and urbanization reach a certain threshold, it will show the dual effects of energy conservation and emission reduction at the same time, and can have a direct impact on carbon emissions through various positive externalities (Shao et al., 2019). With the improvement of economic level and technical level, the industrial production mode has undergone intelligent changes. Under the process of urbanization, changes in residents' lifestyles, such as the increase in the level of electrification, have a certain negative impact on the performance of spatial carbon emissions. That is, it can reduce the level of carbon emission performance per unit space. At the same time, the development of China's three industries also has a certain impact on carbon emissions. An increase in the number of employees and capital stock in the primary and tertiary sectors leads to a reduction in carbon emissions. The GDP, capital stock, and employees of the secondary industry have a positive effect on carbon emissions (Zheng and Liu, 2011), so reducing the proportion of the secondary industry structure can effectively reduce the carbon emission performance level of urban space.

However, Population growth will lead to an increase in greenhouse gas emissions, on the one hand, a large total population will increase the demand for energy, which in turn will lead to more and more greenhouse gas emissions from energy consumption. On the other hand, the population is growing rapidly, the supply of existing resources is likely to exceed demand, the environment such as forests are destroyed, and the use of land is

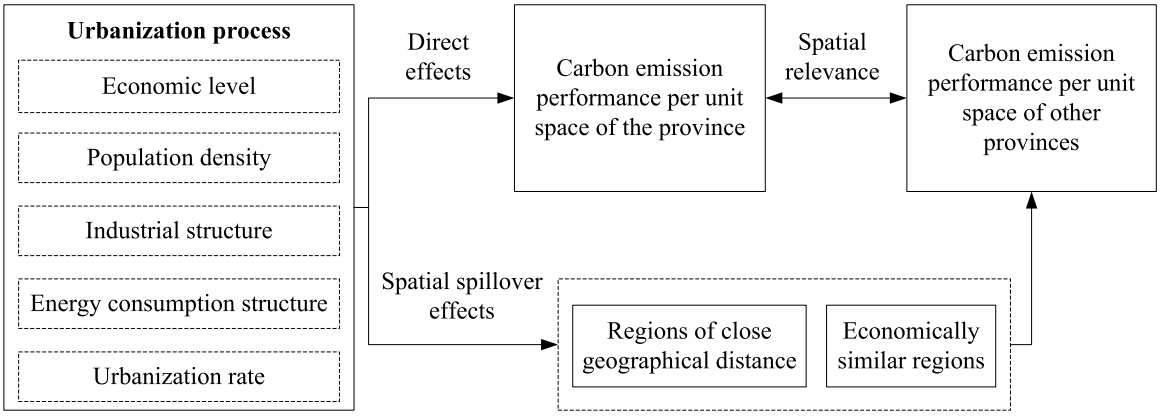


FIGURE 1
Theoretical framework of the impact of urbanization on carbon emission performance per unit space.

changing, resulting in an increase in carbon dioxide emissions (Zhu et al., 2010). With the evolution of urbanization, changes in energy consumption structure, the spread of urban civilization and the improvement of technological level will have a restraining effect on carbon emissions. However, China's coal-dominated energy consumption structure makes coal account for a major share of energy consumption. Even if the energy structure is changed through energy substitution, it is mainly the substitution of oil for coal. The proportion of non-fossil energy use is still low, and oil is a carbonaceous fossil fuel second only to coal, and still has a high level of carbon emissions (Sun, 2010). Therefore, with the advancement of urbanization, the growth of population density and the adjustment of energy structure will still increase the overall carbon emission level, which will have a positive impact on the carbon emission performance level per unit space.

Hypothesis. H_1: Increasing the level of urbanization to a certain extent will reduce the carbon emission performance per unit space. Specifically, economic level, industrial structure, and urbanization rate have a negative impact on the carbon emission performance per unit space, while population density and energy consumption structure have a positive impact on the carbon emission performance per unit space.

2.2 Hypothesis 2: Spatial spillover effects of urbanization on spatial carbon emission performance

Carbon emissions are not only affected by the local urbanization process, but also by the spatial spillover effect brought by the surrounding areas. Adjacent areas have similar cultural environments, social conditions, and economic levels. The frequent flow of transportation, population, technology, etc., creates an agglomeration effect between regions, resulting in interactions. In this process, carbon emissions will be diffused and transferred to the surrounding areas along with the atmospheric circulation and various production activities, which may cause transboundary pollution.

Hypothesis. H_2: There is a spatial spillover effect on the carbon emission performance per unit space of neighboring provinces in the process of urbanization. The theoretical block diagram of the impact of urbanization on carbon emission performance per unit space is shown in Figure 1.

3 Methods and data

3.1 Methods

3.1.1 Space carbon performance

Using the carbon emission performance per unit space as the explanatory variable, the carbon emission is combined with GDP and built-up area, and the carbon emission effect of the city in the whole geographical space is considered, and the sustainability performance of different regions is compared. The provincial carbon emission data is derived from the Carbon Emission Accounts and Datasets (CEADs). The formula is as follows:

$$\mathrm{CE} = \sum_{k=1}^{n} C_k = \sum_{i=1}^{n} AD_i \times EF_i \tag{1}$$

Where: CE is the total carbon emissions, C_k is the carbon emissions of fossil fuels, n is the type of fossil energy, AD_i refers to the consumption of fossil fuels, and EF_i is the emission coefficient of the fuel.

The formula for carbon emission performance per unit space is as follows:

$$Q(CO_2)_{i,t} = CE_{i,t} / GDP_{i,t} / BUA_{i,t} \tag{2}$$

where: $Q(CO_2)_{i,t}$ represents the carbon emission performance per unit space of province i in year t, $CE_{i,t}$ represents the carbon emission of province i in year t, $\mathrm{GDP}_{i,t}$ denotes the GDP of province i in year t, $BUA_{i,t}$ denotes the built-up area of province i in year t.

In this paper, the regression imputation method is used to deal with the missing values of the intermediate years. The average growth rate combined with adjacent time points was

TABLE 1 Measurement system of urbanization process.

Target layer	Quasi-test layer	Indicator layer	unit
Urbanization process	Economic level	Ln (GDP/Area of built-up area)	100 million yuan/km^2
	Population density	Ln (Resident population at the end of the year/built-up area for the year)	10,000 people/km^2
	Industrial structure	GDP of the tertiary sector/GDP of the secondary sector	—
	Energy consumption structure	Coal Consumption/Total Energy Consumption	—
	Urbanization rate	Urban Population/Total Population	—

used to fill in the missing values of the years at both ends to improve the integrity and reliability of the data (Jin, 2001). Due to the differences in regional factors, historical development, industrialization and urbanization processes, if carbon emissions are only used as the explanatory variables, the error of the research results is large, and the conclusions do not have realistic reference value. In order to facilitate the study of the inter-regional carbon emission impact mechanism and draw the conclusion of effective emission reduction, the carbon emission performance per unit space was selected as the explanatory variable.

3.1.2 Estimation of urbanization progress

In this paper, economic level, population density, industrial structure, energy consumption structure, and urbanization rate are used as the criteria for measuring the urbanization process (Gan et al., 2011; Li et al., 2016; Shao et al., 2022). The definitions of indicators are shown in Table 1.

3.1.3 Spatial Durbin model

Due to the interdependence of economic activities at multiple levels such as trade, investment, and industrial chains, economic fluctuations or policy adjustments in one region often affect other regions, forming a strong macroeconomic correlation. At the same time, environmental protection policies and carbon emission reduction policies in various regions will have mutual influences, and regions tend to learn from and imitate each other, so macroeconomic variables such as carbon emissions have obvious spatial spillover effects. In this paper, a spatial Durbin model is constructed. The formula is as follows:

$$\begin{aligned}\ln co_{2kt} &= \eta_0 + \rho\sum\nolimits_j w_{kj}\ln co_{2jt} + \eta_1\ln gdp_{kt} + \eta_2\ln pop_{kt} + \eta_3 is_{kt}\\ &+ \eta_4 es_{kt} + \eta_5 urb_{kt} + \eta_6 X_{kt} + \eta_7\sum\nolimits_j w_{kj}\ln gdp_{jt}\\ &+ \eta_8\sum\nolimits_j w_{kj}\ln pop_{jt} + \eta_9\sum\nolimits_j w_{kj} is_{jt} + \eta_{10}\sum\nolimits_j w_{kj} es_{jt}\\ &+ \eta_{11}\sum\nolimits_j w_{kj} urb_{jt} + \eta_{12}\sum\nolimits_j w_{kj} X_{jt} + \phi_{kt}\end{aligned} \quad (3)$$

Where: k and j correspond to the cross-sectional units of each province; w is the element in the spatial weight matrix W; t represents the year; φ is the random perturbation term. lngdp is the vector of economic level variables; lnpop is the vector of population density; is the vector of industrial structure variables; es is the vector of energy consumption structure variables; urb is the vector of urbanization rate variables; X is the vector of other control variables.

3.1.4 Spatial weights matrix

Spatial autocorrelation is based on the spatial correlation measure, which describes and visualizes the spatial distribution pattern of things or phenomena to discover the degree of spatial agglomeration or dispersion, so as to reveal the spatial interaction mechanism between research objects (Gan et al., 2011). Spatial autocorrelation can be divided into global spatial autocorrelation and local spatial autocorrelation.

3.1.4.1 Spatial weight matrix setting

In the spatial econometric model, the weight matrix is exogenous, and the spatial weight matrix can be constructed as needed. In order to systematically investigate and flexibly respond to different spatial correlation patterns, so as to better understand the correlation between urban density and carbon emission performance per unit space, the following four spatial weight matrices are constructed, including geographic adjacency weight matrix, geographic distance weight matrix, economic distance weight matrix and economic geography weight matrix.

Geographic adjacency weight matrix: W_1. It represents the connection between adjacent units in geographic space, for each geographic unit, the units directly adjacent to it are given a non-zero weight, and the units that are not directly adjacent are given a zero weight. The distance between regions i and j is expressed by d_{ij}, $W_1 = 1$ when $d_{ij} < d$, and $W_1 = 0$ when $d_{ij} \geq d$.

Geo-distance weight matrix: W_2. It represents the spatial distance relationship between geographic units, i.e., the reciprocal of the nearest road mileage between provinces. The surface distance of the provincial capital city calculated by latitude and longitude location is expressed by d_{ij}, $W_{2ij} = 0$ when $i = j$, and $W_{2ij} = 1/d_{ij}$ *when* $i \neq j$.

Economic distance weight matrix: W_3. Due to the spatial correlation between the levels of regional economic development, in order to introduce more information of economic correlation and enhance the analysis of regional economic linkage, the weight matrix of economic distance with economic factors was constructed. The weights are the inverse of the difference in GDP between the two provinces. When $i = j$, $W_{ij} = 0$. When $i \neq j$, $W_{ij} = 1/|Y_i - Y_j|$. Y_i and Y_j are the average regional GDP of province i and province j after GDP deflator processing from 2006 to 2021, respectively.

Economic Geography Weight Matrix: W_4. Since the relationship between geography and economy may be nonlinear, relying only on geographical distance or economic distance to construct a matrix cannot fully capture the complex correlation between regions. The weight is the product of the difference in GDP between the two provinces and the reciprocal of the most recent road mileage

TABLE 2 Results of the global spatial correlation test of the weight matrix.

	Moran's I	*p*-value*	Geary's c	*p*-value*
W_1	0.418	0.000	0.546	0.000
W_2	0.247	0.000	0.726	0.000
W_3	0.135	0.000	0.912	0.012
W_4	0.174	0.000	0.801	0.000

between the two provinces. When $i = j$, $W_{ij} = 0$. When $i \neq j$, $W_{ij} = |Q_i\text{-}Q_j|/d_{ij2}$. Q_i and Q_j are the mean regional GDP of province i and province j after GDP deflator processing from 2006 to 2021, respectively. d_{ij}^2 is the square of the shortest road mileage between the two provinces. W_4 takes into account both the proximity of geographical distance and the impact of economic activities on adjacent areas, which makes the understanding of the spatial correlation between cross-sectional units more comprehensive and accurate.

3.1.4.2 Global Moran index test

In order to investigate whether there is spatial autocorrelation in the whole spatial series, this paper uses the global Moran index to test the samples under each weight matrix. The global Moran index is shown below:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})\left(x_j - \bar{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (4)$$

Where: x_i is the carbon emission intensity per unit space of 29 provinces. S^2 *is the sample variance*. *wij is the* (*i,j*) element of the spatial weight matrix. The Moran index ranges from −1 to 1. When the Moran index is close to 1 or −1, it means that there is an integer or negative spatial autocorrelation in the sample. When the Moran index is close to 0, it indicates that the spatial distribution is basically random, and there is no obvious trend of aggregation or dispersion. At the same time, it is also necessary to consider whether it is significant, and if it is significant, the null hypothesis that spatial autocorrelation does not exist is rejected, and it is believed that there is significant spatial autocorrelation between observations.

According to the results of the global spatial correlation test (Table 2), the Moran's I index is significant under the weight matrix of W_1, W_2, W_3 and W_4, indicating that the distribution of carbon emission intensity per unit space shows spatial autocorrelation characteristics. There are not only spatial correlation characteristics of simple economic differences or geographical differences, but also comprehensive spatial correlation characteristics of geography and economy. In this paper, the empirical results of four weight matrices of W_1, W_2, W_3 and W_4 are used for spatial econometric analysis.

3.2 Data

In this paper, 29 provincial-level administrative regions in China are taken as the research unit, including 22 provinces, four municipalities and 3 autonomous regions (Sun et al., 2015; Yang and zhang, 2024; Xu, 2024). Due to lack of data, the study area does not include Hong Kong, Macau, Taiwan, Xinjiang and Tibet. Based on the existing relevant literature, technological progress, openness to the outside world, building density, and environmental regulation were selected as the control variables in this paper (Zhang and Wei, 2014; An and Xie, 2015; Wei, 2017; SS et al., 2019). Technological progress is expressed as the inverse of energy intensity (Total energy consumption/GDP). The degree of openness to the outside world is expressed as the logarithm of the proportion of import and export trade volume in local GDP of each province. Building density refers to the ratio of the base area to the land area. The degree of environmental regulation is based on the proportion of environmental pollution control investment in each province to local GDP.

The GDP, population, output value of the secondary industry, output value of the tertiary industry, and investment in environmental pollution control are derived from the statistical yearbooks of each province and the statistical yearbook of China in each year. The population density, built-up area and urban area of the city are derived from *China Urban Statistical Yearbook*, *China Urban and Rural Construction Statistical Yearbook*, and *China Urban Construction Statistical Yearbook*. The total energy consumption and coal consumption are from *China Energy Statistical Yearbook*. Since the urban area data provided after 2006 in the China Urban Construction Statistical Yearbook is different from the city area data provided before 2006. In order to ensure the accuracy of the data, the time period of each indicator data is 2006–2021. The descriptive statistics of the indicator data are shown in Table 3.

By comparing the mean, standard deviation, maximum, and minimum values of different variables, an initial understanding of their distribution and variability can be obtained. From the results of Table 1, it can be seen that the carbon emission performance per unit space varies greatly. Due to the differences in economy, technology, regional resources and other aspects, the carbon emission performance per unit space in different regions shows large differences. Among the explanatory variables, the difference in industrial structure is the most obvious, followed by population density, economic level and energy consumption structure, and the urbanization rate is the least different.

In order to better understand the annual trend and regional differences of carbon emission intensity per unit space, this paper divides the 29 provincial-level autonomous regions into four regions, namely, Eastern, Western, Central, and Northeastern, according to the interpretation of the National Development and Reform Commission, as shown in Table 4.

4 Results

4.1 Spatiotemporal evolution characteristics of spatial carbon emission performance

According to Eqs 1 and 2, the carbon emissions of each region and the carbon emission performance per unit space in China are calculated. As can be seen from Table 5 (orange for the larger value and blue for the smaller value), China's carbon emission performance per unit space is declining based on the time perspective. Except for the northeast, the east, west and central parts of the country showed a continuous downward trend, and the decline rate was about the same.

TABLE 3 Descriptive statistics of indicator data.

Sign	Variable	Observations	Mean	Standard deviation	Min	Max
lnCO_2	Carbon emissions performance per unit space	464	−11.214	1.279	−14.04	−7.71
ln*gdp*	Economic level	464	2.455	0.463	0.93	3.59
ln*pop*	population density	464	7.854	0.437	6.39	8.75
is	Industrial structure	464	1.135	0.663	0.5	5.3
es	Structure of energy consumption	464	0.589	0.356	0	1.76
urb	Urbanization rate	464	0.565	0.138	0.27	0.9
ee	Technological advancements	464	1.189	0.822	0	4.82
ln*tdp*	Degree of openness to the outside world	464	2.872	1.061	−1.26	5.14
bula	Building density	464	0.159	0.145	0	0.81
er	Degree of environmental regulation	464	1.366	0.832	0.3	9.38

TABLE 4 Major provinces included in the four regions (Excluding Tibet, Xinjiang, Hong Kong, Macao and Taiwan).

Region	Province
Eastern	Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan
Northeastern	Liaoning, Jilin and Heilongjiang
Central	Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan
Western	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai and Ningxia

TABLE 5 Regional differences in carbon emission performance per unit space from 2006 to 2021.

year	Eastern	Western	Central	Northeastern	Average
2006	−11.069	−9.516	−10.457	−11.053	−10.405
2007	−11.193	−9.683	−10.708	−10.537	−10.504
2008	−11.336	−9.753	−10.802	−10.632	−10.607
2009	−11.404	−9.799	−10.826	−10.651	−10.653
2010	−11.502	−9.958	−10.966	−10.691	−10.775
2011	−11.599	−10.084	−11.104	−10.793	−10.891
2012	−11.735	−10.206	−11.251	−10.895	−11.021
2013	−11.873	−10.386	−11.289	−11.070	−11.156
2014	−11.981	−10.521	−11.409	−11.147	−11.273
2015	−12.097	−10.721	−11.528	−11.188	−11.411
2016	−12.239	−10.808	−11.631	−11.253	−11.518
2017	−12.370	−10.959	−11.750	−11.294	−11.644
2018	−12.472	−11.084	−11.935	−11.390	−11.770
2019	−12.547	−11.166	−12.043	−11.393	−11.847
2020	−12.602	−11.257	−12.129	−11.443	−11.921
2021	−12.689	−11.416	−12.243	−11.499	−12.035

TABLE 6 Moran's I value of carbon emission performance per unit space of Chinese provinces from 2006 to 2021.

Year	Moran's I	*p*	Year	Moran's I	*p*
2006	0.139	0.215	2014	0.291	0.022
2007	0.256	0.038	2015	0.313	0.014
2008	0.290	0.022	2016	0.317	0.013
2009	0.289	0.022	2017	0.319	0.013
2010	0.290	0.022	2018	0.333	0.010
2011	0.295	0.020	2019	0.363	0.005
2012	0.305	0.017	2020	0.380	0.003
2013	0.290	0.023	2021	0.369	0.004

With the increase of years, the Northeast region showed a trend of first increasing and then declining, reaching a peak in 2007 and then beginning to decline, and the decline rate was significantly lower than that in other regions. This is because China was in a relatively fast economic growth and high energy consumption in the early stage, which led to an increase in carbon performance. As the government's attention to environmental sanitation continues to increase, a series of emission reduction measures have reduced carbon dioxide emissions. For example, in recent years, the western region has gradually formed a new pattern of large-scale protection, large-scale opening-up and high-quality development, so the carbon performance in the later period has shown a downward trend. From a spatial perspective, there are large regional differences in China's carbon emission performance per unit space.

The lowest is in eastern China, including Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan, followed by Northeast China, including Liaoning, Jilin and Heilongjiang, whose carbon emissions per unit space are roughly in the range of −11 to −13, all lower than the national average carbon emission performance per unit space. The carbon emission performance per unit space in the western region is higher than the national average. The performance of carbon emissions per unit space in the western provinces of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, and Yunnan is about 1.35 times the national average.

The above phenomenon shows that the carbon emission performance per unit space is closely related to the level of economic development, energy consumption structure, industrial structure and other factors. The eastern region has a prosperous economy and a leading level of science and technology. The environmental capacity space is relatively sufficient, with advanced manufacturing and many cities with trillions of GDP. In particular, in recent years, China has accelerated its modernization and become a strategic highland in China's science and technology, economy, and governance. However, due to the limitations of the geographical environment and ecological environment, the economic development level of the western region lags behind that of the eastern region. The technological level of environmental protection in the western region is relatively lagging behind, and there is a phenomenon of excessive exploitation of resources. As an economically underdeveloped and resource-endowed central region, its economic development has long relied on fossil fuels such as coal. In particular, in major coal provinces such as Shanxi and Henan, coal accounts for 80% and 76% of the energy consumption structure respectively, resulting in high carbon emissions.

4.2 Spatially correlated characteristics of spatial carbon emission performance

4.2.1 Global spatial autocorrelation feature

As an important basis for distinguishing the traditional model from the spatial econometric model, the spatial correlation analysis can reduce the deviation in the measurement results. According to Eq. 4, 2), the global Moran's I value and the corresponding *p*-value of each province from 2006 to 2021 can be obtained, as shown in Table 6.

As can be seen from Table 5, the Moran's I value was below 0.05 in all years except 2006. Moran's I values from 2007 to 2017 passed the test at the 5% significance level, and in all other years, the Moran's I values passed the test at 1% significance. This indicates that the performance of carbon emissions per unit space of each province is not random, and there is a strong spatial positive correlation and a certain agglomeration effect. In other words, the provinces surrounding the provinces with high carbon emission performance per unit space also have high carbon emission performance per unit space, and the provinces with low carbon emission performance per unit space are clustered together. The performance level of carbon emission per unit space of each province is not only affected by its own economic activities, carbon production and consumption, but also by the carbon emissions, economic level, population density, industrial structure and other factors of surrounding provinces, such as the transfer of production activities, energy use diffusion, carbon trading market, etc.

4.2.2 Local spatial autocorrelation features

The results of the global Moran index test show the overall situation of each province in terms of spatial carbon emissions, but cannot reflect the local spatial autocorrelation and spatial agglomeration of carbon emission performance per unit space, so the local Moran index is used for testing. The local Moran index formula is as follows:

$$I_i = \frac{y_i - \bar{y}}{\frac{1}{n}\sum (y_i - \bar{y})^2} \sum_{j \neq i}^{n} \omega_{ij} (y_i - \bar{y}) \tag{5}$$

Where: n is the total number of regions; y_i is the carbon emission performance value per unit space of the 29 provinces;y is the average value of carbon emission performance per unit space, which is the (i,j) element of the spatial weight matrix.

According to Eq. 5, the Moran scatter plot is calculated and plotted. Moran scatter plots reflect the tendency of data to accumulate or disperse in space, and it divides observations into four quadrants.

First quadrant: High-High value agglomeration (HH) area. It indicates that the carbon emission performance per unit space of the observed provinces and their surroundings is high, showing a positive spatial correlation.

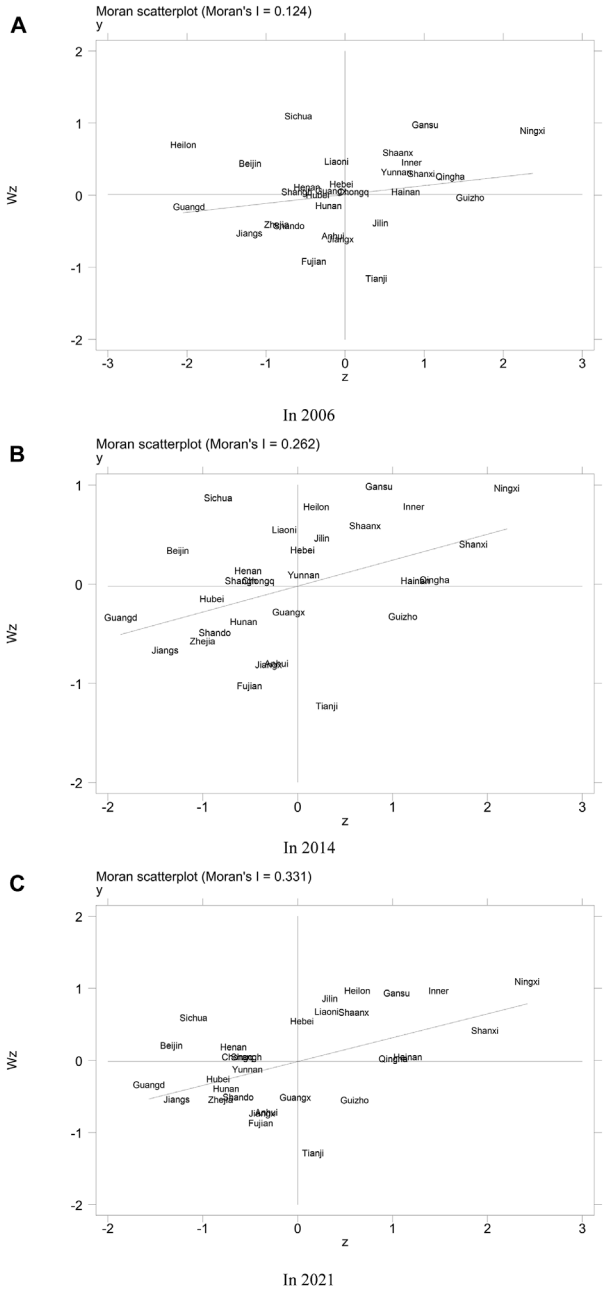


FIGURE 2
The performance of carbon emissions per unit space in 29 provinces in 2006 **(A)**-2014 **(B)**-2021 **(C)**.

Second quadrant: Low-High value agglomeration (LH) region. It indicates that the carbon emission performance per unit space of the observed provinces is low, while the carbon emission performance per unit space of the surrounding provinces is high.

Third quadrant: Low- Low value agglomeration (LL) region. It indicates that the carbon emission performance per unit space of the observed province itself and its surroundings is low.

Fourth quadrant: high-low value agglomeration (HL) region. It indicates that the carbon emission performance per unit space of the observed provinces is high, while the performance per unit space of the surrounding provinces is low.

There is a positive correlation between the carbon emission performance per unit space in the first quadrant and the third quadrant. There is a negative correlation between the second quadrant and the fourth quadrant for carbon emission performance per unit space.

Based on the geographical adjacency weight matrix, the local Moran scatter plots for three representative years in 2006, 2014 and 2021 were drawn, as shown in Figure 2. The horizontal axis represents the standardized carbon emission performance value per unit space, and the vertical axis represents the spatial lag value of carbon emission performance per unit space. The figure shows that the carbon emission performance per unit space of most provinces is located in the HH and LL regions, that is, there is a positive spatial correlation. Specifically, in 2006, the provinces with HH carbon emission performance per unit space were Gansu, Ningxia, Shaanxi, Inner Mongolia, Yunnan, Shanxi, and Qinghai, which were concentrated in western China. The provinces located in the LL region include Hubei, Hunan, Anhui, Zhejiang, Shandong, Fujian, Jiangsu, Guangdong, Jiangxi, and most of them are concentrated in eastern China. In 2014, the number of HH regional provinces increased slightly, from 7 provinces in 2006 to 9, including Gansu, Ningxia, Inner Mongolia, Shaanxi, Shanxi, Hainan, Qinghai, Heilongjiang and Jilin. From 2006 to 2014, the concentration shifted from the western region to the western and northeastern regions. However, the number of LL-type provinces has changed little, from 9 districts in 2006 to 10 districts. The increase is in Guangxi, and the provinces are still concentrated in eastern China. In 2021, the HH-type region increased the number of Liaoning Province and the LL-type region increased the number of Yunnan Province, both of which were concentrated in the western, northeastern, and eastern parts of China, respectively, which were consistent with the results in 2014.

The above results are closely related to practical factors such as economic structure and industrial layout.

From a spatial perspective, most of the HH regions are provinces in the central and western regions. This is because the level of economic development in the central and western regions is limited and the level of urbanization is low. In addition, the western region, especially Shanxi, is more dependent on traditional energy sources, such as oil and coal, which makes the carbon emission performance per unit space of the provinces show a trend of high value agglomeration. The LL area is mostly in the eastern regions. Due to the relatively good level of economic development in the eastern region, it is easier to carry out industrial upgrading and technological innovation, and the level of urbanization is relatively high. At the same time, natural resources are relatively abundant, the climatic conditions are more suitable, and the energy utilization is more efficient. Therefore, the carbon emission performance per unit space of the provinces showed a trend of low value agglomeration. The phenomenon of high-value agglomeration in the eastern province and the low-value agglomeration in the western region are relatively stable, with strong path dependence.

From a time perspective, comparing the spatial agglomeration in 2006, 2014 and 2021, it can be seen that the number of low-value agglomeration provinces is increasing year by year, and is stable in the eastern region. The high-value agglomeration provinces are gradually concentrated in the western and northeastern regions

TABLE 7 Spatial panel model adaptation results.

Spatial panel model test		Spatial weight matrix type			
		W_1 Value	W_2 Value	W_3 Value	W_4 Value
LM test	Moran's I	1.718* [0.086]	−8.2323 [2.000]	−172.810 [2.000]	0.356 [0.722]
	LM-lag	146.172*** [0.000]	6.880*** [0.009]	0.880 [0.348]	0.287 [0.592]
	Robust-LM-lag	133.177*** [0.000]	5.932** [0.015]	0.322 [0.570]	0.493 [0.482]
	LM-error	28.897*** [0.000]	3.762* [0.052]	9.092*** [0.003]	2.567 [0.109]
	Robust-LM-error	15.902*** [0.000]	2.814* [0.093]	8.534*** [0.003]	2.773* [0.096]
Spatiotemporal-temporal fixed effects test	LR-both/ind	64.00*** [0.0000]	33.86*** [0.0002]	21.00** [0.0211]	77.67*** [0.0000]
	LR-both/time	1136.27*** [0.0000]	1183.14*** [0.0000]	1088.72*** [0.0000]	1192.85*** [0.0000]
Hausman test		45.20*** [0.0000]	37.74*** [0.0000]	32.67*** [0.0002]	103.57*** [0.0000]
Wald test	Wald-SDM/SAR	128.24*** [0.0000]	67.65*** [0.0000]	22.19*** [0.0083]	74.68*** [0.0000]
	Wald-SDM/SEM	104.70*** [0.0000]	61.87*** [0.0000]	23.53*** [0.0051]	60.81*** [0.0000]
LR test	LR-SDM/SAR	117.29*** [0.0000]	62.27*** [0.0000]	21.78*** [0.0096]	68.17*** [0.0000]
	LR-SDM/SEM	111.28*** [0.0000]	57.77*** [0.0000]	22.94*** [0.0063]	58.56*** [0.0000]

Note: ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively, and the *p*-value in [] is the value.

from the western region. The number of provinces with low and high value agglomeration shows a decreasing trend year by year, while the number of provinces with high and low value agglomeration has been small or almost none.

4.3 The spatial spillover effect of urbanization on the performance of carbon emissions per unit space

4.3.1 Spatial econometric model

Based on Eq. 3, a suitable spatial panel model is selected before exploring the spatial spillover effects of economic level, population density, industrial structure, energy consumption structure and urbanization rate on the performance of carbon emissions per unit space, so as to more accurately capture the possible spatial dependence and spatial spillover effects between variables. This paper uses the test idea of Elhorst (2014) to test the adaptability of the spatial panel model of the four weight matrices, and the results are shown in Table 7.

The results show that when W_1, W_2, W_3 and W_4 weight matrices are used, the LM test statistics are significant, indicating that the choice of spatial econometric model is reasonable and the hybrid panel model is rejected. The spatial-temporal fixed-effect test of LR for W_1, W_2, and W_4 all rejected the null hypothesis at the 1% level. The spatiotemporal fixed effect of W_3 was significant at the 5% level and the temporal fixed effect was significant at the 1% level, indicating that the time-spatiotemporal double fixed effect model was more effective. The Hausman test of the four weight matrices was significant at the 1% level, which strongly rejected the null hypothesis and suggested that the fixed-effect model should be used. Both LR and Wald's test were significant at the 1% level, indicating that the SDM model would not degenerate to the SEM model or the SAR model, and the SDM model was superior to the SEM model and the SAR model. Therefore, the spatial Durbin model with time-space-time double fixed effect is selected for analysis.

4.3.2 Spatial spillover effects

In order to better describe the interaction and dependence in geographic space, Stata was used to estimate the parameters of Equation 4 under the premise of considering spatial factors such as spatial correlation, spatial dependence, and spatial heterogeneity. The estimated results are shown in Table 8.

As can be seen from Table 7, the values of R^2 under different weight matrices are all greater than 0.87, indicating that the model fits well. On the whole, economic level, urbanization rate, technological progress, and openness to the outside world all have a negative impact on the carbon emission performance per unit space. Except for the degree of openness, it is significant at the level of 1%, and the degree of openness to the outside world is only significant at the level of 10% under the weight matrix of geographical distance. Population density, building density, and environmental regulation have a positive impact on the carbon emission performance per unit space. Population density is significant at the 1% level in all four matrices. However, the degree of environmental regulation has no significant impact on the carbon emission performance per unit space. In addition, the industrial structure and energy consumption structure have negative and positive effects on the carbon emission performance per unit space under the geographical adjacency matrix, respectively, and are significant at the 1% level, but fail the significance test in other matrices. The results of the study are as follows:

(1) Economic level. An increase in the economic level within a reasonable range can curb the increase in carbon emissions.

TABLE 8 Parameter estimation results.

Variable	W_1	W_2	W_3	W_4
ln*gdp*	−0.906*** [0.000]	−0.859*** [0.000]	−0.873*** [0.000]	−0.855*** [0.000]
ln*pop*	0.245*** [0.000]	0.206*** [0.000]	0.222*** [0.000]	0.254*** [0.000]
is	−0.155*** [0.000]	−0.101 [0.101]	0.026 [0.682]	−0.038 [0.553]
es	0.443*** [0.000]	0.026 [0.782]	−0.089 [0.357]	−0.015 [0.886]
urb	−4.023*** [0.000]	−1.939*** [0.000]	−2.583*** [0.000]	−2.011*** [0.000]
ee	−0.106*** [0.001]	−0.193*** [0.000]	−0.167*** [0.001]	−0.214*** [0.000]
ln*tdp*	−0.052 [0.113]	−0.066* [0.083]	−0.056 [0.127]	−0.064 [0.104]
bula	0.710*** [0.000]	0.504** [0.022]	0.519** [0.017]	0.627*** [0.005]
er	0.020 [0.157]	0.003 [0.877]	0.020 [0.218]	0.014 [0.397]
W*ln*gdp*	0.448*** [0.000]	−0.349* [0.058]	0.190 [0.143]	0.151 [0.611]
W*ln*pop*	0.386*** [0.000]	0.085 [0.549]	0.007 [0.939]	0.081 [0.797]
W**is*	−0.250*** [0.000]	−0.978*** [0.000]	−0.370*** [0.000]	−0.578*** [0.006]
W**es*	−0.461*** [0.000]	0.502*** [0.003]	0.236* [0.055]	0.865** [0.026]
W**urb*	1.734*** [0.005]	2.809** [0.042]	−1.203 [0.143]	−0.944 [0.673]
W**ee*	0.109* [0.072]	0.002 [0.986]	0.107 [0.152]	−0.014 [0.925]
W*ln*tdp*	−0.042 [0.536]	−0.574*** [0.000]	0.124* [0.078]	−0.514*** [0.001]
W**bula*	−0.787* [0.081]	−0.252 [0.692]	−0.536 [0.333]	−0.705 [0.447]
W**er*	−0.012 [0.607]	−0.008 [0.851]	0.070* [0.061]	0.031 [0.693]
R^2	0.8891	0.8877	0.8806	0.8788
LogL	31.6852	4.2916	−11.8456	−14.1086
Obs	464	464	464	464

Note: ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively, and the *p*-value in [] is the value.

With the development of the economy, the government has strengthened environmental awareness, enterprises have been transformed and upgraded, and cleaner and energy-saving technologies and equipment have been adopted to effectively reduce carbon emissions. However, the spatial lag term coefficient of the economic level is only significant in some spatial matrices, and some of the significance is not high. This indicates that the economic level of the province will have an impact on the carbon emission performance per unit space of neighboring provinces and geographically similar provinces, but the impact is not obvious.

(2) Population density. There is a positive correlation between population density and carbon emission intensity. It has a significant impact not only on the performance of carbon emissions per unit space of the local area, but also on the carbon emissions of neighboring regions. From the perspective of scale effect, areas with high population density have a larger scale of production, often have more enterprises and factories, and at the same time, regions need to provide more infrastructure services such as transportation, heating, and power supply, which increases overall energy consumption and carbon emissions. From the perspective of agglomeration effect, areas with high population density usually face more congested traffic, more intensive residential energy consumption, and relatively higher energy needs for residents' lives, which in turn increases carbon emissions.

(3) Industrial structure. The regression coefficient of industrial structure to carbon emission performance per unit space is only significant at W1, but the spatial lag term coefficient is significantly negative under the four spatial matrices. This suggests that spatial proximity plays an important role in the impact between industrial structure and carbon emissions. Neighboring provinces and provinces with similar geographical distances have a strong interaction and similar economies have a significant agglomeration trend in terms of carbon emissions per unit space. With the adjustment and upgrading of industrial structure, economic development has gradually changed to the direction of high-tech and low-carbon, and the emergence of new high-tech industries, the support of green finance policies and a number of policy guidance have had a negative effect on the carbon emission performance per unit space.

(4) Energy consumption structure. The local energy consumption structure has a promoting effect on the carbon emission performance per unit space of the region

TABLE 9 Decomposition results of spatial effects.

Weight matrix	Effects	lngdp	lnpop	is	es	urb	ee	bula
W_1	Direct effects	−0.897***	0.312***	−0.198***	0.412***	−4.103***	−0.095***	0.607***
	Indirect effects	0.089	0.714***	−0.469***	−0.380***	0.019	0.092	−0.702
	Total effect	−0.808***	1.025***	−0.667***	0.032	−4.083***	−0.003	−0.095
W_2	Direct effects	−0.858***	0.199***	−0.093	0.029	−2.021***	−0.189***	0.471**
	Indirect effects	−0.280	0.068	−0.937***	0.495***	2.897*	0.006	−0.261
	Total effect	−1.138***	0.268*	−1.030***	0.524***	0.877	−0.184**	0.209
W_3	Direct effects	−0.870***	0.217***	0.027	−0.082	−2.692***	−0.161***	0.480**
	Indirect effects	0.180	0.014	−0.384***	0.245*	−1.212	0.105	−0.566
	Total effect	−0.690***	0.230**	−0.357***	0.163	−3.904***	−0.056	−0.086
W_4	Direct effects	−0.856***	0.247***	−0.032	−0.011	−2.084***	−0.210***	0.596***
	Indirect effects	0.237	0.041	−0.530***	0.843**	−0.655	−0.007	−0.709
	Total effect	−0.618*	0.289	−0.562***	0.832**	−2.739	−0.216	−0.113

Note: ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

and the economically similar regions. However, it has a restraining effect on carbon emissions in adjacent areas. China's total energy consumption ranks among the top in the world, accounting for about 23% of the global total. Coal still accounts for a significant proportion of energy consumption, resulting in relatively high carbon emissions. Economically similar regions often have similar economic activities and industrial structures, and there is a certain supply and demand relationship. When local coal consumption increases, energy consumption in economically similar regions may also move in the same direction. However, due to the cross-regional balance between energy supply and demand, the surrounding areas will reduce their own coal consumption or adjust their energy structure, and stimulate technological progress and technology transfer, so that the carbon emission performance per unit space of the surrounding areas will be reduced.

(5) Urbanization rate. To a certain extent, strengthening urbanization has an inhibitory effect on the performance of carbon emissions per unit space. But too much aggregation will lead to a waste of resources. The spatial lag coefficient of urbanization rate was significantly positive in W_1 and W_2, and passed the test of significance of 1% and 5%, respectively. This indicates that the increase in local urbanization will have a promoting effect on carbon emissions in neighboring areas or areas with close geographical distances, but the effect is not obvious. As building traffic in cities becomes more compact and concentrated, energy losses in the transportation and supply process will gradually decrease, economic activities will become more concentrated, and resource utilization will be higher. At the same time, the mutual reinforcing effect between population and economic activity contributes to innovation and technological progress. However, due to the diffusion effect of economic activity, the number of businesses and residents in the periphery of the city has increased. This, in turn, creates more demand for energy consumption, which increases carbon emissions in the surrounding area.

For the other control variables, only technological progress and building density coefficient are significant in the four matrices, but they act in completely opposite directions. Technological progress can curb carbon emissions to a certain extent, and the increase in building density will increase carbon emissions. The spatial lag coefficients of technological progress, building density, openness to the outside world and environmental regulation are only significant in some matrices, indicating that the impact of these four variables on carbon emissions in the surrounding areas is not obvious.

In summary, economic level, industrial structure, and urbanization rate have a negative impact on carbon emissions. Population density and energy consumption structure have a positive impact on carbon emissions. The hypothesis H_1 is demonstrated, that is, increasing the level of urbanization to a certain extent will reduce the carbon emission performance per unit space.

4.3.3 Spatial effect decomposition

Due to the spatial spillover effect, the change of a variable will not only cause the change of carbon emission performance per unit space in the region, but also cause the change of carbon emission performance per unit space in adjacent areas. In order to accurately measure the influence of spatial effects on the relationship between variables, this paper will further decompose the impact of each variable on the performance of carbon emissions per unit space, including direct and indirect effects. Direct effects: the impact of a variable change on the carbon emission performance per unit space of the region, including the cyclic feedback effect of the variable change on the environmental factors in the surrounding neighboring areas and in turn the impact on the region. Indirect effects: the impact of a change of a variable on the performance of carbon emissions per unit space in adjacent areas and a series of

TABLE 10 Robustness test results.

Variable	W_1	W_2	W_3	W_4
ln*gdp*	−0.120***	−0.108***	−0.154***	−0.114***
ln*pop*	0.245***	0.183***	0.235***	0.244***
is	0.258	0.076	−0.172	−0.017
es	0.413***	0.123	0.056	0.074
urb	−5.255***	−3.968***	−2.593***	−3.720***
ee	−0.101***	−0.134***	−0.129***	−0.140***
ln*tdp*	−0.058*	−0.078**	−0.101***	−0.069*
bula	0.376*	0.382*	0.143	0.369*
Er	0.011	0.004	0.006	0.011
W*ln*gdp*	0.029**	0.109***	0.081***	0.066
W*ln*pop*	0.238***	0.153	0.188**	0.798**
W**is*	−0.254	1.513***	0.613*	1.439**
W**es*	−0.389***	−0.094	0.117	0.165
W**urb*	1.938***	−2.813**	−2.461***	−2.763
W**ee*	0.094	0.152*	0.1	0.151
W*ln*tdp*	0.068	−0.252***	0.069	−0.205*
W**bula*	−0.624	−1.010*	−0.695	−1.321
W**er*	0.013	−0.073*	0.019	−0.055
rho	0.345***	0.218**	0.128**	0.219
lgt_theta	−2.941***	−2.934***	−3.001***	−2.971***
sigma2_e	0.035***	0.038***	0.038***	0.039***

Note: ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

chain reactions and adjustments, i.e., spatial spillover effects. In this paper, the model is decomposed according to the partial differential method, and the direct effects, indirect effects, and total effects of each variable under different weight matrices are obtained as shown in Table 9.

Since the coefficients of the degree of openness to the outside world and the degree of environmental regulation are not significant, the spatial effect is not statistically significant, so it is not discussed here.

Overall, the total effect of the four weight matrices is basically the same. The direct effects of the geographic adjacency matrix and the geographic distance matrix affect the same direction. However, there are some differences in the direction of the direct effects of the economic distance matrix and the economic geography matrix. This is because economic factors are introduced into these two matrices, and China has a vast territory, there are obvious differences in economic development between regions, and it is affected by many factors such as history, culture, and policy, so there are differences in the direction of influence. At the same time, there are certain differences in the direction of the indirect effects of the four weight matrices. This is due to the fact that there are obvious spatial externalities in China's economic and social activities. Moreover, the inter-regional connection network is very complex, including transportation, population flow, industrial chain and other contact methods between cities, and the interaction of multiple effects leads to the diversification of indirect effects.

At the specific level, the direct effects of economic level, population density and urbanization rate under the four matrices all passed the significance test of 1%. However, the indirect effect is only significant in some matrices. This indicates that these three factors have a certain spatial spillover effect, but it is not obvious. The indirect effects of industrial structure and energy consumption structure are significant. However, the direct effect was only significant in W_1. This indicates that the impact of industrial structure and energy consumption structure on carbon emissions in geographically adjacent or economically similar regions is more significant than that on this region.

In the energy consumption structure, the order of the coefficient of indirect effect estimation of each matrix is as follows: $W_4(0.843) > W_2(0.495) > W_1(-0.380) > W_3(0.245)$. This reflects that among the spillover factors that affect the carbon emission performance per unit space of energy consumption structure, economic geographic nesting is the main factor, and proximity is a secondary factor. This may be due to the impact of the dual carbon policy, which is prone to strategic competition among regions. Therefore, it is necessary to strengthen cooperation, consultation and experience sharing when formulating emission reduction policies to achieve greater emission reduction benefits.

Among the control variables, although the direct effects of technological progress and building density are significant in the four matrices, the total effects are only significant in some matrices, indicating that although the introduction of new technologies can reduce the carbon emission intensity of buildings, transportation and industry. But it may lead to more resource consumption and environmental pollution. Increased building density helps reduce commuting distances and traffic demands. However, it may lead to higher energy consumption. The combined effects of the two cancel each other out to a certain extent, resulting in insignificant results.

In summary, economic level, population density, industrial structure, energy consumption structure, and urbanization rate all have spatial spillover effects. That is, there is a spatial spillover effect of urbanization process on the carbon emission performance per unit space of neighboring provinces, and hypothesis H_2 is demonstrated.

4.4 Robustness test

In order to further verify the robustness of the model, this paper uses the method of substituting explanatory variables to test. Drawing on the research ideas of Cheng et al. (2013) and Liu and Liu (2021), the *per capita* GDP is used to represent the economic level, and the proportion of the output value of the secondary industry in the GDP represents the industrial structure, and the model regression is carried out after substituting the explanatory variables. The regression results are shown in Table 10. The results show that there is no significant change in the main regression results, indicating that the test in this paper is robust.

5 Conclusion and suggestions

5.1 Conclusion

Based on the consideration of multiple spatial factors, this paper conducts a new empirical analysis of the regional differences, spatial autocorrelation, and spatial effects of carbon emission performance

per unit space. This paper studies whether promoting urbanization can help achieve the goals of carbon neutrality and carbon peaking.

(1) To a certain extent, increasing the level of urbanization will reduce the carbon emission performance per unit space. Population density has a significant effect on the performance of carbon emissions per unit space in both local and adjacent areas. Spatial proximity plays an important role in the impact between industrial structure and carbon emissions. The energy consumption structure has a promoting effect on the carbon emission performance per unit space in local and economically similar regions, but has a restraining effect on the carbon emissions in adjacent areas. From 2006 to 2021, China's carbon emission performance per unit space showed a downward trend year by year. The decline rate was similar in the east, west and central part of the country, with the northeast rising first and then decreasing. In terms of intensity, the eastern part is the lowest, followed by the central and northeastern regions, and the western part is the highest. The level of economic development, energy consumption structure, and industrial structure are closely related to the carbon emission performance per unit space.
(2) The urbanization process has a spatial spillover effect on the carbon emission performance per unit space of neighboring provinces. Among them, the spatial spillover effects of industrial structure and energy consumption structure are more obvious than those of economic level, population density and urbanization rate. Economic geographic nesting is the main factor that affects the spillover of energy consumption structure on carbon emission performance per unit space. There is a strong positive correlation and stable path dependence on the performance of carbon emissions per unit space in each region. The number of LL agglomeration provinces is increasing year by year, and it is stable in the eastern region. The HH agglomeration provinces are gradually concentrated in the western and northeastern regions from the western region. There are few LH agglomeration provinces and HL agglomeration provinces, which show a decreasing trend year by year.

5.2 Suggestions

Based on the research conclusions of this paper, such as the impact of urbanization level on carbon emission performance per unit space and the spatial spillover effect, some policy suggestions are put forward for urban development.

(1) Strengthen the management of carbon emissions in densely populated areas and adjacent areas. Focus on public transportation, energy-saving buildings and green space construction, and promote low-carbon production and clean energy utilization. Strengthen the formulation and enforcement of environmental protection laws and regulations, and impose restrictions and penalties on enterprises with high carbon emissions.
(2) Promote the upgrading and optimization of industrial structure and strengthen regional cooperation. Due to the important role of spatial proximity, the government needs to continue to promote technological innovation in the process of industrial restructuring and upgrading. Realize the withdrawal of old production capacity and the construction of new production capacity. Strengthen inter-regional industrial ties and economic cooperation to promote the further reduction of carbon emissions.
(3) Adjust the energy consumption structure and promote the transformation of the energy consumption structure to clean energy. Increase investment in R&D and promotion of clean energy technologies, and encourage enterprises and residents to use clean energy. At the same time, preferential policies such as loan support and tax incentives are provided to promote the development and application of clean energy.
(4) Strengthen cross-regional cooperation mechanisms, such as building a cross-regional environmental protection information platform to share environmental protection management experience, monitoring data and technological achievements. Promote experience sharing and technology transfer to achieve greater carbon emission reduction and environmental protection benefits.

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

YY: Methodology, Supervision, Writing–review and editing, ZJ: Formal Analysis, Software, Writing–original draft, HJ: Data curation, Writing–review and editing. KX: Investigation, Resources, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This work was supported by the Key Project of Beijing Social Science Foundation (Project No. 19YJA001).

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

An, C., and Xie, J. (2015). Research on the relationship between carbon dioxide emissions, energy intensity and economic growth. *J. Commer. Econ.* (15), 38–39.

Chen, C. C., Liu, C. L., and Wang, H. (2014). Examining the impact factors of energy consumption related carbon footprints using the STIRPAT model and PLS model in Beijing. *China Environ. Sci.* 34 (6), 1622–1632. doi:10.1016/j.apenergy.2013.01.036

Cheng, Y. Q., Wang, Z. Y., and Zhang, S. Z. (2013). Spatial econometric analysis of carbon emission intensity and its driving factors from energy consumption in China. *Acta Geogr. Sin.* 68 (10), 1418–1431.

Daly, H. E. (1974). The world dynamics of economic growth:the economics of the steady state. *Am. Econ. Rev.* 64 (2), 15–23.

Du, H. B., Li, N., and Wang, Y. Y. (2013). Study on China's carbon emission performance and influencing factors from the perspective of spatial economics. *J. Tianjin Univ. Soc. Sci.* 15 (05), 411–416.

Elhorst, J. P. (2014). Matlab software for spatial panels. *Int. Regional Sci. Rev.* 37 (3), 389–405. doi:10.1177/0160017612452429

Ewing, R., and Rong, F. (2008). The impact of urban form on U.S. residential energy use. *Hous. Policy Debate* 19 (1), 1–30. doi:10.1080/10511482.2008.9521624

Feng, R. (2011). *Study on the methods and application of estimation of CO_2 emission on urban household energy consumption [D]*. Nankai University

Fu, S., and Fu, B. (2019). Concept clarification of eco-geography and analysis of related classical studies. *Scien. Geogra. Sinica.* 39 (1), 70–79. doi:10.13249/j.cnki.sgs.2019.01.008

Gan, C. H., Zheng, R. G., and Yu, D. F. (2011). An empirical study on the effects of industrial structure on economic growth and fluctuations in China. *Econ. Res. J.* 46 (05), 4–16+31.

Hilber, C. A. L., and Palmer, C. (2014). *Urban development and air pollution: evidence from a global panel of cities*. Social Science Electronic Publishing. doi:10.2139/ssrn.2541387

Hu, C. Z., Huang, X. J., and Zhong, T. Y. (2008). Characteristics of carbon emission in China and analysis on its cause. *China Popul. Resour. Environ.* 18 (03), 38–42. doi:10.1016/s1872-583x(09)60006-1

Hua, J., Ren, J., and Xu, M. (2013). Evaluation of Chinese regional carbon dioxide emissions performance based on a three-stage DEA model. *Resour. Sci.* 35 (07), 1447–1454.

Ishii, S., Tabushi, S., Aramaki, T., and Hanaki, K. (2009). Impact of future urban form on the potential to reduce greenhouse gas emissions from residential, commercial and public buildings in Utsunomiya, Japan. *Energy Policy* 38 (9), 4888–4896. doi:10.1016/j.enpol.2009.08.022

Jin, Y. J. (2001). Imputation adjustment method for missing data. *J. Appl. Statistics Manag.* (06), 47–53. doi:10.13860/j.cnki.sltj.2001.06.012

Jing, Q. N., Hou, H. M., and Bai, H. T. (2019). A top-bottom estimation method for city-level energy-related CO_2 emissions. *China Environ. Sci.* 39 (01), 420–427. doi:10.19674/j.cnki.issn1000-6923.2019.0052

Li, J., and Zhou, H. (2012). Correlation analysis of carbon emission intensity and industrial structure in China. *China Popul. Resour. Environ.* 22 (01), 7–14.

Li, X. P., Wang, S. B., and Hao, L. L. (2016). Environmental regulation, innovation-driven and inter-provincial carbon productivity changes in China. *J. China Univ. Geosciences Soc. Sci. Ed.* 16 (01), 44–54.

Liang, Q. (2005). Spatial economy: past, present future -in review of the spatial economy: cities, regions and international trade. *China Econ. Q.* (03), 1067–1086.

Lin, B. Q., and Liu, X. Y. (2010). China's carbon dioxide emissions under the urbanization process: influence factors and abatement policies. *Econ. Res. J.* 45 (08), 66–78.

Liu, G. P., and Zhu, D. J. (2013). Research on provincial wellbeing performance of carbon emissions in China. *Account. Econ. Res.* 27 (06), 74–81.

Liu, X. B, and Liu, Q. M. (2021). Study on the relationship between economic growth, urbanization and carbon dioxide emission intensity from spatial perspective. *J. Commer. Econ.* (12), 184–188.

Ou, J., Liu, X., Li, X., and Chen, Y. (2013). Quantifying the relationship between urban forms and carbon emissions using panel data analysis. *Landsc. Ecol.* 28 (10), 1889–1907. doi:10.1007/s10980-013-9943-4

Shao, S., Fan, M. T., Yang, L. L., and Restructuring, E. (2022). Green technical progress, and low-carbon transition development in China: an empirical investigation based on the overall technology frontier and spatial spillover effect. *J. Manag. World* 38 (02), 46–69+4-10. doi:10.19744/j.cnki.11-1235/f.2022.0031

Shao, S., Zhang, K., and Dou, J. M. (2019). Effects of economic agglomeration on energy saving and emission reduction: theory and empirical evidence from China. *J. Manag. World* 35 (01), 36–60+226. doi:10.19744/j.cnki.11-1235/f.2019.0005

Shen, Y. F., Shi, X. P., Zhao, Z. B., Sun, Y. P., and Shan, Y. L. (2023). Measuring the low-carbon energy transition in Chinese cities. *iScience* 26 (01), 105803. doi:10.1016/j.isci.2022.105803

Song, D. Y., and Lu, Z. B. (2009). The factor decomposition and periodic fluctuations of carbon emission in China. *China Popul. Resour. Environ.* 19 (03), 18–24.

SS, H., and Zhu, X. A. (2019). Spatial econometrics for influencing factors of regional green development of China. *Econ. Surv.* 36 (01), 10–17. doi:10.15931/j.cnki.1006-1096.20181213.011

Sun, C. L., Jin, N., and Zhang, X. L. (2013). The impact of urbanization on the CO2 emission in the various development stages. *Sci. Geogr. Sin.* 33 (03), 266–272. doi:10.13249/j.cnki.sgs.2013.03.006

Sun, H., Liang, H. M., and Chang, X. L. (2015). Land use patterns on carbon emission and spatial association in China. *Econ. Geogr.* 35 (03), 154–162. doi:10.15957/j.cnki.jjdl.2015.03.023

Sun, M. (2010). *Empirical study on the effects of China's energy consumption and carbon emissions changes*. Jilin University.

Wang, D. (2012). *Study on calculation and carbon emission reduction approaches in Chinese residents' consumption in the process of urbanization*. Nankai University.

Wei, G. Q. (2017). Study on the influence of population structure change and consumption pattern on carbon emission. *J. Commer. Econ.* (16), 37–39.

Xu, X. (2024). Multidimensional measurement, spatial differences and dynamic evolution of high-quality development of new-type urbanization. *Statistics Decis.* 40 (10), 100–105.

Yan, W. T., Xiao, J. H., and Hu, H. (2012). Urban spatial structure and environmental performance: review and thought. *Urban Plan. Forum* (05), 50–59.

Yang, C. Y., and Zhang, N. (2024). Research on the heterogeneous consumption effect of urbanization under different development models: based on the observation perspective of human urbanization and urbanization of production factors. *J. Commer. Econ.* (11), 60–63.

Zahabi, S. A. H., Miranda-Moreno, L., Patterson, Z., Barla, P., and Harding, C. (2012). Transportation greenhouse gas emissions and its relationship with urban form, transit accessibility and emerging green technologies: A Montreal case study. *Procedia - Soc. Behav. Sci.* 54 (2375), 966–978. doi:10.1016/j.sbspro.2012.09.812

Zhang, H., and Wei, X. P. (2014). Green paradox or forced emission-reduction: dual effect of environmental regulation on carbon emissions. *China Popul. Resour. Environ.* 24 (09), 21–29.

Zhang, T. F., Yang, J., and Sheng, P. F. (2016). The impacts and channels of urbanization on carbon dioxide emissions in China. *China Popul. Resour. Environ.* 26 (02), 47–57.

Zheng, C. D., and Liu, S. (2011). Industrial structure and carbon emissions: an empirical analysis based on inter-provincial panel data in China. *Res. Dev.* (02), 26–33. doi:10.13483/j.cnki.kfyj.2011.02.013

Zhu, Q., Peng, X. Z., and Lu, Z. M. (2010). Analysis model and empirical study of impacts from population and consumption on carbon emissions. *China Popul. Resour. Environ.* 20 (02), 98–102.

Zhuang, G. Y. (2021). Challenges and countermeasures for China to achieve the "dual carbon" goal. *People's Trib.* (18), 50–53.

Zuo, S., Dai, S., Ju, J., Meng, F., Ren, Y., Tian, Y., et al. (2022). The importance of the functional mixed entropy for the explanation of residential and transport CO2 emissions in the urban center of China. *J. Clean. Prod.* 380, 134947. doi:10.1016/j.jclepro.2022.134947

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 01 August 2024
DOI 10.3389/fenvs.2024.1433044

Check for updates

OPEN ACCESS

EDITED BY
Ji Zheng,
The University of Hong Kong, Hong Kong SAR, China

REVIEWED BY
Diby Francois Kassi,
Henan University, China
Maham Furqan,
Oregon State University, United States

*CORRESPONDENCE
Li Wang,
wl15132820798@163.com

RECEIVED 15 May 2024
ACCEPTED 16 July 2024
PUBLISHED 01 August 2024

CITATION
Jiang S and Wang L (2024), All paths to the same end?—a comparative study on carbon emissions reduction effects of digital finance and green finance.
Front. Environ. Sci. 12:1433044.
doi: 10.3389/fenvs.2024.1433044

COPYRIGHT
© 2024 Jiang and Wang. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

All paths to the same end?—a comparative study on carbon emissions reduction effects of digital finance and green finance

Shasha Jiang[1] and Li Wang[1,2]*

[1]School of Management, Hebei University, Baoding, China, [2]The Center of Common Prosperity Research, Hebei University, Baoding, China

The massive CO2 emission has caused frequent occurrence of climate problems, and a typical response to climate change has reached international consensus. Digital finance and green finance, as a subversion of the traditional financial model, have become significant drivers of global carbon emissions reduction efforts. Based on the panel data, this paper profoundly compares the effects of carbon emissions reduction, mechanisms, and heterogeneous results of two forms of finance. Research finds that technology-centered digital finance focuses on suppressing carbon emissions through technological innovation, and the higher the level of regional economic is, the stronger the role of digital finance in suppressing carbon emissions through technological innovation. The concept-centered green finance focuses on carbon emissions reduction through industrial ecologization, and government-led environmental regulation plays a positive regulatory role. Although the paths of affecting carbon emissions are different, there is a natural fit between the two in terms of the essential goal of carbon emissions reduction. Based on the consideration of the differences in geographic location and financial development level, the carbon emission reduction effects of two forms of finance show apparent heterogeneity. Based on the spatial characteristics of digital finance and carbon emissions, this paper further finds that the digital finance's carbon emission reduction effects have apparent spatial spillovers. These findings provide an essential direction to formulate a reasonable carbon emissions reduction plan and accelerate realizing the "double carbon" goal.

KEYWORDS

global climate, digital finance, green finance, carbon emission reduction, "double carbon" goal

1 Introduction

China's economic strength has significantly increased, but the excessive pursuit of economic benefits has neglected environmental benefits. As a result, the sharp contradiction between economy and environment has become a critical issue facing China for a long time. In 2017, China officially launched the unified carbon emissions trading market, and then In 2021, the goal of "carbon peak, carbon neutral" highlights the China's determination to develop a green economy. As a core element of modern market economy development, finance is a powerful support to ensure enterprise development and promote national economic growth. Based on digital technology, digital finance is a financial means that integrates emerging tools such as the Internet, cloud computing and artificial intelligence

into the traditional financial system to achieve innovation in the form of financial services, enrich the content of financial services and expand the scope of financial services (Wu, Guo, Tian and Hong, 2022). Compared to digital finance, the origin of green finance dates back to the 1990s when developed countries proposed the concept of "green finance". At the beginning of this century, in response to intense criticism from international non-governmental organizations (NGOs) of the environmental damage caused by specific financing projects, green finance, which is based on the principles of sustainable development, became a powerful tool for the international financial industry to address climate change (X. Wang, Huang, Xiang and Huang, 2021). Specifically, green finance is a form of finance that responds to the United Nations' call, promotes the environmental greening of industries.

As products of development in different times, digital finance and green finance have had a profound impact on China's economy. Digital finance focuses on encouraging the transformation of heavily polluted industries with the help of technological means, to reduce the carbon emissions of traditional sectors (Song et al., 2023); in contrast, green finance adheres to the core of green development, restricting the production scale of polluted industries through financial constraints to curb industrial carbon emissions (J. Wang and Ma, 2022). Obviously, both digital finance and green finance are important tools for reducing carbon dioxide emissions and protecting the ecological environment in the context of low-carbon economic development. However, the strength of the contribution of digital finance and green finance in carbon reduction, which side has a stronger carbon reduction effect, and whether China's future carbon reduction work will prioritize technology or philosophy are still unresolved issues.

Although existing research provides a solid foundation for our research, there are still the following shortcomings: Firstly, existing research focuses on the single impact of digital finance or green finance on carbon reduction, lacking a comprehensive analysis that puts the three within the same research framework; Secondly, green concepts and digital technologies provide endogenous and external support for carbon reduction, and there is still a lack of comparative research on the endogenous and exogenous forces of carbon reduction; Thirdly, both the financial system and the ecological environment have obvious regional characteristics, but there are still relatively few studies on finance and carbon emissions that consider spatial factors and overlook the spatial effects of carbon reduction.

The contributions of this research are as follows. Firstly, in terms of research topics. Comprehensively consider the carbon reduction effects of digital finance and green finance, and conduct vertical comparisons to highlight the importance of digital finance or green finance in carbon reduction work, with novel themes to compensate for the shortcomings of single research; Secondly, in terms of research methods. In order to explore the differences in the transmission paths of digital finance and green finance in the process of emission reduction, this article integrates regulatory effects on the basis of a simple mediation model, explores the transmission paths of carbon reduction through different financial means, and based on the consideration of geographical proximity, uses spatial econometric models to test their spatial correlation. The methods are rich and expand the breadth and depth of existing research. Thirdly, in terms of policy value. On the basis of exploring the carbon reduction effect mechanism of digital finance and green finance, this article further verifies the differences in carbon reduction between digital finance and green finance, and further clarifies the direction of policy implementation, providing theoretical reference for accelerating China's economic green transformation and global carbon reduction work.

The rest of the article is organized as follows. Section 2 reviews and evaluates existing literature on carbon emissions, digital finance, and green finance, and proposes research hypotheses based on theoretical analysis. Section 3 proposes the research design. Section 4, the benchmark regression results, mechanism testing results, and robustness results were reported. Section 5 reports on the heterogeneity of carbon reduction effects between digital finance and green finance, respectively. Section 6, because digital finance has a more significant carbon reduction effect, we delves into the spatial effects of it. Section 7 synthesizes conclusions from the empirical findings and offers reliable recommendations for future carbon emission reduction efforts. The content of the study is illustrated in Figure 1.

2 Literature review and hypothesis development

2.1 Literature review

2.1.1 Research on carbon emissions

The global climate issue is a realistic challenge facing humankind at present. Since the 19th century, most experts and scholars have conducted many exploration on the greenhouse effect. The study has arrived at a unanimous conclusion: human beings are the initiators of global warming. In recent years, some countries have blindly pursued the benefits of economic development, seriously ignoring the harm economic development has brought to the global environment and human health. Therefore, solving the global climate problem is the common goal of humanity. With the continuous deterioration of global climate, various countries' carbon emission reduction actions have become the main force to mitigate global climate change, and a new pattern of global climate governance has gradually taken shape. The mainstream research on carbon emissions includes the following two categories: First, many study investigates the factors affecting carbon emissions. From the macro level, introducing high-end production equipment and technology from other countries through international trade can reverse the carbon pollution situation with a technology spillover effect (X. Xu et al., 2021). In addition, the government sends environmental protection signals to high-energy-consuming industries through environmental regulation. From the medium level, carbon emission reduction is a crucial measure to promote industrial green transformation to achieve industrial ecology under the call for carbon neutrality and a critical path to enhance national industrial resilience and urban economic resilience (H. Chen et al., 2021). From the micro level, individual education level directly affects personal environmental awareness (Bülbül et al., 2023). In general, the more educated the group, the stronger the ecological concept and the more inclined to use. The second is evaluating the role of national policies on carbon emission reduction. Most studies evaluate the pilot effects of national policies from multiple perspectives through the method of differential differentiation to verify the policies' effectiveness and further promote them widely (H. Zhang et al., 2021).

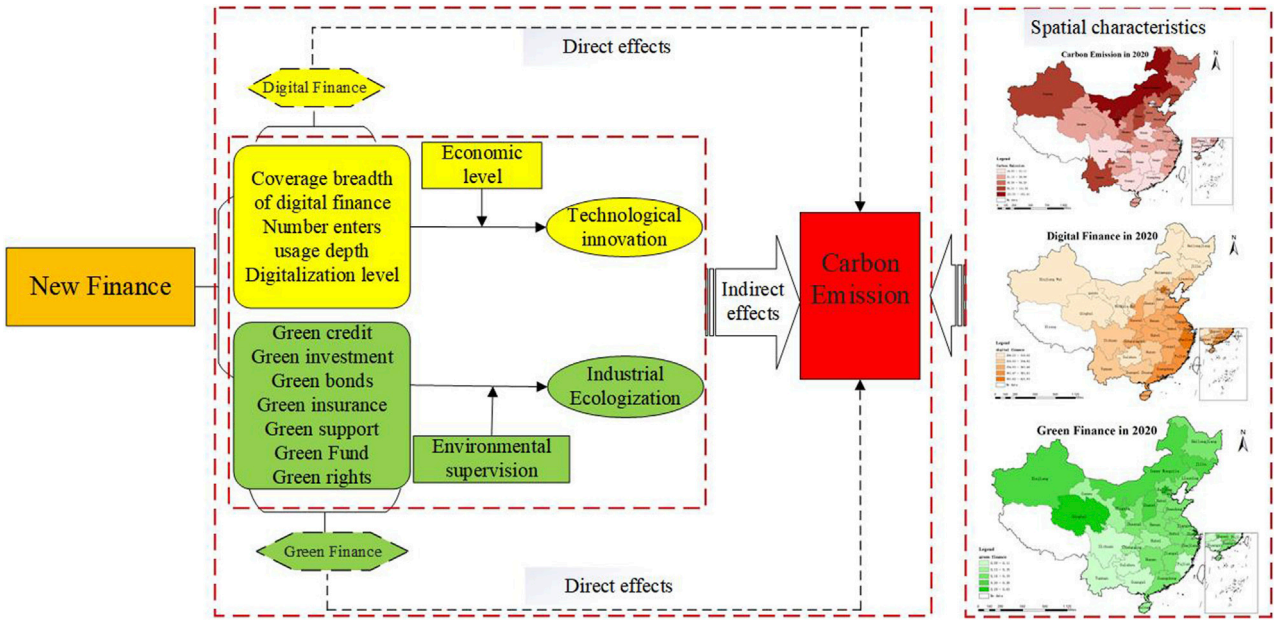


FIGURE 1
Research content.

2.1.2 Related research on digital finance and carbon emissions

The wide application of digital technologies has opened the door to the digital era and pushed China's economy into a new stage (Chu et al., 2023). The digital finance can effectively overcome the drawbacks of the traditional financial, enrich the form and content of financial, enhance the flexibility and convenience (Feng et al., 2023). Studies mainly focus on two aspects: at the macro level, studies on the mechanism of digital finance on restraining carbon emissions (X. Liu et al., 2023); At the micro level, for individuals, it provides individual consumers with convenient online transaction channels and dramatically reduces the CO2 emissions generated by offline travel (Pu and Fei, 2022). For enterprises, digital finance provides financial support for enterprises through the redistribution of production factors, promotes the green innovation (Ding et al., 2022). Part of researchs show that the digital finance does not affect CO2 emissions (Chang, 2022; Zheng and Li, 2022); the other part of the research results show that the rapidly developing information technology, as an essential driving force for industrial adjustment, is the core force to curb the industrial carbon emissions (Yin, 2022).

The digital finance, as a critical driving force for China's economy, is a significant starting point for inclusive green growth. However, its identity positioning and mechanism role in carbon emission reduction work still needs to be further clarified to indicate the precise direction of carbon emission reduction.

2.1.3 Research on green finance and carbon emissions

The Kyoto Protocol, signed in 1997, has made green finance widely concerned by the international community (Sinn, 2008). Later, some scholars put forward the green finance theory that integrates finance with the green environmental industry, aiming at redistributing financial resources with the help of market forces to achieve the purpose of protecting the ecosystem (Huang et al., 2023). China has permanently attached great importance to the green finance. In 2016, the Guiding Opinions on Building a Green Financial System issued by relevant departments in China clarified the policy framework for green finance and point out it is a financial service to maintain economic activities such as resource conservation and efficiency and to combat climate change.

While there is no universally accepted definition globally, the connotation of guiding financial resource allocation with green financial instruments to improve the environment is consistent (Ran and Zhang, 2023). From the measurement of green finance, one is measured by a single indicator, such as public expenditure on environmental protection, interest expenditure of high-energy consumption industry (J. Xu et al., 2023). The other is to comprehensively evaluate by selecting multiple indicators (X. Chen and Chen, 2021; J. Wang et al., 2023). For research content, based on the environmental protection concept of green finance, most existing studies focus on its protection effect on the ecological environment. For example, green finance can reduce pollution by optimizing energy (Yuan et al., 2020; Bai et al., 2022). Specifically, the issuance of green bonds significantly improves enterprises' green innovation capability and environmental performance (W. Zhang et al., 2022), while green credit improves environmental performance by controlling the financing of high-emission industries (X. Liu et al., 2019; Lv et al., 2023).

2.2 Hypothesis development

The digital finance, as an essential financial means derived from technological change, is strong support to achieve the goal of

"double carbon." From a micro point of view, mobile payment brought by digital finance significantly reduces residents' dependence on offline financial institutions' outlets (S. Liu et al., 2023), reduces residents' transportation frequency, and helps to reduce CO_2 emissions. Moreover, the "Ant Forest" and "Green Apple" public welfare activities launched by digital financial platforms have greatly improved residents' awareness of environmental protection and formed a "positive incentive" for the transformation of residents' consumption structure (Zheng and Li, 2022). From a macro point of view, digital finance, mainly supported by digital technology, is a vital force in promoting industrial digitalization and digital industrialization. The development of modern information technology has overturned the production mode of traditional industries, transforming intangible modern information technology into tangible information technology industries, which is an inevitable measure to reduce pollutant emissions in the digital era (Zhao, Yang, Li, Liu and Li, 2021). Digital finance provides a basic guarantee for industrial technology investment, reduces technology cost risks, and is a key means to promote industrial digital transformation and reduce carbon pollution (Z. Zhu, Liu, Yu and Cao, 2022).

> "Green" is a kind of environmental protection concept; its concept is more abstract, involving a more comprehensive range. On the premise of accurately identifying green enterprises, green finance tracks and locates the flow of financial resources, gives priority to providing financial support for enterprises' environmental production and environmental governance, and thus reduces carbon pollution production activities (Lin et al., 2022). Although the internal concepts of digital finance and green finance are different, the essential goals of pollution reduction and of them have a natural consistency.

Hypothesis 1: Both digital finance and green finance have significant carbon reduction effects.

Driven by the fourth industrial Revolution, technology has become a key production factor for modern industries to improve productivity. However, the high cost of technology makes most enterprises prohibitive, and this development bottleneck of enterprises provides an important direction for digital finance to achieve environmental protection goals. Digital finance focuses on embedding digital technology into the financial system, adjusting traditional industrial structure by employing financial technology, promoting industrial digital transformation, and thus reducing the emission of industrial pollutants (J. Xu et al., 2023). Digital finance empowers traditional industries through digital technologies, promotes the transparency and synergy of data factor flow, realizes the accurate matching of production factors, reduces the number of polluting industries (Xue et al., 2022). Digital finance has significantly improved the ability to identify, and deal with financial risks, and encourage enterprises to innovate (M. Zhang and Liu, 2022).

The widespread popularity of digital finance is guaranteed by a strong foundation of economic development. A sound economic foundation not only provides strong material guarantees for technological innovation to play a role in carbon reduction in digital finance, but also provides strong conditions for deepening the development of digital finance and realizing its economic and social benefits. Generally speaking, the higher the level of economic development in a region, the stronger its ability to accept and adapt to emerging things such as digital finance, and the more it can fully leverage the impact of digital finance on regional social production activities. Therefore, the economic level plays an important role that cannot be ignored in promoting technological innovation through digital finance and thereby affecting the process of carbon emissions. Based on this, hypotheses 2a and 2b are proposed.

Hypothesis 2a: The digital finance inhibits carbon emissions by promoting technological innovation.

Hypothesis 2b: Economic growth can strengthen the mediating role of technological innovation in the process of carbon emission reduction in digital finance.

The "green" and "financial" attributes of green finance make it adhere to the essential goal of "environmental sustainability." in addition to directly helping China to "reduce carbon," (Zhan, Wang and Zhong, 2023), it can also further indirectly affect carbon emission reduction by driving the ecological transformation of industrial development. The green finance promotes the green industry and tertiary industry by reallocating financial elements, focusing on providing credit support and preferential incentives (Zhou and Qi, 2022), and strictly constraining the financing of projects in "two high" industries to force them to accelerate industrial transformation and promote industry development in the direction of ecology (W. Xu et al., 2023). The transformation of industrial ecology means that the proportion of green industries will gradually increase. In contrast, industries with heavy pollution will gradually withdraw or be reconfigured. This industrial structure adjustment effectively inhibits carbon emissions from economic activities (B. Wang et al., 2023).

Although green finance can reduce carbon pollution, the realization of carbon reduction goals needs to be escorted by mandatory legal means (Feng, Bilivogui, Wu and Mu, 2023). Environmental regulation is a mandatory means to compel enterprises to adopt emission reduction strategies, in the context of loose environmental regulations, enterprises face lower costs of environmental violations. Although green finance provides preferential dividends for green production activities, it is difficult to truly encourage enterprises to abandon traditional production models with high efficiency, Ding et al., 2022). Under strict environmental supervision, enterprises face high costs of environmental violations. Under the dividend effect of green finance, they will actively adopt industrial transformation strategies, and the carbon reduction effect of green finance will be strengthened. In this process, the government will play the role of a "guide" to guide financial institutions to carry out green finance-related businesses and play a regulatory complementary role in driving the transformation of industry (J. Wang and Ma, 2022; S. Zhu et al., 2014). Hypotheses 3a and 3b are proposed.

Hypothesis 3a: Green finance achieves carbon reduction by promoting industrial ecological transformation.

Hypothesis 3b: Environmental regulation can strengthen the intermediary role of industrial ecological transformation in the process of carbon emission reduction in green finance.

Unbalanced regional development is one of the main contradictions in China. China's industrial distribution and industrial structure are important reasons for the differences in carbon emissions in different regions. Generally speaking, economically developed areas pay attention to the economic benefits and sustainability of industrial development. Therefore, compared with economically underdeveloped areas, their industrial structure is more reasonable, environmental awareness is more potent, and environmental pollution is relatively small (Zhang, Bao, Liu and Yang, 2022). As an innovative form based on the old financial model, digital finance and green finance are deeply affected by the old finance. The richer the financial resources, and the stronger the financial allocation capacity, the more favorable it is to enjoy the financial resource allocation dividends. On the contrary, it is difficult for regions with financial disadvantages to capture the development opportunities of emerging financial forms, and it is even more difficult to extend them to industrial transformation.

Hypothesis 4: The carbon reduction effects of digital finance and green finance are significantly heterogeneous.

The green finance pays more attention to promoting carbon emission reduction by cutting into the "green" concept of sustainable development, which is essential in alleviating regional ecological pollution. Digital technology has alleviated information asymmetry and weakened traditional difficulties in economic interaction caused by geographical distance, while digital finance based on digital technology can fully leverage modern information technology to achieve the diffusion of financial resources (Wang and Guo, 2022). Therefore, in contrast, the spatial characteristics of digital finance are more prominent. Unlike traditional finance, the unique network diffusion and external effects of digital finance help to break the spatial boundaries of financial markets, accelerate the flow of different production factors between regions, accelerate the trading progress of financial markets, and to some extent promote technological innovation. In this process, the "radiation effect" of digital finance not only accelerates the flow of funds and technology in surrounding areas, but also provides practical references for the development model of digital finance, economic growth effects, and ecological protection effects in surrounding areas, which can effectively drive regional digital finance to play a role in carbon reduction (M. Zhang and Liu, 2022). Meanwhile, the "radiation effect" of digital finance accelerates the flow of technology in the surrounding areas. The last hypothesis is proposed.

Hypothesis 5: The carbon emission reduction effect of digital finance has obvious spatial and geographical radiation effect.

3 Variable selection, data sources and model settings

3.1 Variable selection, data sources

Firstly, the explained variable in this research is carbon emissions. Concerning the methods proposed by the IPCC, we use the standard coal method to calculate the total carbon emissions.

$$CO_{2it} = \sum_{i=1}^{9} CO_{2it_p} = \sum_{i=1}^{9} E_{it_p} \times A_p \times B_p \times \frac{44}{12}$$

In this, CO_{2it} indicates the CO_2 emissions of province i in year t, E_{it_p} indicates the CO_2 emissions from the p-th type of fossil fuel in province i in year t, A_p is the physical consumption of the p-th type of fossil fuel, B_p is the carbon element conversion factor for the p-th type of energy, and 44/12 is the CO_2 emission coefficient for the p-th type of energy. Compared with the total carbon emission, this study believes that *per capita* carbon emission (pCO_2) can better reflect the degree of carbon pollution.

Secondly, the core explanatory variable are digital Finance (digf) and green Finance (gref). Existing studies primarily employ three methods to measure digital finance: The first approach involves measuring the regional development level of digital finance based on the frequency of related keywords searched by web crawlers (Ding et al., 2022). The second is to evaluate the effect of policies (Zhong and Jiang, 2021). The third is to build a digital financial index based on comprehensive indicators (Cao et al., 2021). Among them, the third measurement method is the most widely used. This paper utilizes the Digital Financial Inclusion Index, which is jointly compiled by the Digital Financial Research Center of Peking University and Ant Group.

Since its establishment in 2010, the Green Climate Fund (GCF) has been defined as "investment financing that provides environmental benefits" for developing countries to address climate change through various financial instruments and financing Windows for climate-resilient development (D. Zhang et al., 2019). Compared with the Green Climate Fund, the content of the green financial system is more abundant. Based on these opinions, this paper has further enriched and established a comprehensive evaluation index system of green finance. Finally, the score is calculated by the entropy method through the steps of standardization processing, sample weight calculation, index information entropy calculation, information entropy redundancy calculation, and index weight calculation.

Thirdly, technological innovation (tech) and industrial ecolonization (ie) are selected as the mediating variables for digital finance carbon reduction and green finance carbon reduction, respectively. Here, technological innovation is represented by the logarithm of the market technology contract transaction amount, while industrial decolonization is measured using an environmental efficiency indicator.

$$ie = \frac{n}{\sum_{i=1}^{n} pi_i}$$

where pi_i represents the total GDP unit emissions of the ith class of pollutants, and n is the number of indicators.

Economic foundation (eco) and environmental regulation (env) are chosen as moderating variables. The logarithm of the *per capita* GDP represents the economic foundation. Environmental regulation is indicated by the frequency of terms related to carbon emission reduction in local government reports.

Finally, according to the existing research literature, this paper selects some control variables. (1)The industrial structure is represented by the ratio of the added value of the secondary industry to GDP (ind). (2) The level of openness (open) is represented by the ratio of total imports and exports to GDP. (3)

TABLE 1 Statistical description of variables.

	Variable	Mean	S.D	Med	Max	Min
Explained variable	pCO_2	11.228	8.276	8.219	49.474	3.732
Core explanatory variable	digf	217.246	96.968	224.103	431.93	18.33
	coverage breadth	198.01	96.334	198.495	397	1.96
	usage depth	212.036	98.106	203.655	488.68	6.76
	digitization level	290.238	117.644	323.25	462.23	7.58
	gref	0.746	0.065	0.744	0.879	0.62
	grecre	0.041	0.004	0.041	0.052	0.033
	greinv	0.063	0.006	0.063	0.077	0.051
	greins	0.079	0.007	0.078	0.095	0.064
	greb	0.123	0.011	0.124	0.148	0.101
	gresup	0.019	0.003	0.019	0.026	0.013
Intermediate variable	tech	6.318	9.349	7.05	16.16	0.57
	ie	7.673	1.38	7.74	10.874	3.219
Moderating variable	eco	9.833	0.856	9.874	11.615	7.421
	env	57.2	19.701	54	124	6
Control variable	ind	0.431	0.088	0.445	0.59	0.158
	open	0.267	0.297	0.141	1.548	0.008
	urb	58.658	12.217	56.82	89.6	34.96
	pop	472.492	703.978	292.896	3924.29	7.864
	fore	34.527	18.117	38.4	66.8	4.2

Urbanization level (urb), indicated by the proportion of urban population to the total population. (4) Population density (pop) is included as a control variable, measured by the number of permanent residents per square kilometer. (5) Forest cover rate (fore), with forests serving as the 'lungs of the Earth,' significantly contribute to reducing carbon dioxide in the air. At the same time, we also include the level of economic foundation (eco) and environmental regulation (env) in the range of control variables.

Taking into account that a significant turning point in the development of digital finance and green finance may alter their carbon reduction effects, this study, to highlight the most recent developments in the role of digital finance and green finance in carbon reduction, sets the important milestones in their development as the starting point of the research, thereby determining the study interval. The launch of Yu'E Bao in 2013 is regarded as the inaugural year of China's digital finance development. In 2015, China issued the "Overall Plan for Ecological Civilization System Reform" first established the goal of creating a green financial system. Therefore, the panel data of 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) in China from 2013 to 2020 is selected as the research sample to test the impact of digital finance on carbon emissions. The data of 30 provinces from 2015 to 2020 is selected as the research sample to test the relationship between green finance and carbon emissions. The data mainly come from the Center for Digital Inclusive Finance of Peking University, China Statistical Yearbook, and Local Government Reports. The statistical description of variables are shown in Table 1.

3.2 Model setting

Based on the research objectives and the above research hypotheses, the following econometric model is constructed to empirically test the carbon emission reduction effects of digital finance and green finance.

The first one is the direct effects model, which explores the impact of digital finance and green finance on carbon emissions (Y. Wu and Liu, 2024). The specific formula is as follows:

$$pCO_{2_{ij}} = \alpha_0 + \alpha_1 digf_{ij} + \alpha_2 controls_{ij} + \mu_i + \nu_j + \varepsilon_{ij}$$
$$pCO_{2_{ij}} = \beta_0 + \beta_1 gref_{ij} + \beta_2 controls_{ij} + \mu_i + \nu_j + \varepsilon_{ij}$$

i and j are regions and years, $pCO_{2_{ij}}$ represents *per capita* carbon emission, $digf_{ij}$ stands for digital finance, α_0 stands for constant term, α_1 represents the coefficient to be estimated for the impact of digital finance on carbon emissions, which is a key factor to focus on in the empirical results of this section, μ_i and ν_j stand for region fixed and time fixed respectively, and ε_{ij} stands for random disturbance term., $gref_{ij}$ is green finance, β_1 is the coefficient to be estimated for the impact of green finance on carbon emissions.

The second is the mediation effect model, which tests the mechanism and path of carbon reduction in digital finance and green finance (Song et al., 2023). The specific formula is as follows:

$$pCO_{2_{ij}} = \chi_0 + \chi_1 digf_{ij} + \chi_2 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$tech_{ij} = \omega_0 + \omega_1 digf_{ij} + \omega_2 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$pCO_{2_{ij}} = \lambda_0 + \lambda_1 digf_{ij} + \lambda_2 tech_{ij} + \lambda_3 controls + \mu_i + \nu_j + \varepsilon_{ij}$$

$$pCO_{2_{ij}} = m_0 + m_1 gref_{ij} + m_2 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$te_{ij} = n_0 + n_1 gref_{ij} + n_2 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$pCO_{2_{ij}} = z_0 + z_1 digf_{ij} + z_2 te_{ij} + z_3 controls + \mu_i + \nu_j + \varepsilon_{ij}$$

$tech_{ij}$ is technological innovation, te_{ij} is industrial ecologization, and the other variables are the same as above.

The third is a mediation model with regulation, which tests the moderating role of economic growth and environmental regulation in the transmission path (McLarnon & O'Neill, 2018). This study constructs the following mediation effect model with moderation:

$$tech_{ij} = a_0 + a_1 digf_{ij} + a_2 eco_{ij} + a_3 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$tech_{ij} = b_0 + b_1 digf_{ij} + b_2 eco_{ij} + b_3 digf_{ij} \times eco_{ij} + b_4 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$pCO_{2_{ij}} = c_0 + c_1 digf_{ij} + c_2 eco_{ij} + c_3 digf_{ij} \times eco_{ij} + c_4 controls + \mu_i + \nu_j + \varepsilon_{ij}$$

$$te_{ij} = e_0 + e_1 gref_{ij} + e_2 env_{ij} + e_3 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$te_{ij} = f_0 + f_1 gref_{ij} + f_2 env_{ij} + f_3 gref_{ij} \times env_{ij} + f_4 controls + \mu_i + \nu_j + \varepsilon_{ij}$$
$$pCO_{2_{ij}} = h_0 + h_1 gref_{ij} + h_2 env_{ij} + h_3 gref_{ij} \times env_{ij} + h_4 controls + \mu_i + \nu_j + \varepsilon_{ij}$$

eco_{ij} is economic growth, env_{ij} is the environmental regulation, the other variables are the same as above.

The fourth is the spatial regression model, which tests the spatial spillover of carbon reduction in digital finance and green finance. This paper first conducts empirical analysis based on the spatial geographical weight matrix (W_1). If the distance(d) between two cities is closer, the weight will be smaller; otherwise, the weight will be more enormous. The expression is as follows:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}^2}, i \neq j \\ 0, i = j \end{cases}$$

The spatial adjacency matrix (W2) is a traditional 0–1 matrix and a classical non-negative matrix, which is often used to reflect whether there is an adjacency relationship between regions. If two regions are not adjacent, the value is 0; if they are adjacent, the value is 1. The specific expression is as follows:

$$W_{ij} = \begin{cases} 0, \text{The two study areas are not adjacent} \\ 1, \text{The two study areas are adjacent} \end{cases}$$

The spatial economic distance matrix (W3) is measured by regional GDP.

$$W_{ij} = \begin{cases} \left| \frac{1}{G_i - G_j} \right|, i \neq j \\ 0, i = j \end{cases}$$

Based on the proximity of geographical locations and the mobility of economic resources, this paper uses a spatial econometric model to examine the spatial impact (L. Wang, Sun and Xv, 2023).

$$pCO_{2_{ij}} = \tau_0 + \tau_1 digf_{ij} + \tau_2 controls_{ij} + \rho W \times pCO_{2_{ij}} + \theta W \times digf_{ij} + \eta W \times controls_{ij} + \mu_i + \nu_j + \varepsilon_{ij}$$

W is the spatial weight matrix, and the remaining variables are the same as above.

4 Empirical analysis

4.1 Benchmark regression analysis

Theoretically, both digital finance and green finance will have a particular effect on carbon emissions. We first test this effect of them using the SUR method, which pushes the heterogeneity of group coefficients. We obtain the test statistic x2 (1) = 11.68, and the p-value is 0.0004. The null hypothesis was rejected at the 1% significance level, indicating a clear disparity in their carbon reduction effects. Next, this part analyzes and compares the carbon reduction effects of them, respectively.

In the global digital era, all walks of life are grasping the opportunities for digital development and gradually transforming to digital. This part focuses on the impact of digital finance on carbon emissions and further explores the effects from its three dimensions, as shown in Table 2. Whether in univariate regression analysis or in regression controlling for other variables, the result passes the significance test with a negative coefficient, indicating that it can exert a restraining influence on carbon emissions, and the three control variables of industrial structure, environmental regulation, and urbanization level can effectively suppress carbon emissions. Model three shows the impact of coverage breadth on carbon emissions. Under the dual fixed effect model controlling individuals and time, it has an obvious negative effect. Model four show that there is also a negative correlation between the usage depth and carbon emissions. Likewise, model five show that the negative impact of digitalization on carbon emissions is tested at 1% level. Comparatively speaking, the coverage breadth has the most noticeable impact, which once again demonstrates the importance of improving the inclusiveness of digital finance.

In addition to the form of digital finance in the new era, it is also necessary to consider the green finance policy that has attracted global attention. Green finance is a sustainable finance integrating "green" and "finance." Its positive externality features play a crucial role in balancing economiy and climate environment. In the coming decades, China will need a lot of investment to protect environment, so green finance may be a breakthrough to solve this problem. Therefore, this part analyzes the impact of green finance and its sub-dimensions on China's carbon emissions explicitly, and the results are shown in Table 3.

Model one shows the impact of green finance on carbon emissions under the dual fixed effects of individual and time. It is found that it passes the test at 1%, indicating that it has a pronounced carbon emission reduction effect. After adding a series of control variables to Model 1, Model two found that the significance and correlation of the impact of green finance on carbon emissions remained unchanged, once again verifying the role of green finance, and the industrial structure, economic foundation, and the level of openess can also suppress carbon emissions.

TABLE 2 The impact of digital finance on carbon emissions.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
digf	−1.470*** (0.214)	−1.576*** (0.224)			
coverage breadth			−1.434*** (0.337)		
usage depth				−0.762*** (0.135)	
digitization level					−0.511*** (0.100)
ind		−0.226* (0.126)	−0.173*** (0.062)	−0.152 (0.101)	−0.155 (0.103)
eco		−0.031 (0.050)	−0.018 (0.029)	−0.022 (0.015)	−0.012 (−0.008)
env		−0.104*** (0.023)	−0.112*** (0.024)	−0.114* (0.060)	−0.112* (0.062)
open		−0.245 (0.163)	−0.267* (0.148)	−0.214 (0.143)	−0.210 (0.140)
urb		−0.252** (0.130)	−0.195 (0.130)	−0.331* (0.184)	−0.178 (0.136)
pop		−0.327 (0.210)	−0.291 (0.203)	−0.345 (0.231)	−0.388 (0.301)
fore		−0.909 (0.606)	−0.815** (0.408)	−0.953* (0.502)	−0.890* (0.468)
regional fixed effect	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	240	240	240	240	240
R-square	0.295	0.444	0.380	0.409	0.397

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

Specifically, among the various financial instruments included in green finance, it is found that only green investment, insurance, and bonds substantially impact carbon emissions, as shown in Models three to five in Table 3. Green investment suppressed carbon emissions at a significant level of 1%, and green insurance and green bonds hid carbon emissions at a level of 5%. Table 3 reflect the importance of green finance's capital guidance function in restraining and limiting carbon emissions.

The results presented in Tables 2, 3 indicate that both are important financial instruments for carbon reduction, thus preliminarily validating Hypothesis 1. This result is in line with the actual situation of China's economic development and is consistent with the results obtained in existing research, indicating that this study has certain practical reference value. Although the concepts of digital finance and green finance are different, their essential carbon emission reduction goals have natural compatibility and internal unity.

4.2 Mediating effect analysis

Digital finance promotes the transformation of traditional industries by using industrial digitalization and digital industrialization, alleviates the environmental pollution caused by carbon emissions. In Table 4 Models one to Model 2, it is found that digital finance has a positive promoting effect on technological innovation. Technological innovation significantly impact carbon emissions; that is, digital finance has a mechanism to inhibit carbon emissions by fostering technological innovation, and hypothesis 2a is verified.

As the critical factor of technological progress, the economic base will inevitably play a role in this mechanism. Therefore, we further investigated the regulating role of economic growth in the digital financial carbon emission reduction transmission path mediated by technological innovation. In Models 3 to 5, the correlation coefficient of digital finance is 0.729, and that of economic growth is 0.591, indicating that the economic growth is a key factor influencing the promotion of technological progress. The interaction term between the digital economy and economic growth is added, and it is found that the interaction term coefficient passes the test and is positive. Finally, the results of Model five show that the coefficient of the intermediary variable is significantly negative, and the coefficient of the interaction term is positive, indicating that economic growth can strengthen the intermediary role of technological innovation. Hypothesis 2b is verified.

Environmental regulation will encourage to innovate green technology, and promote green development. As an essential ecological regulation tool, green finance can stimulate enterprises to innovate technology by increasing polluting enterprises' financing costs, sunk costs, and environmental violation costs, thus curbing

TABLE 3 The impact of green finance on carbon emissions.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
gref	−1.138*** (0.259)	−1.115*** (0.307)			
greinv			−0.506*** (0.181)		
greins				−0.491** (0.223)	
greb					−0.353** (0.160)
ind		−0.173** (0.070)	−0.196*** (0.070)	−0.164** (0.070)	−0.180*(0.100)
eco		−0.409* (0.215)	−0.385*** (0.143)	−0.421* (0.234)	−0.419** (0.190)
env		−0.321 (0.220)	−0.309 (0.171)	−0.341 (0.204)	−0.365 (0.331)
open		−0.222* (0.117)	−0.227** (0.114)	−0.218*** (0.064)	−0.225* (0.125)
urb		−0.034 (0.155)	−0.020 (0.154)	−0.005 (0.155)	−0.043 (0.155)
pop		−0.860 (0.873)	−0.812 (0.868)	−0.709 (0.875)	−0.910 (0.873)
fore		−0.458 (0.327)	−0.461 (0.325)	−0.462 (0.327)	−0.447 (0.328)
regional fixed effect	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	180	180	180	180	180
R-square	0.191	0.324	0.332	0.326	0.323

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

TABLE 4 The moderating effect of economic growth on carbon emission reduction of digital finance mediated by technological innovation.

Variable	Model 1 tech	Model2 CO2	Model3 tech	Model4 tech	Model 5 CO2
digf	0.636*** (0.227)	−1.103*** (0.394)	0.729*** (0.260)	0.826*** (0.295)	−1.620*** (0.251)
tech		−0.928** (0.422)			−0.905*** (0.323)
eco			0.591*** (0.211)	0.962* (0.506)	0.058** (0.026)
digf×eco				0.811*** (0.290)	0.912*** (0.326)
Controls	Yes	Yes	Yes	Yes	Yes
regional fixed effect	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	240	240	240	240	240
R-square	0.298	0.365	0.444	0.387	0.406

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

carbon emissions and improving ecological benefits. Model 1 to Model 2 in Table 5 test the mediating effect of industrial ecologization. We found that green finance has a significantly positive promoting effect on industrial ecology, and the negative relationship between industrial ecologization and carbon emissions passes the test. Hypothesis 3a is verified.

TABLE 5 The Moderating effect of environmental regulation on carbon emission reduction through green finance mediated by industrial ecologization.

Variable	Model 1, ie	Model 2 CO2	Model 3, ie	Model 4, ie	Model 5 CO2
gref	0.715*** (0.255)	−1.582** (0.688)	0.681*** (0.243)	0.729*** (0.260)	−1.285* (0.664)
ie		−0.112*** (0.025)			−0.386*** (0.138)
env			0.723* (0.402)	0.625*** (0.223)	0.421* (0.234)
gref×env				0.543** (0.247)	0.599** (0.272)
Controls	Yes	Yes	Yes	Yes	Yes
regional fixed effect	Yes	Yes	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	180	180	180	180	180
R-square	0.324	0.380	0.311	0.430	0.496

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

TABLE 6 Robustness test results of carbon emission reduction effect of digital finance.

Variable	Substitute the dependent variable	Subsample regression	
	Carbon emissions per unit of output	2013–2016	2017–2020
digf	−1.582*** (0.419)	−0.894*** (0.319)	−0.635*** (0.227)
ind	−0.672 (0.448)	−0.376 (0.288)	−0.287** (0.130)
eco	−0.304 (0.251)	−0.317 (0.310)	−0.320 (0.288)
env	−0.379** (0.190)	−0.511*** (0.183)	−0.496* (0.261)
open	−0.620 (0.477)	−0.505** (0.230)	−0.621 (0.414)
urb	−0.264 (0.203)	−0.376** (0.171)	−0.418** (0.190)
pop	−0.013 (0.010)	−0.028 (0.112)	−0.015 (0.130)
fore	−0.841*** (0.443)	−0.492** (0.224)	−0.363*** (0.130)
regional fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	240	240	240
R-square	0.302	0.316	0.320

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

The results of Model 3 to Model 5 show that environmental regulation has a specific positive role in promoting industrial ecologization, and the interaction coefficient is positive, indicating that ecological regulation plays an essential positive regulating role in green finance's impact on industrial ecology. In Model 4 and Model 5, we found that environmental regulation plays a positive regulating role in the transmission path of green finance to promote industrial ecological transformation. Hypothesis 3b is verified.

This part of the empirical research differs from existing studies that mainly rely on simple mediation models for mechanism testing. This study considers the complexity of various factors in the carbon reduction path of digital finance and green finance, and constructs a complex mediation model with moderating effects, further expanding the methods used in existing research. The empirical results obtained are more convincing and provide feasible directions for carbon reduction work.

TABLE 7 Robustness test results of carbon emission reduction effect of green finance.

Variable	Substitute the dependent variable	Subsample regression	
	Carbon emissions per unit of output	2015–2017	2018–2020
gref	−1.275*** (0.455)	−0.612** (0.278)	−0.328** (0.031)
ind	−0.535** (0.243)	−0.529** (0.240)	−0.563** (0.256)
eco	−0.278*** (0.099)	−0.750* (0.417)	−0.639* (0.355)
env	−0.310 (0.281)	−0.376 (0.203)	−0.311 (0.219)
open	−0.392*** (0.140)	−0.485** (0.220)	−0.528** (0.240)
urb	−0.628 (0.419)	−0.529** (0.240)	−0.518** (0.235)
pop	−0.176 (0.117)	−0.682* (0.379)	−0.620* (0.344)
fore	−0.621 (0.414)	−0.584** (0.265)	−0.539* (0.284)
regional fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	180	180	180
R-square	0.314	0.305	0.362

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

TABLE 8 Results of regional heterogeneity in the impact of digital finance on carbon emissions.

Variable	Eastern region	Central region	Western region
digf	−0.457*** (0.131)	−1.834*** (0.342)	−2.638** (1.039)
ind	−0.055 (0.041)	−0.125 (0.079)	−0.626*** (0.172)
eco	−0.120 (0.008)	−0.134 (0.103)	−0.127 (0.110)
env	−0.005 (0.023)	−0.153*** (0.050)	−0.125*** (0.044)
open	−0.127* (0.071)	−0.228* (0.120)	−0.246 (0.337)
urb	−0.074 (0.074)	−0.109 (0.399)	−0.203* (0.107)
pop	−0.287 (0.201)	−0.210 (0.321)	−0.238 (0.152)
fore	−0.535*** (0.162)	−0.278 (1.476)	−1.597** (0.766)
regional fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	88	64	88
R-square	0.412	0.328	0.337

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

TABLE 9 Green finance affects the regional heterogeneity of carbon emissions.

Variable	Eastern region	Central region	Western region
gref	−0.144* (0.004)	−0.541* (0.029)	−1.072*** (0.238)
ind	−0.090* (0.050)	−0.188* (0.103)	−0.576*** (0.202)
eco	−0.216*** (0.082)	−1.319*** (0.384)	−0.765 (1.119)
env	−0.321 (0.302)	−0.289 (0.221)	−0.311 (0.209)
open	−0.198*** (0.060)	−0.224*** (0.083)	−0.515 (0.378)
urb	−0.010 (0.093)	−0.175 (0.518)	−1.504* (0.839)
pop	−0.239 (0.330)	−1.582 (6.442)	−0.728 (1.022)
fore	−0.400** (0.168)	−0.845 (1.786)	−1.956** (0.979)
regional fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	66	48	66
R-square	0.398	0.365	0.432

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

TABLE 10 Results of the impact of digital finance on carbon emissions under different levels of financial development.

Variable	High-level finance	Low-level finance
digf	−1.277*** (9.374)	−1.757*** (0.306)
ind	−0.511*** (0.135)	−0.155** (0.067)
eco	−0.235 (0.171)	−0.274 (0.206)
env	−0.095*** (0.033)	−0.117*** (0.041)
open	−0.025 (0.189)	−0.234*** (0.060)
urb	−0.217 (0.271)	−0.419 (0.265)
pop	−0.103 (0.009)	−0.118 (0.103)
fore	−0.476 (0.693)	−0.839** (0.401)
regional fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Observations	80	160
R-square	0.495	0.486

Clustering robust standard errors in the.*$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

TABLE 11 Results of the impact of green finance on carbon emissions under different levels of financial development.

Variable	High-level finance	Low-level finance
gref	−0.178* (0.142)	−2.618*** (0.818)
ind	−0.467*** (0.159)	−0.109 (0.079)
eco	−0.445** (0.221)	−0.375 (0.258)
env	−0.183 (0.161)	−0.192 (0.170)
open	−0.196 (0.244)	−0.149** (0.067)
urb	−0.630** (0.279)	−0.005 (0.292)
pop	−0.602 (1.155)	−6.812*** (2.609)
fore	−0.116 (0.782)	−0.694 (0.428)
regional fixed effect	Yes	Yes
time fixed effect	Yes	Yes
Observations	60	120
R-square	0.404	0.410

Clustering robust standard errors in the.*$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

4.3 Robustness test

The above research hypothesis is preliminarily verified by benchmark regression. Nonetheless, it would be premature to draw definitive conclusions at this juncture. This paper test the robustness: First, replace the explained variables. Considering that carbon emissions come not only from the lives of social residents but also from the

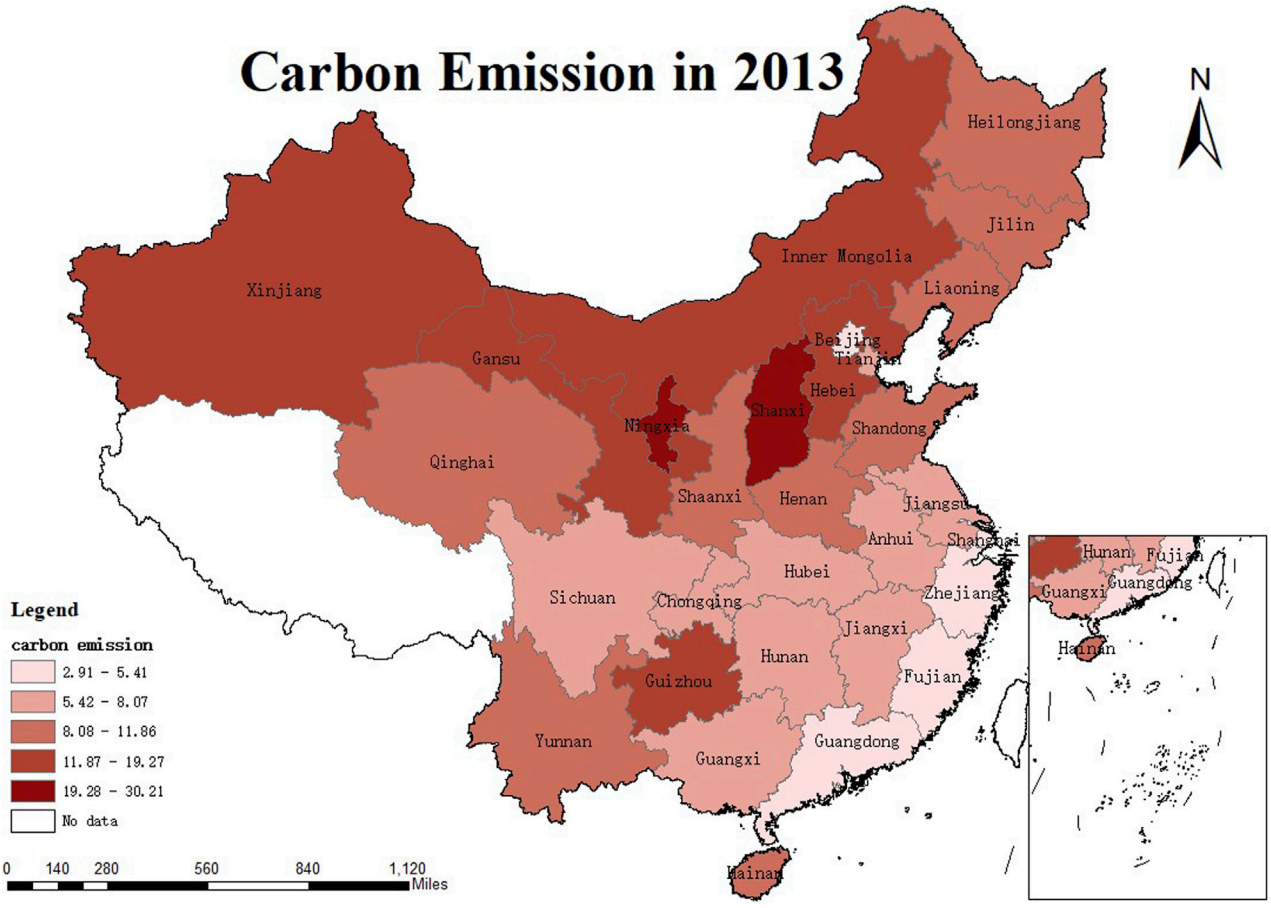


FIGURE 2
Spatial distribution of China's carbon emissions in 2013.

emission of pollutants from social and economic production, replacing carbon emissions *per capita* with carbon emissions per unit of output can also reflect the intensity of carbon emissions. Second, subsample regression. According to the sample period, the whole sample was divided into sub-samples of different sample periods and tested respectively to observe whether the research results were reliable.

In Table 6, the significance and correlation have not changed significantly after replacing explanatory variables, indicating that digital finance can effectively reduce carbon emission intensity. In the sub-sample regression, the results during 2013–2016 and 2017-2020 are consistent with the results of the total sample. In Table 7, the statistical results after replacing explanatory variables and sub-sample regression are roughly consistent with the baseline results. Moreover, it is found that the carbon emission reduction effect of digital finance is still more significant than that of green finance, which again confirms Hypothesis 1.

5 Heterogeneity analysis

5.1 Heterogeneity analysis based on regional development

Uneven regional development has been an essential feature of China's social and productive development for a long time. Therefore, this section analyzes the heterogeneity of the impacts of digital finance and green finance on carbon emissions in the three major regions of China, respectively (Sun and Chen, 2022). In Table 8, we found that the carbon emissions of digital finance in the three major regions of eastern, central, and western China have passed significance tests at the 1%, 1%, and 5% levels, with correlation coefficients of −0.457, −1.834, and −2.638, respectively. In the eastern region, the level of openness and forest coverage can effectively suppress carbon emissions; The inhibitory effect of environmental regulation and the level of openness on carbon emissions in the central region has passed a significance test; In the western region, industrial structure, environmental regulation, urbanization level, and forest cover rate have effectively suppressed carbon emissions. Obviously, digital finance is able to inhibit carbon emissions in different regions, but in comparison, its inhibitory effect in the western region is more substantial. The reasons for this result may include: first, the economic foundation of the region of the west is significantly weaker than that of the eastern and central areas, so it is more sensitive to digital financial services; second, in the eastern and central regions of China, the industrial structure tends to be optimized and upgraded, but the western region is still dominated by the traditional industries, which is more harmful to the environment.

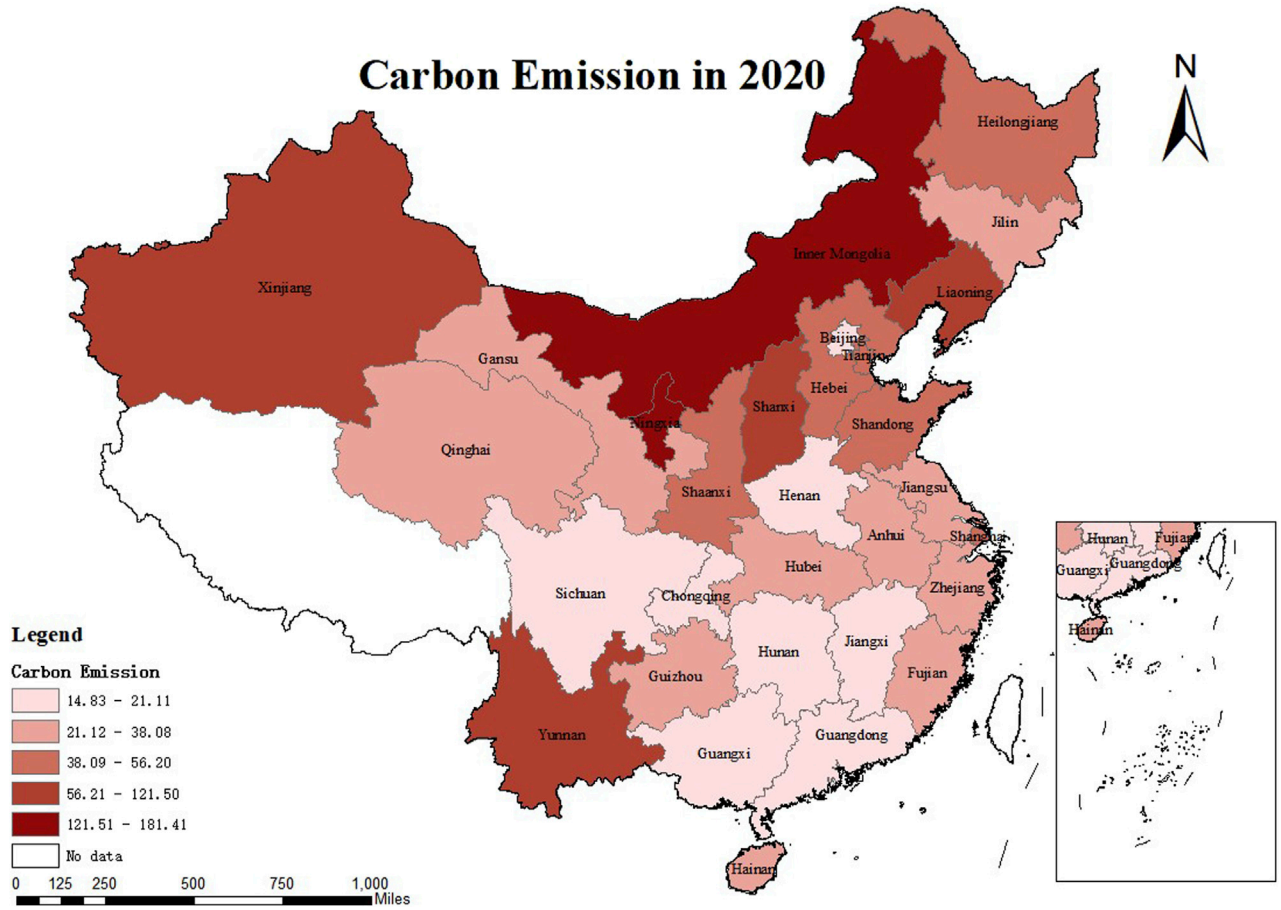


FIGURE 3
Spatial distribution of China's carbon emissions in 2020.

There are significant differences between geographic regions, which may lead to the heterogeneity of emission reduction, and we will verify this conjecture in the following regression analysis of different regional sub-samples. In Table 9, we find that green finance passes the test at the 1% or 10% level for carbon emissions in three regions, the correlation coefficients are negative, and the industrial structure of the three major regions has effectively suppressed local carbon emissions, which suggests that green finance has a specific inhibitory effect on carbon emissions in the three major areas of China, especially in the western area, where the inhibitory effect is the most significant. Possible reasons for this include the following two points: First, the region of the west is rich in energy resources, especially the large scale of natural gas and coal reserves, which provides favorable conditions for the energy industry. Green finance reduces regional carbon emissions by guiding capital into green industries with higher production efficiency, constraining financial support for highly polluting industries. Second, following the inclusion of Guizhou and Xinjiang in China's first batch of Green Finance Reform and Innovation Pilot Zones, Chongqing and Gansu have also been integrated, which highlights the remarkable results of green finance development in the western region.

5.2 Heterogeneity analysis based on financial development level

How does digital finance affect carbon emissions under different economic levels? Will there be significant differences? This section measures the level of financial development by the deposit to loan ratio of each province, and uses the median as the standard to divide high-level and low-level financial regions (Wang and Guo, 2022), exploring the impact of digital finance and green finance on carbon emissions at different levels of financial development. Table 10 gives the answers to these questions. We find that digital finance passes the significance test at the 1% level for carbon emissions in high-level and low-level financial regions, and whether it is a high-level financial region or a low-level financial region, industrial structure and environmental regulation are conducive to reducing carbon emissions. However, comparing the effect of carbon emission reduction of digital finance in high-level financial regions and low-level financial regions, it is found that digital finance has a more prominent role in carbon emission reduction in low-level economic development regions, which may be because emerging forms of financial services such as digital finance provide more opportunities for the development of low-financial level regions so that low-financial level regions can fully tap and enjoy the digital economic dividend, and then apply this dividend in carbon

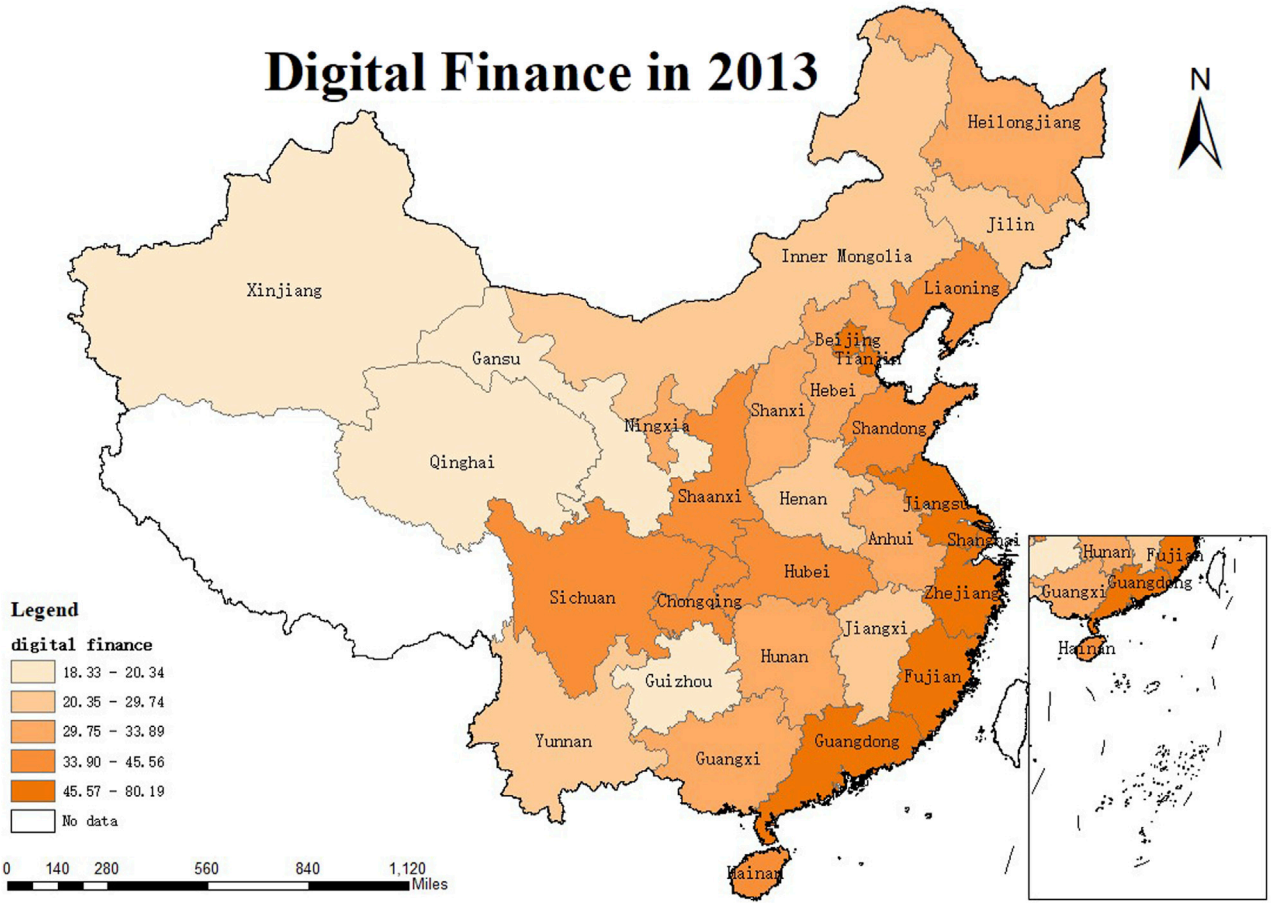


FIGURE 4
Spatial distribution of digital finance in China in 2013.

emission reduction work, to realize the double benefits of economy and ecology.

Green finance realize low-carbon economic transformation. Financial resources are the core body of green finance and the critical factor for the continuous operation and development of microeconomic activities, and the effects of it on carbon emissions in different financial environment may differ. Table 11 indicates that green finance plays a role in mitigating carbon emission pollution in both high-level financial and low-level financial regions. The control variables of industrial structure, economic foundation, population density, level of openess to the outside world, and level of urbanization have a positive effect on suppressing carbon emissions. Still, the significance and absolute value of the regression coefficients of it in the sample group of lower levels of economic development are significantly more considerable than those in the sample group of higher levels of economy. The possible reason is that regions with lower levels of financial have lower eco-efficiency and more substantial financing constraints, and green finance promotes green technological innovation by guiding the rational flow of capital.

The results in Tables 8–11 fully illustrate the heterogeneity of the carbon emission reduction effects of two financial types in different regions and other financial levels in China, and Hypothesis four is verified.

Existing research on financial carbon reduction only considers regional heterogeneity caused by geographical differences in heterogeneity analysis, ignoring the impact of differences in financial development levels on the role of financial carbon reduction. Therefore, in the heterogeneity analysis section, this study comprehensively analyzed the carbon emission reduction effects of digital finance and green finance in the eastern, central, and western regions of China, as well as regions with different levels of financial development, based on geographical location and financial development level. The research results are consistent with the economic and financial development levels of different regions in China, which is conducive to formulating carbon emission reduction plans according to local conditions.

6 Further analysis

6.1 Patterns of spatial evolution

The industrial structure of a region is a critical factor in determining the degree of carbon pollution. Since industrial agglomeration and uneven regional development are significant problems facing China's economic development for a long time, there are bound to be specific spatial differences in carbon emissions per unit of output. In order to further observe the distribution of carbon emissions, digital finance, and green finance in different

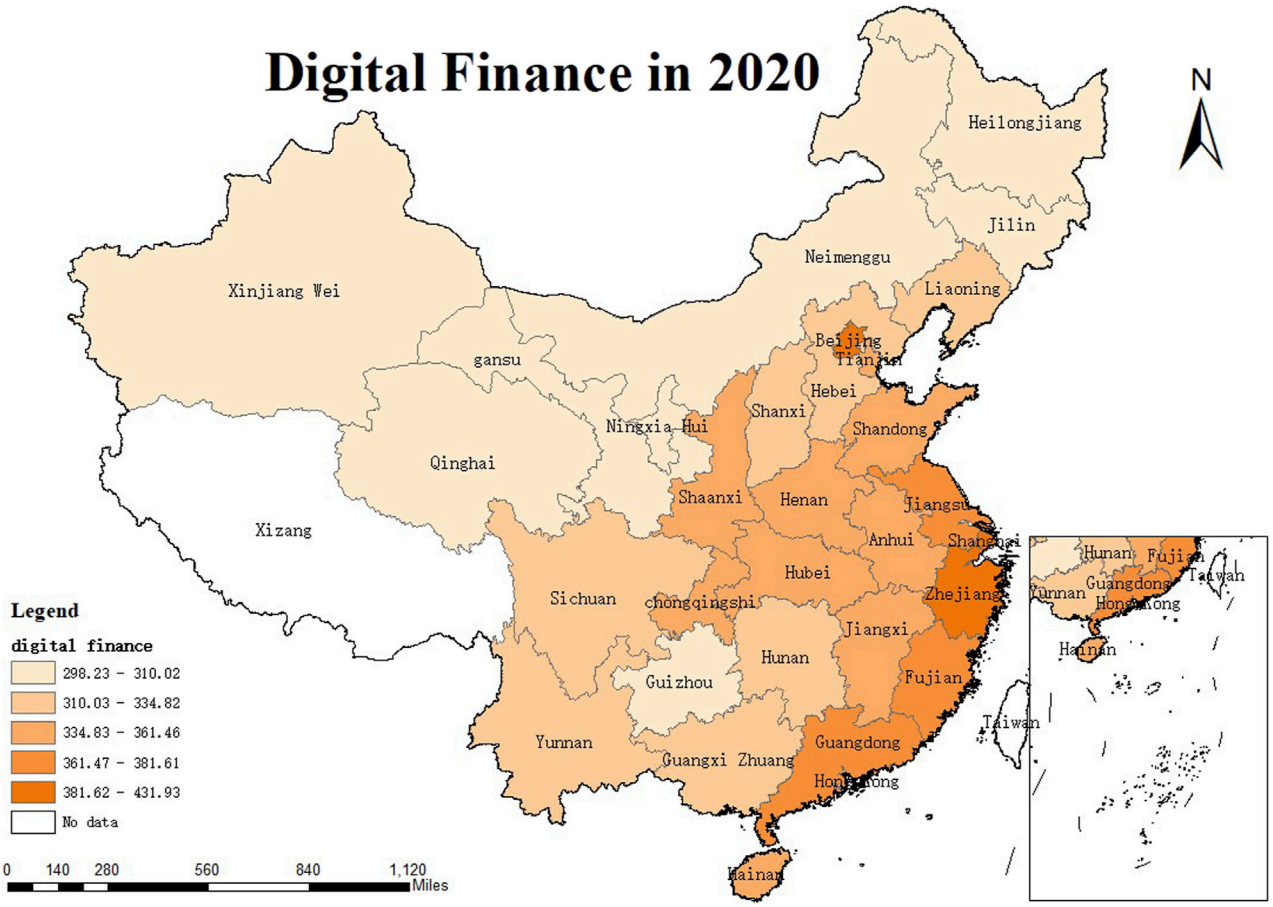


FIGURE 5
Spatial distribution of digital finance in China in 2020.

provinces of China, this study utilizes Arcgis to map the spatial evolution patterns of the three, respectively, as shown in Figures 2–7. Figures 2, 3 show the spatial pattern of carbon emission intensity of China in 2013 and 2020. We find that the intensity of carbon pollution in the northern region is significantly higher than in the southern region. In contrast, the intensity of carbon emission in the eastern coastal region is smaller.

Figures 4, 5 show the spatial distribution pattern of digital finance levels in different provinces in China in 2013 and 2020. From the perspective of time evolution, from 2013 to 2020, China's overall digital finance level increased significantly, which also indicates that the digital economy based on digital technology injects new vitality into the traditional financial system and brings infinite dividends to the financial industry; from the perspective of spatial pattern, the level of digital finance in China's southeastern coastal is significantly higher than that in the inland, and it shows a gradual decrease from the seaside to the inland. This spatial distribution result is consistent with that of China's regions. The result of this spatial distribution is related to the economic foundation and the popularity of digital infrastructure. Generally speaking, the advanced location advantage and good economic foundation make the eastern coastal region more capable of taking the lead in enjoying digital dividends than the inland region to promote the optimization and enhance industrial and economic resilience.

The concept of "green finance" arose in the context of international governmental organizations restraining the financing of polluting projects and has gradually become an essential financial tool for countries to protect environment. Figures 6, 7 show the spatial distribution of the level of green finance in each region of China in 2015 and 2020. Figures 6, 7 show that the level of green finance in most regions of China has been improved, with the level of green finance in the northern region being particularly prominent, which is a particular fit with the spatial distribution of high-carbon emission industries. From the viewpoint of the time series evolution of green finance level from 2015 to 2020, most regions' green finance level has improved.

6.2 Spatial correlation and dependence tests

We find that the carbon emission reduction effect of digital finance is more significant than that of green finance, reflecting that digital finance supported by technology will become the critical direction for China to realize the "dual carbon" goal. According to the "information hinterland theory," the distribution of financial

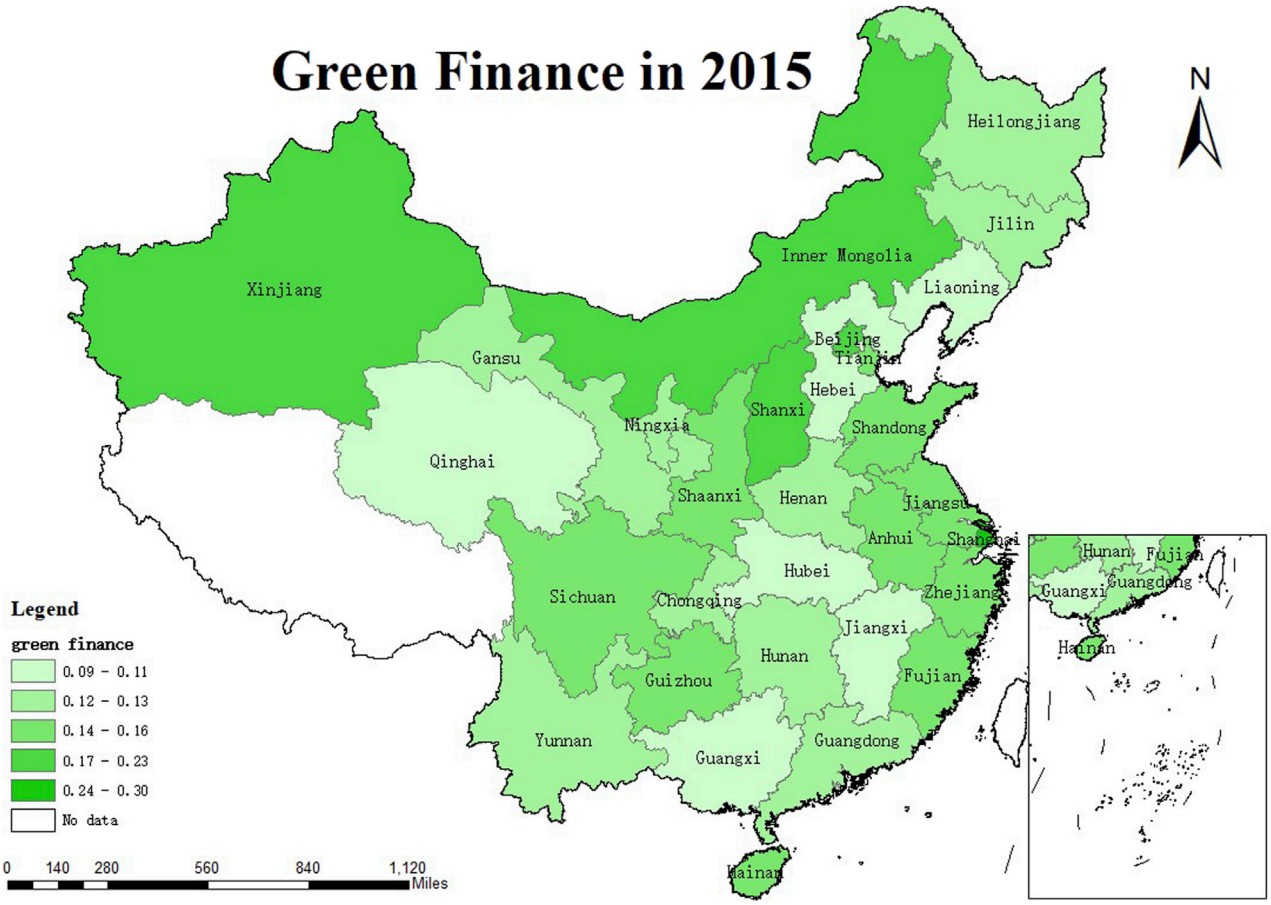


FIGURE 6
Spatial distribution of green finance in China in 2015.

resources in China shows apparent spatial unevenness. In this section, we focus on digital finance to further test whether there is spatiality in the impact of digital finance on carbon emissions.

First, we test the spatial autocorrelation. In Table 12, the global Moran's I in 2013–2020 pass the significance test, indicating that both digital finance and carbon emissions have strong spatial autocorrelation. Secondly, this study follows the rules of "specificity to generality" and "generality to specificity." It combines the LM and LR tests to select the optimal model. The statistical results in Table 13 show that using the SDM is most suitable for this study. Finally, the Hausman test was used to select random or fixed effects, and it was found that this study needs to use the SDM model with both time and individual sets.

Regional linkage development has become the geo-economics development trend. Based on geographic proximity, the characteristics of digital financial inclusion and inclusiveness determine that there may be a specific spatial radiation effect, i.e., digital financial benefits can not only have an impact on the economic development of the region but also have a spillover effect on the economic development of the surrounding areas. In addition, carbon emissions are the primary source of pollution in heavily polluted industrial agglomeration areas, and the resulting air pollution has a robust spatial diffusion, seriously affecting the production and living activities of people. Therefore, we use the SDM to empirically test the "neighborhood effect" of digital finance on carbon emissions. In model one of Table 14, the spatial effect is assumed to be under the spatial geographic distance matrix, and we find that the spatial regression coefficient is −1.732 and passes the test of significance, which means that digital finance has apparent spatial effects on carbon emissions. In order to strengthen the reliability of this result, we replace the spatial geographic distance matrix in Model 1 with the spatial neighboring matrix and spatial economic distance matrix, respectively, and the results are reported in Models two and 3, respectively. We found that the correlation and significance of the spatial coefficients did not change either under the different matrix, and most of the control variables have passed the significance test for their impact on carbon emissions. Hypothesis five can be verified.

Previous studies on spatial regression analysis mostly used only one matrix for testing, and the results lacked reliability. This study tested the spatial effect of digital finance carbon emission reduction under three different matrices, and the results obtained were basically consistent, fully demonstrating that the carbon emission reduction effect of digital finance has spatial spillover and is similar to the spatial test results of digital finance carbon emission reduction in some existing studies.

Since SDM contains the lag terms of the dependent and independent variables, the direct estimates in the model can not



FIGURE 7
Spatial distribution of green finance in China in 2020.

TABLE 12 Global Moran's I for core variables 2013-2020.

Year	Digf	p	pCO2	p
2013	0.128***	0.000	0.084***	0.001
2014	0.128***	0.000	0.081***	0.001
2015	0.101***	0.000	0.078***	0.001
2016	0.123***	0.000	0.077***	0.001
2017	0.129***	0.000	0.067***	0.003
2018	0.140***	0.000	0.065***	0.003
2019	0.144***	0.000	0.061***	0.004
2020	0.149***	0.000	0.047***	0.016

*$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

TABLE 13 Spatial dependence test.

Test	z-value	*p*-value
LM-Err	20.565***	0.000
Robust LM-Err	9.141***	0.003
LM-Lag	12.060***	0.001
Robust LM-Lag	10.763***	0.000
LR-spatial-error	65.43***	0.000
LR-spatial-lag	66.99***	0.000
Hausman	18.58***	0.009

*$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

directly explain the real impact between the variables. It is necessary to decompose the spatial effects using the partial division method, and the results of the decomposition are shown in Table 15. From Table 15, we find that the total impact, direct impact, and indirect impact all pass the significance test. The correlation coefficients are all harmful, indicating that digital finance has a noticeable spatial carbon emission reduction effect. This result means that digital financial dividend can benefit the neighboring areas, inhibit the carbon emissions of the adjacent regions, and then alleviate the negative impacts on the socio-economic development. The digital financial dividend can benefit neighboring regions and curb carbon emissions, thus helping its adverse effects on social and economic development. Whether based on relevant theories or practical tests, the carbon emission reduction benefits of digital finance to the region are always more significant than the benefits to the neighboring areas, and this conclusion also reflects the

TABLE 14 Results of spatial regression analysis.

Variable	Model 1 Spatial geographic distance matrix	Model 2 spatial adjacency matrix	Model 3 Spatial economic distance matrix
digf	−1.757*** (0.264)	−1.721*** (0.615)	−1.689*** (0.582)
ind	−0.236*** (0.057)	−0.367*** (0.131)	−0.276*** (0.099)
eco	−0.312** (0.156)	−0.318** (0.151)	−0.323** (0.147)
env	−0.100*** (0.021)	−0.165* (0.087)	−0.154** (0.070)
open	−0.335*** (0.057)	−0.326** (0.148)	−0.269*** (0.096)
urb	−0.364*** (0.132)	−0.289*** (0.013)	−0.327*** (0.117)
pop	−0.298 (0.201)	−0.311 (0.253)	−0.309 (0.200)
fore	−0.956*** (0.290)	−1.234* (0.649)	−0.883* (0.491)
W digf	−1.732*** (0.619)	−1.564*** (0.559)	−1.629*** (0.582)
W ind	−1.276** (0.580)	−1.261** (0.573)	1.182** (0.537)
W eco	−0.320*** (0.007)	−0.309*** (0.003)	−0.375*** (0.009)
W env	−0.598** (0.272)	−0.552** (0.251)	−0.529** (0.240)
W open	−0.721*** (0.258)	−0.689*** (0.246)	−0.572*** (0.204)
W urb	−0.936** (0.425)	−0.872** (0.396)	−0.727** (0.330)
W pop	−0.124 (0.103)	−0.134 (0.148)	−0.139 (0.177)
W fore	−0.874 (0.583)	−0.906 (0.604)	−0.736* (0.409)
regional fixed effect	Yes	Yes	Yes
time fixed effect	Yes	Yes	Yes
Observations	240	240	240
R-square	0.326	0.306	0.298

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

significance of continuously improving the universality, inclusiveness, and sharing of digital finance.

7 Research conclusions and recommendations

7.1 Conclusions

Excessive CO_2 emission, as a significant threat to the global ecological environment, is a challenge of the times shared by all countries worldwide. Digital finance and green finance, as essential products in different eras, have changed the traditional financial model with technology and concept as the core, respectively, providing essential opportunities for green development. We empirically analyze the impact, mechanism of action, and heterogeneity results of digital finance and green finance on carbon emissions and compare the degree of contribution, respectively. Meanwhile, we further analyze the spatial effect of digital finance carbon emission reduction, which has a more substantial carbon emission reduction effect, as the main body. The study has several findings:

First, both digital finance and green finance have inhibited carbon emissions, and both can point out the direction for envirmental protection.

Second, digital finance mainly realizes carbon emission reduction through technological innovation, and the level of economic development plays an essential positive regulating role in the link of digital finance influencing technological innovation as well as in the whole transmission mechanism. Green finance centered on the green concept is more inclined to reduce pollution through industrial ecologization, in which the stronger the environmental regulation, the stronger the carbon emission reduction effect of green finance mediated by industrial ecology.

Third, due to the variability of geographic regions and the level of financial development, the carbon emission reduction effect of digital finance and green finance presents obvious heterogeneity. Fourth, finance and carbon emissions in China have obvious spatial geographic characteristics, and the inhibitory effect has a robust geographic radiation effect.

Compared with existing research, this study comprehensively compares the carbon reduction effects of digital finance and green finance, expands the boundaries of existing research, and draws

TABLE 15 Spatial effects decomposition results.

Variable	Direct effect	Indirect effect	Aggregate effect
digf	−1.276*** (0.456)	−0.647*** (0.231)	−1.923*** (0.687)
ind	−0.527** (0.240)	−0.344** (0.156)	−0.871** (0.396)
eco	−0.123* (0.068)	−0.102* (0.057)	−0.225* (0.124)
env	0.217** (0.099)	−0.755** (0.343)	−0.538** (0.245)
open	0.116*** (0.041)	−0.437*** (0.156)	−0.321*** (0.115)
urb	0.287** (0.130)	−0.714** (0.325)	−0.427** (0.194)
pop	−0.008 (0.005)	−0.003 (0.009)	−0.011 (0.010)
fore	0.251 (0.167)	−0.790 (0.527)	−0.539 (0.359)

Clustering robust standard errors in the *$P < 0.1$,**$P < 0.05$,***$P < 0.01$.

research conclusions that further enrich existing research, which is beneficial for providing useful references for global carbon reduction work.

7.2 Recommendations

We proposes the following recommendations.

First, strengthen the construction of digital infrastructure and improve the universality and inclusiveness of digital finance. As an emerging financial model of information modernization, the inhibiting effect of digital finance on carbon emissions mainly comes from the popularization of digital financial technology. From the viewpoint of the spatial pattern of digital finance, there is apparent regional variability in digital finance, which mainly stems from the differences in the distribution of digital infrastructure. Efforts should be made to improve the digital infrastructure in less developed regions and rural areas to prevent them from falling into the "middle-level trap" and improve the accessibility and universality of digital infrastructure. At the same time, for the "digital refugee" groups arising from the digital divide, specific digital financial care models should be designed to expand digital finance coverage further and improve digital finance's inclusiveness.

Second, improve the green finance system and unleash the carbon suppression potential of green finance. On the one hand, guiding financial institutions to expand the scale of green finance, innovate green finance products, enrich green financing methods, and provide a good green finance foundation for the green transformation and development of industries; On the other hand, establishing special credit projects for green finance to support energy conservation and emission reduction, increasing credit support, providing strong financial support for environmentally friendly enterprises, and stimulating the transformation and upgrading of the traditional energy industry.

Third, relying on digital technology to promote industrial optimization and upgrading and help traditional industries transform into a green economy. The government should publicize and popularize digital technology and application training, enhance the direct transmission effect of digital technology on industrial empowerment, and strengthen the positive driving effect on industrial transformation and upgrading. At the same time, micro-enterprises should dare to accept the challenges brought by new things, seize the critical opportunities brought by digital technology to improve the production efficiency of enterprises and realize the upgrading and modernization of traditional industries with the support of technological innovation.

Fourth, strengthen the flow of regional financial resources and enhance the synergy of cross-regional digital financial carbon suppression. In the process of the deep integration of digital finance and traditional finance, to give full play to the spillover effect of digital finance on carbon emission reduction, it is necessary to enhance the exchanges and cooperation of financial institutions in neighboring regions, and set up a unified platform for standard trans-regional early warning and pollution data sharing, so as to create multi-party cooperation and mutual support of the Low-carbon life circle, with the city circle as a pilot, to point and face, promote the whole country, strengthen the cross-regional flow of digital financial innovations, encourages the formation of spatial radiation effect of digital economic green economy effect.

Fifthly, the Government's environmental regulation should be increased to enhance the synergistic emission reduction power of financial digitization and greening. Although the carbon emission reduction effect of green finance is weaker than that of digital finance, green finance has added an essential impetus to carbon emission reduction by guiding capital flow, in which government-led environmental regulation has strengthened the carbon emission reduction effect of green finance. Local governments should effectively utilize the information advantage of ecological

management to strictly control carbon emissions by formulating command policies such as market access restrictions, total pollution control, and corporate emission standards. In addition, the Chinese Government should focus on the international carbon tax system and introduce incentive policies such as carbon tax specifically targeting carbon emissions at the right time, focusing on guiding the flow of financial resources from high-emission, heavily polluting traditional overcapacity industries to green and environmentally friendly strategic emerging industries, in order to strengthen further the synergistic carbon-suppression power of finance.

7.3 Limitations and future research

This study still has more deficiencies, which are worth exploring further. Firstly, in the analysis of carbon emission reduction mechanism of digital finance and green finance, we only analyze their respective carbon emission reduction mechanisms individually, and we do not explore the synergistic effect of both on carbon emission reduction, which is a critical content that needs to be deeply explored; Secondly, the whole study is carried out from a macro perspective, exploring the carbon emission reduction effects of digital finance and green finance through industrial adjustment or ecological improvement, but not yet considering how they affect micro households or residents' lives and thus reduce carbon emissions, which provides potential space for future related research.

Data availability statement

The original contributions presented in the study are included in the article, other information is available from the corresponding author upon request.

Author contributions

SJ: Writing–original draft, Writing–review and editing. LW: Conceptualization, Data curation, Methodology, Writing–review and editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2024.1433044/full#supplementary-material

References

Bai, J., Chen, Z., Yan, X., and Zhang, Y. (2022). Research on the impact of green finance on carbon emissions: evidence from China. *Econ. Research-Ekonomska Istraživanja* 35 (1), 6965–6984. doi:10.1080/1331677x.2022.2054455

Chang, J. (2022). The role of digital finance in reducing agricultural carbon emissions: evidence from China's provincial panel data. *Environ. Sci. Pollut. Res.* 29 (58), 87730–87745. doi:10.1007/s11356-022-21780-z

Chen, H., Guo, W., Feng, X., Wei, W., Liu, H., Feng, Y., et al. (2021). The impact of low-carbon city pilot policy on the total factor productivity of listed enterprises in China. *Resour. Conservation Recycl.* 169, 105457. doi:10.1016/j.resconrec.2021.105457

Chen, X., and Chen, Z. (2021). Can green finance development reduce carbon emissions? Empirical evidence from 30 Chinese provinces. *Sustainability* 13 (21), 12137. doi:10.3390/su132112137

Chu, H., Yu, H., Chong, Y., and Li, L. (2023). Does the development of digital finance curb carbon emissions? Evidence from county data in China. *Environ. Sci. Pollut. Res.* 30 (17), 49237–49254. doi:10.1007/s11356-023-25659-5

Ding, N., Gu, L., and Peng, Y. (2022). Fintech, financial constraints and innovation: evidence from China. *J. Corp. Finance* 73, 102194. doi:10.1016/j.jcorpfin.2022.102194

Feng, S., Liu, J., and Xu, D. (2023). Digital financial development and indirect household carbon emissions: empirical evidence from China. *Environ. Dev. Sustain.* doi:10.1007/s10668-023-03603-4

Feng, W., Bilivogui, P., Wu, J., and Mu, X. (2023). Green finance: current status, development, and future course of actions in China. *Environ. Res. Commun.* 5 (3), 035005. doi:10.1088/2515-7620/acc1c7

Huang, J., An, L., Peng, W., and Guo, L. (2023). Identifying the role of green financial development played in carbon intensity: evidence from China. *J. Clean. Prod.* 408, 136943. doi:10.1016/j.jclepro.2023.136943

Lin, Z., Liao, X., and Yang, Y. (2022). China's experience in developing green finance to reduce carbon emissions: from spatial econometric model evidence. *Environ. Sci. Pollut. Res.* 30 (6), 15531–15547. doi:10.1007/s11356-022-23246-8

Liu, S., Zhu, M., and Ling, W. (2023). Research on the impact of population aging and endowment insurance on household financial asset allocation- Evidence on CFPS data. *Finance Res. Lett.* 54, 103719. doi:10.1016/j.frl.2023.103719

Liu, X., Chong, Y., Di, D., and Li, G. (2023). Digital financial development, synergistic reduction of pollution, and carbon emissions: evidence from biased technical change. *Environ. Sci. Pollut. Res.* 30 (50), 109671–109690. doi:10.1007/s11356-023-29961-0

Liu, X., Wang, E., and Cai, D. (2019). Green credit policy, property rights and debt financing: quasi-natural experimental evidence from China. *Finance Res. Lett.* 29, 129–135. doi:10.1016/j.frl.2019.03.014

Lv, C., Fan, J., and Lee, C.-C. (2023). Can green credit policies improve corporate green production efficiency? *J. Clean. Prod.* 397, 136573. doi:10.1016/j.jclepro.2023.136573

McLarnon, M. J. W., and O'Neill, T. A. (2018). Extensions of auxiliary variable approaches for the investigation of mediation, moderation, and conditional effects in mixture models. *Organ. Res. Methods* 21 (4), 955–982. doi:10.1177/1094428118770731

Pu, Z., and Fei, J. (2022). The impact of digital finance on residential carbon emissions: evidence from China. *Struct. Change Econ. Dyn.* 63, 515–527. doi:10.1016/j.strueco.2022.07.006

Shi, F., Ding, R., Li, H., and Hao, S. (2022). Environmental regulation, digital financial inclusion, and environmental pollution: an empirical study based on the spatial spillover effect and panel threshold effect. *Sustainability* 14 (11), 6869. doi:10.3390/su14116869

Sinn, H.-W. (2008). Public policies against global warming: a supply side approach. *Int. Tax Public Finance* 15 (4), 360–394. doi:10.1007/s10797-008-9082-z

Song, X., Yao, Y., and Wu, X. (2023). Digital finance, technological innovation, and carbon dioxide emissions. *Econ. Analysis Policy* 80, 482–494. doi:10.1016/j.eap.2023.09.005

Sun, H., and Chen, F. (2022). The impact of green finance on China's regional energy consumption structure based on system GMM. *Resour. Policy* 76, 102588. doi:10.1016/j.resourpol.2022.102588

Wang, B., Wang, Y., Cheng, X., and Wang, J. (2023). Green finance, energy structure, and environmental pollution: evidence from a spatial econometric approach. *Environ. Sci. Pollut. Res.* 30 (28), 72867–72883. doi:10.1007/s11356-023-27427-x

Wang, H., and Guo, J. (2022). Impacts of digital inclusive finance on CO2 emissions from a spatial perspective: evidence from 272 cities in China. *J. Clean. Prod.* 355, 131618. doi:10.1016/j.jclepro.2022.131618

Wang, J., and Ma, Y. (2022). How does green finance affect CO2 emissions? Heterogeneous and mediation effects analysis. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.931086

Wang, J., Tian, J., Kang, Y., and Guo, K. (2023). Can green finance development abate carbon emissions: evidence from China. *Int. Rev. Econ. Finance* 88, 73–91. doi:10.1016/j.iref.2023.06.011

Wang, L., Sun, Y., and Xv, D. (2023). Study on the spatial characteristics of the digital economy on urban carbon emissions. *Environ. Sci. Pollut. Res.* 30 (33), 80261–80278. doi:10.1007/s11356-023-28118-3

Wang, X., Huang, J., Xiang, Z., and Huang, J. (2021). Nexus between green finance, energy efficiency, and carbon emission: covid-19 implications from BRICS countries. *Front. Energy Res.* 9, 786659. doi:10.3389/fenrg.2021.786659

Wu, M., Guo, J., Tian, H., and Hong, Y. (2022). Can digital finance promote peak carbon dioxide emissions? Evidence from China. *Int. J. Environ. Res. Public Health* 19 (21), 14276. doi:10.3390/ijerph192114276

Wu, Y., and Liu, Y. (2024). How does the digital economy affect urban CO2 emissions? Mechanism discussion and empirical test. *Environ. Dev. Sustain.* doi:10.1007/s10668-024-04502-y

Xu, J., Chen, F., Zhang, W., Liu, Y., and Li, T. (2023). Analysis of the carbon emission reduction effect of Fintech and the transmission channel of green finance. *Finance Res. Lett.* 56, 104127. doi:10.1016/j.frl.2023.104127

Xu, W., Feng, X., and Zhu, Y. (2023). The impact of green finance on carbon emissions in China: an energy consumption optimization perspective. *Sustainability* 15 (13), 10610. doi:10.3390/su151310610

Xu, X., Wang, Q., Ran, C., and Mu, M. (2021). Is burden responsibility more effective? A value-added method for tracing worldwide carbon emissions. *Ecol. Econ.* 181, 106889. doi:10.1016/j.ecolecon.2020.106889

Xue, Q., Feng, S., Chen, K., and Li, M. (2022). Impact of digital finance on regional carbon emissions: an empirical study of sustainable development in China. *Sustainability* 14 (14), 8340. doi:10.3390/su14148340

Yin, Y. (2022). Digital finance development and manufacturing emission reduction: an empirical evidence from China. *Front. Public Health* 10, 973644. doi:10.3389/fpubh.2022.973644

Yuan, Q., Yang, D., Yang, F., Luken, R., Saieed, A., and Wang, K. (2020). Green industry development in China: an index based assessment from perspectives of both current performance and historical effort. *J. Clean. Prod.* 250, 119457. doi:10.1016/j.jclepro.2019.119457

Zhan, Y., Wang, Y., and Zhong, Y. (2023). Effects of green finance and financial innovation on environmental quality: new empirical evidence from China. *Econ. Research-Ekonomska Istraživanja* 36 (3), 2164034. doi:10.1080/1331677X.2022.2164034

Zhang, D., Zhang, Z., and Managi, S. (2019). A bibliometric analysis on green finance: current status, development, and future directions. *Finance Res. Lett.* 29, 425–430. doi:10.1016/j.frl.2019.02.003

Zhang, H., Huang, L., Zhu, Y., Si, H., and He, X. (2021). Does low-carbon city construction improve total factor productivity? Evidence from a quasi-natural experiment in China. *Int. J. Environ. Res. Public Health* 18 (22), 11974. doi:10.3390/ijerph182211974

Zhang, M., and Liu, Y. (2022). Influence of digital finance and green technology innovation on China's carbon emission efficiency: empirical analysis based on spatial metrology. *Sci. Total Environ.* 838, 156463. doi:10.1016/j.scitotenv.2022.156463

Zhang, W., Zhu, Z., Liu, X., and Cheng, J. (2022). Can green finance improve carbon emission efficiency? *Environ. Sci. Pollut. Res.* 29 (45), 68976–68989. doi:10.1007/s11356-022-20670-8

Zhang, X., Bao, K., Liu, Z., and Yang, L. (2022). Digital finance, industrial structure, and total factor energy efficiency: a study on moderated mediation model with resource dependence. *Sustainability* 14 (22), 14718. doi:10.3390/su142214718

Zhao, H., Yang, Y., Li, N., Liu, D., and Li, H. (2021). How does digital finance affect carbon emissions? Evidence from an emerging market. *Sustainability* 13 (21), 12303. doi:10.3390/su132112303

Zheng, H., and Li, X. (2022). The impact of digital financial inclusion on carbon dioxide emissions: empirical evidence from Chinese provinces data. *Energy Rep.* 8, 9431–9440. doi:10.1016/j.egyr.2022.07.050

Zhong, W., and Jiang, T. (2021). Can internet finance alleviate the exclusiveness of traditional finance? evidence from Chinese P2P lending markets. *Finance Res. Lett.* 40, 101731. doi:10.1016/j.frl.2020.101731

Zhou, C., and Qi, S. (2022). Has the pilot carbon trading policy improved China's green total factor energy efficiency? *Energy Econ.* 114, 106268. doi:10.1016/j.eneco.2022.106268

Zhu, S., He, C., and Liu, Y. (2014). Going green or going away: environmental regulation, economic geography and firms' strategies in China's pollution-intensive industries. *Geoforum* 55, 53–65. doi:10.1016/j.geoforum.2014.05.004

Zhu, Z., Liu, B., Yu, Z., and Cao, J. (2022). Effects of the digital economy on carbon emissions: evidence from China. *Int. J. Environ. Res. Public Health* 19 (15), 9450. doi:10.3390/ijerph19159450

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 22 August 2024
DOI 10.3389/fenvs.2024.1458029

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Irina Georgescu,
Bucharest Academy of Economic Studies, Romania
Georgiana Raluca Ladaru,
Bucharest Academy of Economic Studies, Romania

*CORRESPONDENCE
Shuyang Zhu,
zhushuyang@szcu.edu.cn

RECEIVED 01 July 2024
ACCEPTED 13 August 2024
PUBLISHED 22 August 2024

CITATION
Zhu S (2024) Advancing towards a low-carbon urban future in China: the role of producer services agglomeration.
Front. Environ. Sci. 12:1458029.
doi: 10.3389/fenvs.2024.1458029

COPYRIGHT
© 2024 Zhu. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Advancing towards a low-carbon urban future in China: the role of producer services agglomeration

Shuyang Zhu*

School of Digital Economics and Management, Suzhou City University, Suzhou, China

The reduction of greenhouse gas emissions is a shared challenge encountered by nations worldwide. As China is on its way toward a green economy, it is worth studying whether producer services agglomeration, a key driver of economic transition, can promote low-carbon urban development. Using panel data of 257 cities across China from 2006 to 2019, this paper examines the influence of producer services agglomeration on urban carbon emissions with spatial econometric models. The findings reveal a positive spatial correlation in regional carbon emissions. The agglomeration of producer services notably decreases the intensity of local carbon emissions, yet it appears to have minimal influence on the emissions from adjacent regions. Enhancing energy efficiency and adjusting the industrial structure are two critical mechanisms by which producer services agglomeration reduces urban carbon emissions. This beneficial effect varies with city type, the abatement effect of producer services agglomeration is more pronounced in non-resource-based cities. When considering city size, the carbon reduction potential of producer services agglomeration is not apparent in smaller cities. As city size increases, the emission reduction effect becomes more apparent. However, in mega-cities, this impact is somewhat diminished. Accordingly, this paper proposes exploring methods of coordinated air pollution management across cities, promoting producer services agglomeration in line with market mechanisms, and driving low-carbon urban development in a manner tailored to local conditions.

KEYWORDS

producer services agglomeration, industrial structure adjustment, energy efficiency improvement, carbon emission intensity, spatial model

1 Introduction

In light of global climate change, all nations are grappling with the substantial challenge of reducing greenhouse gas emissions. As of 2023, China has released 12.05 billion tons of carbon, making up 32.22% of the global CO_2 emissions total[1]. As the globe's top carbon contributor, China's ability to effectively balance economic expansion with environmental conservation is crucial to its sustainability and has far-reaching effects on global climate management. In this context, the high-tech and environmentally-friendly producer services sector is emerging as a significant player. In the "Eleventh Five-Year Plan" (2006–2010), the Chinese government first proposed expanding the producer services sector, refining and

1 Data sourced from the *CO_2 Emissions in 2023* published by the International Energy Agency (IEA).

deepening the specialization of labor, and improving the efficiency of resource allocation. Since then, producer services have seen rapid growth and increased agglomeration. However, the relationship between the agglomeration of producer services (PSA) and urban carbon emissions remains unclear. This ambiguity gives rise to the central research question of this study: How does the PSA influence urban carbon emissions?

The producer services sector, spearheaded by industries such as finance, information services, and technology services, was spun off from manufacturing. Compared to traditional energy-intensive manufacturing, producer services generally require fewer physical inputs in their operations, leading to lower energy consumption and waste production. This sector is seen as greener due to its more sustainable practices. With the restructuring of China's economy, the producer services have seen rapid growth, forming extensive agglomerations in the developed regions of eastern China and the national central cities. These conglomerates not only spark regional economic growth but also influence urban energy consumption patterns and the trajectories of carbon emissions.

PSA produces a series of environmental effects. While industrial agglomeration can promote resource efficiency through economies of scale, encouraging knowledge sharing, and aiding in the establishment and implementation of green technologies (Lan et al., 2021; Fan et al., 2023; Du and Zhang, 2023), it can also augment energy requirements (Zhao et al., 2021; Wu J. et al., 2021). Furthermore, the conglomeration of the service sector could intensify urbanization, leading to increased traffic congestion, real estate development, and lifestyle changes, all of which could significantly impact a city's carbon emissions. Understanding the link between PSA and urban carbon emissions is vital for stimulating the growth of the producer services sector and for encouraging the establishment of green, low-carbon production and lifestyle habits.

This study empirically explores the research question by examining the influence of PSA on urban carbon emissions using spatial models. It evaluates the influence mechanism of PSA and examines the heterogeneity of its impact on carbon emissions. Through these endeavors, the paper seeks to assist China in enhancing the quality of PSA, crafting differentiated carbon reduction policies, and providing insights and guidance for achieving low-carbon development goals both in China and globally.

The structure of this research is organized for clarity and progression. Section 2 presents a literature review, setting the stage for the theoretical framework discussed in Section 3. Section 4 introduces the econometric model and describes the dataset used for analysis. Section 5 delves into the results, interpreting the estimations. Finally, Section 6 concludes the study, highlighting key findings and their policy relevance.

2 Literature review

Prior studies have expounded on how elements such as urban development (Wang et al., 2021; Xiao et al., 2023), trade liberalization (Dou et al., 2021; Wang et al., 2024), environmental policy (Chen and Lin, 2021; Dong et al., 2022b), technological innovation (Suki et al., 2022; Dong et al., 2022), energy efficiency optimization (Mahapatra and Irfan, 2021; Li et al., 2022a), and industrial restructuring (Wu et al., 2021b; Zhao et al., 2022) can substantially impact regional carbon emissions. The correlation between industrial agglomeration and carbon emissions has been a common theme in research investigating the environmental impacts of industrial structuring, yet a definitive conclusion has not been reached. Much of the research posits that industrial agglomeration facilitates a decrease in carbon emissions through improved research and development (R&D), knowledge transfer and spillover effects (Yu et al., 2018; Lan et al., 2021). Conversely, some studies suggest that the growth of production scale caused by industrial concentration could expedite resource usage, thereby potentially contributing to a rise in carbon emissions (Wu et al., 2021a). The final impact may well depend on the equilibrium between these advantageous and disadvantageous effects, which implies a nonlinear relationship (He et al., 2019).

Producer services emerged from the manufacturing sector, later evolving and separating due to the outsourcing of non-essential functions by manufacturing industries. Research on PSA, an important form of industry agglomeration, has mainly focused on two aspects: its synergistic relationship with the manufacturing sector (Gao et al., 2020; Zeng et al., 2021; Xu et al., 2023; Yang and Shen, 2023) and its contributions to sustainable development (Li W. et al., 2022; Du and Zhang, 2023). Although some studies consider the impact of PSA on carbon emissions, these largely revolve around the manufacturing sector. For example, Jin et al. (2022) and Liu et al. (2022) illustrated how the carbon intensity and efficiency of the manufacturing industry can be improved by the advancement and agglomeration of producer services, respectively. Other research explores the impacts of the co-agglomeration of manufacturing and producer services on carbon emissions, but the findings have been inconsistent. Xiao et al. (2024) argue that this co-agglomeration leads to an improvement in carbon emission efficiency, while other studies suggest a nonlinear relationship (Xu et al., 2023; Meng and Xu, 2022).

So far, the direct impact of PSA on the environment remains underexplored. Only a few studies have addressed this issue. Zhao et al. (2021) reported that PSA might increase carbon emissions by promoting economic scale. Fang et al. (2022) investigated the factors influencing urban carbon emission efficiency, revealing that PSA could boost local carbon emissions efficiency and also enhance the carbon efficiency in nearby regions through demonstration effects. There is a need for more comprehensive research on the ecological effect of PSA. Moreover, further examination is needed to understand how PSA impacts the environment. Past research has studied PSA's mechanisms, focusing on its scale, technology, composition, and demonstration effects (Zhao et al., 2021; Liu et al., 2022; Fanget al., 2022). Some study examined its relationship with industrial structures, indicating that modernization of this structure could help improve urban carbon productivity (Xu et al., 2023). Sun and Li (2022) found that PSA decreases technical efficiency locally, while this negative effect could be reduced by improving industrial structure. Still, the impact of PSA on carbon emissions through energy efficiency has not been fully explored. Additionally, exiting research is insufficient in examining the endogeneity between PSA and carbon emissions. Studies typically focus on how the supply of producer services affects city-level emissions. However, the correlation could also

be reversed. Areas with high carbon emissions could suffer environmental degradation and resultant diminishing standards of living. This scenario may cause a migration of skills and businesses elsewhere, thus inhibiting the accumulation of the producer service sector. In contrast, if a city is burdened with elevated carbon emission levels, the government could incentivize the congregation of service industry businesses through tax benefits, financial aid, or infrastructural investment. These strategies could potentially reduce total carbon emissions. In these instances, a misleading link between PSA and carbon emissions might be discerned. Current literature aims to counter this issue of reverse causality by introducing a 1-year lag for PSA (Liu et al., 2022). However, forecasts of the forthcoming year's emissions could influence government policies and workforce behavior within the current year. Consequently, the effectiveness of using lagged terms may not be particularly strong.

This paper aims to address the recognized lacunae in current research, offering several potential contributions. First, it introduces a fresh viewpoint. The productive service industry is characterized by high added value, high knowledge content, and a relatively low environmental impact. The emergence of PSA not only provides support and services to the manufacturing sector, enhancing its efficiency, but can also generate positive externalities that extend beyond their direct contributions to manufacturing. This work goes beyond the confines of manufacturing to directly assess how PSA influences urban carbon emissions. The findings indicate that PSA substantially lessens the carbon emission intensity in urban areas. Since direct carbon emissions in urban areas contribute to 85% of China's overall carbon emissions (Shan et al., 2019), this work offers a novel perspective for formulating carbon reduction strategies in cities. Second, the paper analyzes the methods by which PSA aids in reducing urban carbon emissions from a novel perspective. It employs the SBM-DEA method to calculate the total-factor energy efficiency and productivity of cities. The results show that PSA contributes to carbon emission reductions by enhancing total-factor energy efficiency. This discovery extends the scope of existing academic discussions. Lastly, the study introduces a novel method to circumvent the endogeneity issues often seen in industrial agglomeration and emission studies. It uses the relief amplitude of various Chinese cities as an instrumental variable for PSA. Relief amplitude is sufficiently exogenous as an instrumental variable and does not directly impact urban carbon emissions intensity, thus providing a robust tool for the analysis.

3 Theoretical analysis

3.1 PSA and energy efficiency improvement

Recent research underscores the importance of energy efficiency in lowering emissions (Akram et al., 2020; He et al., 2021). Dense production and living arrangements can lead to more centralized energy usage, resulting in lower per-unit-area energy consumption (Glaeser and Kahn, 2010). Proque et al. (2020) and Fan et al. (2023) also found that, compared to dispersed production, concentrated production methods benefit from economies of scale, aiding in the reduction of energy use. In the context of PSA, the strategic consolidation of public infrastructure has led to a marked reduction in resource idleness and wastage, which are often a consequence of the geographical dispersion of enterprises. Specifically, the centralized layout of production facilities has reduced energy loss for lighting and heating, thus cutting unnecessary energy consumption. The geographic concentration of employees allows public transportation systems to operate on a larger scale, enhancing operational efficiency and reducing the energy required for commuting. Meanwhile, the shared mechanism of information technology resources effectively prevents redundant labor and resource waste during the R&D process, thereby not only saving on R&D costs but also accelerating the speed of innovation. These shared mechanisms reduce the resource consumption for producing the same quantity of products or services, improve overall energy efficiency, and propose a novel economic development model that emphasizes energy conservation and consumption reduction.

Moreover, the enhancement of energy efficiency heavily relies on advancements in technology (Li and Lin, 2018; Chen and Liu, 2021). Producer services are characterized as talent-intensive, knowledge-intensive, and technology-intensive, which contributes significantly to energy efficiency. Marshall and Guillebaud (1961) found that in areas with a high density of producer services, innovative resources are more concentrated, and the pace of technological advancement is quicker. Furthermore, knowledge-intensive enterprises are more likely to gain the advantage of technology spillovers in an agglomerated environment (Glaeser, 1999). PSA provides geographical convenience, allowing advanced energy-saving and emission-reduction measures to spread through spillover effects, thereby improving labor productivity and energy efficiency on a broader scale. Additionally, the production efficiency of input factors varies across different sectors, and this efficiency difference causes factor flows, with energy factors tending to shift from low-efficiency sectors to high-efficiency sectors. In this process, producer services can propel a comprehensive enhancement of energy efficiency within the agglomeration area.

Hypothesis 1. PSA reduces carbon emission intensity through enhancing energy efficiency.

3.2 PSA and industrial structure adjustment

The adjustment of industrial structure can shift away from an extensive development model, which is favorable for decreasing carbon emissions (Zhao et al., 2022; Zhu, 2022). The agglomeration of producer services is a result of the deepening social division of labor and economic structural adjustment, and the agglomeration will further promote the specialization of producer services, thereby facilitating the enhancement of the overall industrial framework. In economic activities, a significant portion of information is "non-standardized," requiring effective transmission through face-to-face communication among professionals. PSA strengthens the sharing and accumulation of such "non-standardized information" in human capital (Grubel and Walker, 1989). This accumulation of professional talent, in turn, can enhance regional innovation and

management capabilities, promoting the refinement of industrial structure (Cai and Xu, 2017). Furthermore, the agglomeration of producer services increases competition among firms. To capture market share, homogeneous producer service enterprises may reduce prices, which compels them to boost productivity. On the other hand, heterogeneous producer service enterprises are more likely to seek competitive advantages by enhancing technology, improving service quality, and introducing innovative products. This progression encourages the producer services industry to climb from low-end to high-end offerings, ultimately advancing the regional industrial structure.

Hypothesis 2. PSA reduces carbon emission intensity by enhancing the industrial structure.

4 Methods and data

4.1 Model specification

In this section, the study further explores how PSA impacts urban carbon emission intensity through empirical analysis. Influenced by natural conditions, geographic location, industrial transfer and technological spillover, emissions from different regions cannot be spatially isolated. Neglecting spatial correlation when studying regional carbon emissions may lead to inconsistencies between estimated and actual values. To address this, spatial models are utilized. Popular spatial models include the Spatial Lag Model (SAR), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM). Anselin et al. (2013) suggest that the SAR should be chosen when spatial dependence is a significant factor among variables, and the SEM should be selected when the error term is spatially correlated. The SDM, as detailed by Lesage and Pace (2009), is capable of handling both spatial lag and spatial error concurrently, with the SAR and SEM being its simplified variants. In the subsequent analysis, both the Likelihood Ratio (LR) test and the Wald test indicate that the SDM utilized in this study cannot be reduced to either the SEM or the SAR. Therefore, the SDM is selected for empirical analysis, and the model is constructed as follows:

$$\ln CEI_{it} = \rho \sum_{j=1,j\neq i}^{N} W_{ij} \ln CEI_{jt} + \beta \ln PSA_{it} + \gamma \sum_{j=1,j\neq i}^{N} W_{ij} \ln PSA_{jt} + \theta X_{it} + u_i + v_t + \varepsilon_{it} \quad (1)$$

where, $\ln CEI_{it}$, $\ln PSA_{it}$ are the carbon emission intensity and producer services agglomeration for city i in year t, respectively. ρ is the spatial lag coefficient. X_{it} is the set of control variables. u_i, v_t, ε_{it} are individual effect, time effect, and disturbance term, respectively. W_{ij} is the spatial weight matrix and takes the form of:

$$W_{ij} = \begin{cases} e^{-\alpha d_{ij}}, i \neq j \\ 0, i = j \end{cases} \quad (2)$$

Here, d_{ij} is the geographic distance between spatial unit i and spatial unit j. α is a coefficient that takes the reciprocal of the shortest distance between cities.

TABLE 1 Descriptive statistics of variables.

Variable	Obs	Mean	Std	Min	Max
lnCEI	3,598	−0.965	0.725	−3.522	1.748
lnPSA	3,598	−0.214	0.340	−2.128	0.684
lnTE	3,598	−1.122	0.504	−2.657	0.365
lnHD	3,598	0.047	0.096	0.000	2.152
lnSR	3,598	−0.472	1.379	−5.644	4.750
lnHUM	3,598	4.584	1.170	−5.493	7.178
lnINV	3,598	−0.439	0.460	−3.833	0.879
lnFDI	3,598	−4.627	1.392	−17.645	−1.391
lnpGDP	3,598	1.234	0.693	−0.962	3.452
lnFD	3,598	0.701	0.426	−0.580	3.059
lnER	3,598	−1.100	0.439	−4.009	0.032

4.2 Data sources and variable selection

The sample period for this paper is from 2006 to 2019, and the subjects of the study are prefecture-level cities and above[2]. After excluding cities with significant data missing and those with fewer than 100,000 employees, a balanced panel data set comprising 257 cities over 14 years was selected as the analysis sample. All data are sourced from the *China City Statistical Yearbook* of the corresponding years. The following elucidates the choice of variables and the techniques employed to build the indices. Descriptive statistics for these variables are displayed in Table 1.

4.2.1 Dependent variable

Carbon Emission Intensity (CEI). To eliminate the impact of regional economic scale, the CEI for each region is calculated by dividing the total carbon emissions of each city within a specific year by its corresponding GDP. The GDP data used in these calculations is adjusted to constant prices, using 2006 as the base year, to account for inflation. Since urban carbon emissions mainly arise from energy consumption, this study follows the methodology of Wu and Guo (2016), computing urban carbon emissions by estimating and aggregating the emissions produced from four energy sources: electricity, heat, natural gas, and liquefied petroleum gas. The calculation formula is represented as:

$$CO_2 = \sum C_{ij} = \sum E_{ij} \times f_j \quad (3)$$

In Equation 3, C_{ij} is the carbon emissions resulting from the consumption of energy j in city i, E_{ij} is the consumption quantity of energy j in city i, and f_j is the carbon emission coefficient of energy j.

2 The *China City Statistical Yearbook* stopped releasing employment figures categorized by industry after 2019. Therefore, given the research requirements and the constraints of data availability, the sample period is set from 2006 to 2019.

4.2.2 Core explanatory variable

The level of producer services agglomeration (PSA). The primary methods for measuring the degree of PSA include location entropy, the Herfindahl index, and the spatial Gini coefficient. Compared to other methods, location entropy adjusts for the impact of regional scale differences, thereby more accurately reflecting the spatial distribution within smaller areas. Consequently, location entropy is used to measure PSA in this study. Following Fang and Zhao (2021), the producer services are categorized into seven sectors,[3] and the number of individuals employed in these sectors is used as the basic indicator[4].

$$PSA_i = \left(E_{ij} \Big/ \sum_j E_{ij} \right) \Big/ \left(\sum_i E_{ij} \Big/ \sum_i \sum_j E_{ij} \right) \tag{4}$$

In Equation 4, E_{ij}, $\sum_i E_{ij}$ represent the employment in producer service sectors and the total employment in city i, respectively; $\sum_i E_{ij}$, $\sum_i \sum_j E_{ij}$ represent the employment in producer service sectors and the total employment in all cities, respectively. This is a positive index, a higher value corresponds to a greater concentration of producer service sectors.

4.2.3 Mechanism variables

4.2.3.1 Total-factor energy efficiency (TE)

This is estimated using the SBM-DEA model that includes undesired outputs. Specifically, an optimal frontier is established using a non-parametric method. This frontier represents the most efficient production possibility based on the given inputs and outputs. The actual performance of each Decision Making Unit (DMU) is then compared against this optimal frontier to determine its relative efficiency. Assuming there are m DMUs, each of them consumes n inputs, produces u desired outputs, and v undesired outputs. The corresponding vectors are $X = (x_{ij}) \in R^+_{n\times m}$, $Y^g = (y^g_{ij}) \in R^+_{u\times m}$, $Y^b = (y^b_{ij}) \in R^+_{v\times m}$. Then the set of production possibilities can be articulated according to Equation 5:

$$P(x) = \left\{ \left(x, y^g, y^b\right) \middle| x \geq X\lambda, y^g \leq Y^g\lambda, y^b = Y^b\lambda, \sum_{i=1}^{m} \lambda = 0, \lambda \geq 0 \right\} \tag{5}$$

Where λ is the weight of each cross-sectional observation. For a specific DMU, the efficiency score θ^* is obtained by solving the following linear programming problem:

$$\theta^* = \min \frac{1 - \frac{1}{n}\sum_{i=1}^{n} s_i^- \Big/ x_{i0}}{1 + \frac{1}{u+v}\left(\sum_{j=1}^{u} s_j^g \Big/ y_{j0}^g + \sum_{j=1}^{v} s_j^b \Big/ y_{j0}^b \right)} \tag{6}$$

$$s.t.\ x_0 = X\lambda + s^-,\ y_0^g = Y^g\lambda - s^g,\ y_0^b = Y^b\lambda + s^b,\ \lambda, s^-, s^g, s^b \geq 0$$

Where s^-, s^b and s^g are the slack variables of inputs, undesirable outputs and desirable outputs, respectively. In this article, each city is considered as a DMU, and the input indicators used include labor input, capital input, and energy input. Labor input is represented by the count of individuals employed in each city; capital input is estimated using the perpetual inventory method with 2006 as the base year; energy input is calculated using the night light simulation index. The expected output is the constant-price GDP of each city, again with 2006 as the reference year; whereas the unexpected outputs are SO_2 and CO_2 emissions. Given these assumptions, Equation 6 is solved to obtain θ^*, which is the total-factor energy efficiency.

4.2.3.2 Industrial structure rationalization index (SR)

Han et al. (2017) measured the rationality of the industrial structure based on structural deviation and the proportion of output from various industries. The formula is as follows:

$$IS = \sum_{j=1}^{3} \left(\frac{Y_j}{Y} \right) \left| \left(\frac{Y_j}{L_j} \right) \Big/ \left(\frac{Y}{L} \right) - 1 \right| \tag{7}$$

In Equation 7, Y is output, L is labor input, j is the industry (j = 1,2,3). When the productivity levels of all sectors are the same, that is, $Y_j/L_j = Y/L$, the economy is in a state of equilibrium, and the level of industrial structure rationalization is at its highest; at this point, IS = 0. Conversely, the further the economy deviates from the state of equilibrium, the less rational the industrial structure becomes, and the greater the value of IS.

As IS is an inverse indicator, a higher value of IS indicates a lower degree of industrial structure rationalization. In this paper, we take the reciprocal of IS, which makes the explanation of the empirical results in the subsequent text more convenient. The index is constructed according to Equation 8:

$$SR = 1 \Big/ IS = 1 \Big/ \left(\sum_{j=1}^{3} \left(\frac{Y_j}{Y} \right) \left| \left(\frac{Y_j}{L_j} \right) \Big/ \left(\frac{Y}{L} \right) - 1 \right| \right) \tag{8}$$

4.2.3.3 Industrial structure adjustment magnitude (HD)

Following Findeisen and Südekum (2008), it is calculated by the intensity of the re-allocation of employed personnel among industries. The calculation process is as follows:

$$HD_{it} = \left\{ \left[\sum_{j=1}^{n} \left| e_i(j, t+1) - e_i(j,t) \right| \right] - \left| e_i(t+1) - e_i(t) \right| \right\} \Big/ e_i(t) \tag{9}$$

In Equation 9, $e_i(j, t+1)$, $e_i(j,t)$ represent the number of employees in industry j in city i at time $t+1$ and t, respectively. $e_i(t+1)$, $e_i(t)$ are the total number of employees in city i at time $t+1$ and t, respectively. This index is a positive indicator.

3 The seven producer service sectors are: transportation, warehousing and postal services; information transmission, computer services and software industry; financial industry; rental and business services industry; scientific research, technology services and geological exploration industry; wholesale and retail industry; water conservancy, environmental and public facilities management.

4 Given producer service sectors are mainly concentrated in municipal districts, this study is based on persons employed in municipal districts rather than the entire city.

TABLE 2 Results of Moran's I test for China's urban carbon intensity, 2006–2019.

Year	Moran's I	Z-Statistic	Year	Moran's I	Z-Statistic
2006	0.178***	4.536	2013	0.221***	5.626
2007	0.176***	4.496	2014	0.188***	4.802
2008	0.186***	4.749	2015	0.252***	6.392
2009	0.198***	5.050	2016	0.259***	6.571
2010	0.210***	5.343	2017	0.241***	6.125
2011	0.192***	4.894	2018	0.255***	6.470
2012	0.198***	5.058	2019	0.214***	5.444

Note: 1) Prepared based on the processing results from STATA 16 software. 2) *$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

4.2.4 Control variables

(1) Human Capital (HUM) facilitates the dissemination of knowledge and the generation of innovative ideas. The creation of advanced technologies can reduce energy consumption by increasing production efficiency, thereby reducing carbon emissions. Therefore, HUM is used as a control variable and quantified by the ratio of university students per 10,000 individuals.

(2) Physical Capital Investment (INV) not only expands the economic scale but also increases energy consumption, thereby affecting carbon emission intensity. Hence, this indicator is introduced as a control variable and is gauged by the ratio of fixed asset investment to GDP.

(3) Foreign Direct Investment (FDI) is determined by its proportion in relation to GDP. The impact of FDI on carbon emission intensity is complex. On one hand, FDI can stimulate regional economic growth, potentially increasing energy consumption and carbon emissions. On the other hand, FDI can lead to technology spillovers, promoting the optimization of regional industrial structures, potentially reducing carbon emissions.

(4) Economic Development (pGDP), a significant driver of carbon emissions, is included as a control variable and quantified by *per capita* GDP.

(5) Financial Development (FD) has a dual effect on carbon emissions. It can increase carbon emissions by stimulating demand and energy consumption. Simultaneously, it can reduce emissions by facilitating structural adjustments and promoting cleaner production methods. Hence, it is set as a control variable and measured by the ratio of year-end balances of loans and deposits in financial institutions to GDP.

(6) Environmental Regulation (ER) reflects the commitment of local governments to sustainable development and can influence regional carbon emission behaviors. ER is calculated by using Python to tally the occurrence of environmentally related terms in the annual reports of provincial governments. The resulting figure is then adjusted by the output value share of secondary industries in each city within the province for that year.

5 Empirical results and analysis

5.1 Spatial correlation test

Prior to utilizing the spatial econometric approach, it is crucial to initially examine the spatial correlation of the dependent variable. Currently, the most widely used test for this purpose is Moran's I.

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{10}$$

In Equation 10, S^2 is the sample variance, w_{ij} is the spatial weight matrix. Moran's I values range from −1 to 1, with the magnitude indicating the strength of the spatial correlation of the variable in question. According to the results presented in Table 2, the Moran's I values for the intensity of carbon emissions in Chinese cities from 2006 to 2019 are all positive and highly significant, with a noticeable rise in spatial dependence. This means that cities exhibiting high carbon emission intensity are typically neighbored by regions with comparable emission levels. Conversely, cities with low emission intensity are typically near regions with low emissions as well. This pattern of spatial correlation signifies the appropriateness of employing a spatial model.

5.2 Regression results and analysis

To identify the most suitable estimation form of the spatial model, the Lagrange Multiplier (LM) test, the Likelihood Ratio (LR) test, the Wald test, and the Hausman test are conducted sequentially on Equation 2, following the methodology proposed by Elhorst (2014). The findings reveal that both the LM-lag and LM-error are statistically significant at the 1% level, suggesting a preference for the spatial model over the OLS model. Moreover, the LR and Wald tests provide strong evidence against simplifying the SDM to either the SAR or SEM. Additionally, the Hausman test favors fixed effects over random effects. Consequently, a two-way fixed effects SDM is used for analysis. Results from the OLS, SAR, and SEM models are also presented for comparison.

Table 3 shows that the coefficients of PSA are always negative across various models and are statistically significant at the 1% level.

TABLE 3 Baseline results.

	OLS	SAR	SEM	SDM	SDM [Wx]
lnPSA	−0.1406**	−0.1383***	−0.1398***	−0.1468***	0.0096
	(−2.33)	(−5.31)	(−5.33)	(−5.61)	(0.18)
lnHUM	−0.0304	−0.0272*	−0.0242*	−0.0239*	−0.0772***
	(−0.85)	(−1.92)	(−1.70)	(−1.70)	(−2.91)
lnINV	−0.1173***	−0.1125***	−0.1193***	−0.1144***	0.0308
	(−2.91)	(−7.50)	(−7.63)	(−6.65)	(1.22)
lnFDI	0.0046	0.0055	0.0069	0.0115*	−0.0263***
	(0.35)	(0.96)	(1.18)	(1.88)	(-2.76)
lnpGDP	0.0486	0.0703*	0.0884**	0.1981***	−0.4439***
	(0.49)	(1.66)	(1.99)	(4.04)	(-5.79)
lnFD	0.0897	0.1039***	0.1274***	0.1674***	−0.4104***
	(0.84)	(2.58)	(3.06)	(3.95)	(−5.84)
lnER	−0.0574*	−0.0517***	−0.0548***	−0.0232	−0.0326
	(−1.93)	(−2.88)	(−2.80)	(−0.77)	(−0.85)
$\lambda or \rho$		0.1315***	0.1372***		0.1140***
		(5.50)	(5.60)		(4.71)
Time fixed	Y	Y	Y		Y
City fixed	Y	Y	Y		Y
N	3,598	3,598	3,598		3,598

Note: t-statistics are presented in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. This notation applies to all subsequent tables as well.

This suggests that when producer services cluster together, they create beneficial external effects that significantly lower carbon emission intensity in urban areas. Moreover, the spatial lag coefficient ρ is significantly positive, implying a positive spatial correlation or interdependence of carbon emissions among cities in China. This observation underscores the importance of regional collaboration in addressing environmental issues. Further, Wx × lnPSA coefficient is not significant, suggesting that the local development of PSA has minimal influence on carbon emission reduction in adjacent regions. A possible explanation is that China's productive service clusters are predominantly led by government policies, rather than market forces. This approach has somewhat affected the clusters' competitiveness, has not effectively facilitated the exchange of talent, knowledge, and technology, and has thus weakened the positive effects on carbon emissions in neighboring areas.

Regarding the control variables, the inhibitory effects of increased human capital and physical capital on carbon emissions are significantly positive. This may be because skilled individuals and environment-friendly investments contribute to cleaner production, which, in turn, promotes regional decarbonization and sustainable development. Foreign direct investment, economic development, and financial development significantly increase local carbon emission intensity while reducing that of neighboring regions. This could be because the substantial inflow of foreign capital, accelerated economic growth, and rapid financial expansion collectively consume a large amount of natural resources, thus negatively impacting the local ecological environment. However, foreign capital and economic development can bring advanced knowledge and technology, which may spread to neighboring regions, resulting in a decrease in the carbon emission intensity of these areas. Environmental regulations may reduce urban carbon emissions by compelling businesses to use clean energy sources, adopt emission reduction technologies, and by raising public awareness of low carbon practices. The environmental regulation coefficient is not statistically meaningful, potentially due to the diverse intensity of environmental regulation enforcement across various cities.

5.3 Robustness test

To confirm the solidity of the aforementioned analysis, the subsequent methods were employed: (1) Replacing the spatial weight matrix. Since connections between spatial units may be influenced by not only geographic distances but also by regional economic activity, a combined weighting matrix incorporating geographic location and economic linkages is constructed. Equation 1 is then re-estimated. The matrix is in the form of $W_{ij}^{e} = (\overline{Y_i} \times \overline{Y_j})/d_{ij}^{2}$, with diagonal elements taking 0. Where $\overline{Y_i}$ and $\overline{Y_j}$ are average values of GDP *per capita* for city i and j, respectively, during the observation period. (2) Altering the core

TABLE 4 Robustness of baseline results.

	(1)	(2)	(3)	(4)	(5)	(6)
lnPSA	−0.1384***	−0.1086***	−0.1438***	−0.1154***	−0.1403***	−0.0349*
	(-5.32)	(−4.78)	(−5.54)	(−4.19)	(−5.10)	(−1.94)
ρ	0.1525***	0.1108***	0.1076***	0.1114***		0.0534***
	(4.01)	(4.57)	(4.38)	(4.38)		(2.71)
Controls	Y	Y	Y	Y	Y	Y
Time fixed	Y	Y	Y	Y	Y	Y
City fixed	Y	Y	Y	Y	Y	Y
N	3,598	3,598	3,598	3,341	3,598	3,341

independent variable. Narrowing the scope of producer services, and the main regression model is then retested[5]. (3) Changing the dependent variable. Urban carbon emission intensity is recalculated as *per capita* carbon emissions, and the main regression model is reapplied. The outcomes of the robustness tests are presented in the initial three columns of Table 4, demonstrating that the impact of PSA on urban carbon emission intensity is consistent with the findings from the primary model.

To relieve the potential issues of reverse causality and omitted variables between PSA and carbon emissions intensity, the following methods are used for endogeneity testing: 1) First-order lag of PSA. While the likelihood of reverse causality—where urban carbon emission intensity affects the PSA—is relatively low, it is crucial to note that elevated carbon emission intensity could negatively impact the inflow of talent, capital, and technology into urban areas. This effect, often referred to as the crowding-out effect, could subsequently influence the degree of PSA. To mitigate potential bidirectional causation issues, this study substitutes PSA with its first-order lagged value and retest the main model. 2) Instrumental variable method. This method uses relief amplitude as an instrumental variable for PSA. Relief amplitude is a crucial factor in urban construction, as areas with significant relief are unsuitable for housing and CBD development. Underdeveloped CBDs and public service infrastructures can further hinder the clustering of high-tech industries. Moreover, relief amplitude is sufficiently exogenous to serve as an instrumental variable and does not directly impact urban carbon emissions intensity. 3) A dynamic SDM. The dynamic panel model includes the core dependent variable's value from the previous period as a regressor. Since the lagged dependent variable captures the influence of unaccounted variables, accounting for it mitigates the bias due to omitted variables to a certain degree. The regression outcomes, detailed in the final three columns of Table 4, illustrate that after addressing a range of endogeneity issues, PSA continues to be a significant element in diminishing urban carbon emission intensity.

5.4 Heterogeneity test

The above empirical analysis shows that PSA can notably reduce the intensity of urban carbon emissions. However, it is crucial to acknowledge that cities in China vary in size and do not follow the same development path. To account for these differences, the following heterogeneity tests are conducted.

5.4.1 Variations in resource dependency

China is a vast country with diverse resource endowments across regions, and the developmental paths of cities rich in resources differ significantly from those lacking them. In line with the classification provided by the *National Sustainable Development Plan for Resource Cities (2013–2020)*, this study categorizes the sample of 257 cities into 99 resource-based and 158 non-resource-based cities. Table 5 reveals that in non-resource-based cities, PSA notably reduces carbon emission intensity. However, this positive effect is not as prominent in resource-based cities. This difference can be attributed to two factors. First, resource-based cities are less constrained by natural resources, resulting in insufficient motivation to improve energy efficiency. Second, resource-rich areas tend to develop resource-intensive industries and have formed path dependence, resulting in low efficiency of structural adjustment. These two factors together impede the carbon reduction process in resource-based cities.

5.4.2 Variations in city size

The impact of PSA varies with the size of the city. Following the *Notice on Adjustment of City Size Classification Criteria* issued by the State Council in 2014, sample cities are divided into four groups based on the number of permanent residents within each city's municipal district at the end of the year. These groups include large cities I (with populations of 3 million and above), large cities II (with populations ranging from 1 million to 3 million), medium-sized cities (with populations between 5,00,000 and 1 million), and small cities (with populations of 5,00,000 and below).

As depicted in Table 5, PSA can substantially decrease the carbon emission intensity in medium and large cities. Conversely, it appears to increase the same in small cities. This discrepancy may

5 Only five producer service sectors are considered here, they are: transportation, warehousing and postal services; information transmission, computer services and software industry; financial industry; rental and business services industry; scientific research, technology services and geological exploration industry.

TABLE 5 Heterogeneous impacts.

	Resource-based city		City size			
	Yes	No	Small cities	Medium-sized cities	Large cities II	Large cities I
lnPSA	−0.0365	−0.1901***	0.1667**	−0.1408***	−0.2101***	−0.1102*
	(−0.87)	(−5.76)	(2.01)	(−2.66)	(−5.77)	(−1.91)
ρ	0.0605**	0.0419	0.0599	0.0770**	0.1948***	0.1042**
	(1.98)	(1.56)	(1.31)	(2.46)	(6.87)	(2.03)
Controls	Y	Y	Y	Y	Y	Y
Time fixed	Y	Y	Y	Y	Y	Y
City fixed	Y	Y	Y	Y	Y	Y
N	1,386	2,212	336	1,050	1708	504

be due to the insufficient market size in small cities, which prevents the formation of a "clustering effect." Additionally, small cities often suffer from duplicated construction and low-level infrastructure development. This results in resource misallocation and efficiency distortion, which in turn increases the carbon emission intensity. As a city expands in size, the total demand for producer services also increases. As a result, PSA exerts a more significant influence in curbing carbon emissions. It's important to highlight that in large cities I, the advantageous impact of PSA has lessened. Gao and Yuan (2020) argue that this is because the agglomeration of inefficient and homogeneous producer service enterprises in mega-cities leads to resource congestion and energy waste, which ultimately undermines the effectiveness of carbon emission reduction efforts.

TABLE 6 Results of the mechanism test for energy efficiency.

	lnTE	lnSE	lnEC
lnPSA	0.0815***	−0.0854**	0.0455**
	(3.92)	(−2.46)	(2.22)
ρ	0.2721***	0.0918***	0.2245***
	(12.72)	(3.83)	(10.17)
Controls	Y	Y	Y
Time fixed	Y	Y	Y
City fixed	Y	Y	Y
N	3,598	3,598	3,598

5.5 Mechanism test

5.5.1 Energy efficiency improvement

PSA actively promotes the sharing of knowledge and the spread of technology, encouraging regions to adopt cleaner production technologies to optimize their energy use. Moreover, the centralized production approach leads to economies of scale, which, in turn, reduce the resource input required for each unit of output, consequently enhancing regional energy efficiency. Heterogeneity analysis demonstrates that PSA's effect on curbing carbon emissions is more pronounced in cities that do not rely on natural resources. The mechanism of energy efficiency is probably a crucial factor in this observed phenomenon.

The significant role of energy efficiency in influencing carbon emission levels is underscored. To this end, Table 6 offers a detailed regression analysis that isolates and examines the impact of PSA on energy efficiency. Column 1) reveals the impact of PSA on total-factor energy efficiency. The coefficient of PSA indicates that a 1% increase in PSA can enhance total-factor energy efficiency by 0.0815%. In Column 2), single-factor energy efficiency is examined in place of total-factor energy efficiency. This measure of energy efficiency is quantified by the amount of standard coal consumed per unit of GDP, commonly referred to as energy intensity (SE). The results indicate that with a 1% rise in PSA, the energy input per unit of output decreases by 0.0854%. Furthermore, the SMB-GML method is employed to calculate the green total factor productivity (GTFP) of each city. This measurement employs the same inputs and outputs as those used in the assessment of total-factor energy efficiency. GTFP is then decomposed into technical progress (TC) and technical efficiency (EC). Technical efficiency (EC) reflects changes in efficiency resulting from alterations in management, technology, production scale, and other factors, providing a comprehensive assessment of resource efficiency. Technical efficiency (EC) is regressed in Column 3), and the conclusions remain consistent. This implies that PSA can effectively enhance energy efficiency, thus Hypothesis 1 is verified.

5.5.2 Industrial structure adjustment

The adjustment of industrial structure involves two aspects. Firstly, it entails the transition of the dominant industry from the primary sector to the secondary and tertiary sectors within the three major industry categories. Secondly, it involves the replacement of outdated technologies with high-tech alternatives within each industry. A significant amount of research has confirmed the beneficial effect of industrial structure modification on reducing carbon emissions. Therefore, this work reports only the effect of PSA on industrial structure adjustment.

TABLE 7 Results of the mechanism test for structural adjustment.

	lnSRt	lnSRt+1	lnHDt	lnHDt+1
lnPSA	0.2757***	0.2158***	0.0411***	0.0156*
	(5.09)	(3.70)	(4.85)	(1.68)
ρ	0.2389***	0.2262*	0.1313***	0.1391***
	(10.61)	(1.88)	(5.33)	(5.41)
Controls	Y	Y	Y	Y
Time fixed	Y	Y	Y	Y
City fixed	Y	Y	Y	Y
N	3,598	3,341	3,598	3,341

Table 7 shows that the coefficient of PSA is positive at the 1% level when the dependent variable is the industrial structure rationalization index (SR). This result remains consistent when SR is advanced by one period. This suggests that PSA helps to intensify market competition, reduce transaction costs, and promote the effective allocation of production factors within and across industries, thereby promoting the economy towards a more rational industrial structure. Meanwhile, PSA can enhance the division of labor, optimize the business environment, and attract highly skilled talent. This significantly bolsters the modernization of conventional industries and the growth of emerging industries, thereby increasing the magnitude of regional industrial restructuring. Replacing the dependent variable with the industrial structure adjustment amplitude (HD), the results indicate that with each 1% rise in PSA, the industrial structure adjustment amplitude increases by 0.0411%. This suggests that PSA can accelerate economic structure transformation. Hypothesis 2 is verified.

6 Conclusion

This study utilizes data from 257 Chinese cities between 2006 and 2019, and applies a spatial econometric model to explore how PSA impacts the intensity of urban carbon emissions. The results indicate that spatial spillover effects are crucial to understanding patterns of carbon emissions, with high-emission regions often adjacent to others with similarly high levels. PSA can significantly decrease the intensity of local carbon emissions by promoting energy efficiency and refining the industrial structure. However, the absence of effective mechanisms for skill and technology exchange between regions limits the broader impact of local PSA on surrounding area emissions. When considering variations between cities, cities rich in resources may have developed a kind of path dependence, which diminishes the mitigation effects of PSA. Meanwhile, smaller cities might suffer from the duplicated and low-level of construction, leading to an increase in carbon emission intensity. Consequently, the positive effects of PSA on reducing carbon emissions are more evident in non-resource-based cities, as well as in medium-sized and Type II large cities.

These findings yield several significant policy implications. First, there should be a focus on the regional overflow consequences of carbon emissions. Environmental governance framework should break through the restrictions of administrative boundaries, explore a collaborative approach to air pollution management across cities, and promote regional linkage for the transition to low-carbon cities. Second, market mechanisms should be adhered to as the main driver, supplemented by government policy support, to strengthen the construction of producer services clusters. Establish an educational and training cooperation network within the region, promote the circulation of expertise and technological interchange, and accelerate the promotion and application of low-carbon technologies. Third, enhance the sharing of information and infrastructure within clusters to form a scaled factor market and promote energy efficiency improvements. At the same time, optimize the quality of producer services, continuously innovate services and products, and elevate the producer services industry from low-end to high-end, promoting industrial structure optimization. Fourth, formulate differentiated low-carbon development plans according to city types. Resource-based cities can reduce their dependence on traditional resources by introducing and developing circular economies and clean energy industries. Meanwhile, large cities should control the excessive expansion of the producer services industry to avoid redundant construction, whereas medium-sized cities can accept the industrial transfer from large cities by establishing industrial parks, business centers, and other means. Small cities can develop suitable clusters for producer services by identifying their unique advantages and potential for development. For example, they can become outsourcing centers for specific service businesses or develop into professional service centers for certain industries. Such strategies can prevent the environmental negative impacts that may arise from blindly developing clusters of producer services.

It should be noted that this study has certain limitations, primarily due to the difficulty of acquiring data. The research relies chiefly on a sample of urban macro data for empirical analysis. Moreover, data concerning the number of people employed in various industries in Chinese cities post-2020 is unavailable, which may affect the timeliness and relevance of the policy implications derived from this study. Looking towards future research directions, the COVID-19 pandemic has popularized the remote work model, which could potentially change the agglomeration patterns of productive service industries, thereby indirectly affecting the intensity of urban carbon emissions. On the one hand, with the spread of remote work, employees no longer need to be in the same location to perform their jobs. This could significantly decrease the demand for commuting, potentially reducing urban traffic carbon emissions. On the other hand, remote work may increase the reliance on data centers, which could, in turn, increase their energy use and thereby elevate carbon emissions. The specific effects of these impacts may vary depending on the region and the industry. Therefore, more research is necessary to more comprehensively understand the impact of these changes on carbon emissions.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: China City Statistical Yearbook.

Author contributions

SZ: Writing–original draft, Writing–review and editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest

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

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Akram, R., Chen, F., Khalid, F., Ye, Z., and Majeed, M. T. (2020). Heterogeneous effects of energy efficiency and renewable energy on carbon emissions: evidence from developing countries. *J. Clean. Prod.* 247, 119122. doi:10.1016/j.jclepro.2019.119122

Anselin, L., Florax, R., and Rey, S. J. (2013). *Advances in spatial econometrics: methodology, tools and applications*. New York: Springer.

Cai, H., and Xu, Y. (2017). Does trade openness affect the upgrading of China's industrial structure? *J. Quant. Tech. Econ.* 34, 3–22. doi:10.13653/j.cnki.jqte.2017.10.001

Chen, X., and Lin, B. (2021). Towards carbon neutrality by implementing carbon emissions trading scheme: policy evaluation in China. *En. Pol.* 157, 112510. doi:10.1016/j.enpol.2021.112510

Chen, Y., and Liu, Y. (2021). How biased technological progress sustainably improve the energy efficiency: an empirical research of manufacturing industry in China. *Energy* 230, 120823. doi:10.1016/j.energy.2021.120823

Dong, F., Zhu, J., Li, Y., Chen, Y., Gao, Y., Hu, M., et al. (2022a). How green technology innovation affects carbon emission efficiency: evidence from developed countries proposing carbon neutrality targets. *Environ. Sci. Pollut. Res.* 29 (24), 35780–35799. doi:10.1007/s11356-022-18581-9

Dong, Z., Xia, C., Fang, K., and Zhang, W. (2022). Effect of the carbon emissions trading policy on the co-benefits of carbon emissions reduction and air pollution control. *En. Pol.* 165, 112998. doi:10.1016/j.enpol.2022.112998

Dou, Y., Zhao, J., Malik, M. N., and Dong, K. (2021). Assessing the impact of trade openness on CO2 emissions: evidence from China-Japan-ROK FTA countries. *J. Environ. Manag.* 296, 113241. doi:10.1016/j.jenvman.2021.113241

Du, M., and Zhang, Y. J. (2023). The impact of producer services agglomeration on green economic development: evidence from 278 Chinese cities. *Energy Econ.* 106769, 106769. doi:10.1016/j.eneco.2023.106769

Elhorst, J. P. (2014). Matlab software for spatial panels. *Int. Reg. Sci. Rev.* 37 (3), 389–405. doi:10.1177/0160017612452429

Fan, F., Dai, S., Yang, B., and Ke, H. (2023). Urban density, directed technological change, and carbon intensity: an empirical study based on Chinese cities. *Technol. Soc.* 72, 102151. doi:10.1016/j.techsoc.2022.102151

Fang, G., Gao, Z., Tian, L., and Fu, M. (2022). What drives urban carbon emission efficiency? - Spatial analysis based on nighttime light data. *Appl. Energ.* 312, 118772. doi:10.1016/j.apenergy.2022.118772

Fang, H., and Zhao, S. (2021). Has the belt and road initiative promoted the upgrading of China's industrial structure? A difference-in-differences test based on 285 cities of China. *Econ. Res.* 1, 29–42. doi:10.13269/j.cnki.ier.2021.01.003

Findeisen, S., and Südekum, J. (2008). Industry churning and the evolution of cities: evidence for Germany. *J. Urban Econ.* 64 (2), 326–339. doi:10.1016/j.jue.2008.02.003

Gao, K., and Yuan, Y. (2020). Research on resource misallocation effect of producer services agglomeration from the perspective of space. *Mod. Econ. Sci.* 42 (6), 108–119.

Gao, X., Lu, C., and Mao, J. (2020). Effects of urban producer service industry agglomeration on export technological complexity of manufacturing in China. *Entropy* 22 (10), 1108. doi:10.3390/e22101108

Glaeser, E. L. (1999). Learning in cities. *J. Urban Econ.* 46 (2), 254–277. doi:10.1006/juec.1998.2121

Glaeser, E. L., and Kahn, M. E. (2010). The greenness of cities: carbon dioxide emissions and urban development. *J. Urban Econ.* 67 (3), 404–418. doi:10.1016/j.jue.2009.11.006

Grubel, H., and Walker, M. (1989). *Service industry growth: causes and effects*. London: Fraser Institute.

Han, Y., Huang, L., and Wang, X. (2017). Do industrial policies promote industrial structure upgrading? Theory and evidence from China's development-oriented local government. *Econ. Res. J.* 52 (8), 33–48.

He, W., Zhang, H., Chen, X., and Yan, J. (2019). An empirical study on population density, economic agglomeration and carbon emission state of Chinese provinces: from the perspective of agglomeration economy effects, congestion effects and spatial effects. *Nankai Econ. Stud.* 2, 207. doi:10.14116/j.nkes.2019.02.011

He, Y., Liao, N., and Lin, K. (2021). Can China's industrial sector achieve energy conservation and emission reduction goals dominated by energy efficiency enhancement? A multi-objective optimization approach. *En. Pol.* 149, 112108. doi:10.1016/j.enpol.2020.112108

Jin, Z., Li, Z., and Yang, M. (2022). Producer services development and manufacturing carbon intensity: evidence from an international perspective. *En. Pol.* 170, 113253. doi:10.1016/j.enpol.2022.113253

Lan, F., Sun, L., and Pu, W. (2021). Research on the influence of manufacturing agglomeration modes on regional carbon emission and spatial effect in China. *Econ. Model.* 96, 346–352. doi:10.1016/j.econmod.2020.03.016

LeSage, J., and Pace, R. K. (2009). *Introduction to spatial econometrics*. New York: CRC Press, Taylor and Francis Group.

Li, K., and Lin, B. (2018). How to promote energy efficiency through technological progress in China? *Energy* 143, 812–821. doi:10.1016/j.energy.2017.11.047

Li, R., Li, L., and Wang, Q. (2022a). The impact of energy efficiency on carbon emissions: evidence from the transportation sector in Chinese 30 provinces. *Sustain. Cities Soc.* 82, 103880. doi:10.1016/j.scs.2022.103880

Li, W., Zhang, Y., Yang, C., Gong, W., Wang, C., and Zhang, R. (2022b). Does producer services agglomeration improve urban green development performance of the Yangtze River Economic Belt in China? *Ecol. Indic.* 145, 109581. doi:10.1016/j.ecolind.2022.109581

Liu, X., Zhang, X., and Sun, W. (2022). Does the agglomeration of urban producer services promote carbon efficiency of manufacturing industry? *Land Use Policy* 120, 106264. doi:10.1016/j.landusepol.2022.106264

Mahapatra, B., and Irfan, M. (2021). Asymmetric impacts of energy efficiency on carbon emissions: a comparative analysis between developed and developing economies. *Energy* 227, 120485. doi:10.1016/j.energy.2021.120485

Marshall, A., and Guillebaud, C. W. (1961). *Principles of economics: an introductory volume*. London: Macmillan.

Meng, X. N., and Xu, S. C. (2022). Can industrial collaborative agglomeration reduce carbon intensity? Empirical evidence based on Chinese provincial panel data. *Environ. Sci. Pollut. Res.* 29 (40), 61012–61026. doi:10.1007/s11356-022-20191-4

Proque, A. L., dos Santos, G. F., Junior, A. A. B., and Larson, W. D. (2020). Effects of land use and transportation policies on the spatial distribution of urban energy consumption in Brazil. *Energy Econ.* 90, 104864. doi:10.1016/j.eneco.2020.104864

Shan, Y., Liu, J., Liu, Z., Shao, S., and Guan, D. (2019). An emissions-socioeconomic inventory of Chinese cities. *Sci. Data.* 6 (1), 190027. doi:10.1038/sdata.2019.27

Suki, N. M., Suki, N. M., Sharif, A., Afshan, S., and Jermsittiparsert, K. (2022). The role of technology innovation and renewable energy in reducing environmental degradation

in Malaysia: a step towards sustainable environment. *Renew. Energ.* 182, 245–253. doi:10.1016/j.renene.2021.10.007

Sun, S., and Li, X. (2022). Productive services agglomeration, financial development and regional innovation efficiency in the Yangtze River Economic Zone. *FRL* 50, 103221. doi:10.1016/j.frl.2022.103221

Wang, Q., Zhang, F., and Li, R. (2024). Free trade and carbon emissions revisited: the asymmetric impacts of trade diversification and trade openness. *Sustain. Dev.* 32 (1), 876–901. doi:10.1002/sd.2703

Wang, W. Z., Liu, L. C., Liao, H., and Wei, Y. M. (2021). Impacts of urbanization on carbon emissions: an empirical analysis from OECD countries. *En. Pol.* 151, 112171. doi:10.1016/j.enpol.2021.112171

Wu, J., and Guo, Z. (2016). Research on the convergence of carbon dioxide emissions in China: a continuous dynamic distribution approach. *Stat. Res.* 33 (1), 54–60. doi:10.19343/j.cnki.11-1302/c.2016.01.008

Wu, J., Xu, H., and Tang, K. (2021a). Industrial agglomeration, CO2 emissions and regional development programs: a decomposition analysis based on 286 Chinese cities. *Energy* 225, 120239. doi:10.1016/j.energy.2021.120239

Wu, L., Sun, L., Qi, P., Ren, X., and Sun, X. (2021b). Energy endowment, industrial structure upgrading, and CO2 emissions in China: revisiting resource curse in the context of carbon emissions. *Resour. Policy.* 74, 102329. doi:10.1016/j.resourpol.2021.102329

Xiao, Y., Huang, H., Qian, X. M., Zhang, L. Y., and An, B. W. (2023). Can new-type urbanization reduce urban building carbon emissions? New evidence from China. *Sustain. Cities Soc.* 90, 104410. doi:10.1016/j.scs.2023.104410

Xiao, Y., Xu, Y., Li, M., Wang, Y., and Chen, W. (2024). Does the integration of manufacturing and producer services improve carbon emission efficiency? *Clean. Technol. Environ. Policy.* 26 (5), 1603–1619. doi:10.1007/s10098-023-02567-3

Xu, H., Liu, W., and Zhang, D. (2023). Exploring the role of co-agglomeration of manufacturing and producer services on carbon productivity: an empirical study of 282 cities in China. *J. Clean. Prod.* 399, 136674. doi:10.1016/j.jclepro.2023.136674

Yang, Z., and Shen, Y. (2023). The impact of intelligent manufacturing on industrial green total factor productivity and its multiple mechanisms. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.1058664

Yu, X., Chen, H., Wang, B., Wang, R., and Shan, Y. (2018). Driving forces of CO2 emissions and mitigation strategies of China's national low carbon pilot industrial parks. *Appl. Energ.* 212, 1553–1562. doi:10.1016/j.apenergy.2017.12.114

Zeng, W., Li, L., and Huang, Y. (2021). Industrial collaborative agglomeration, marketization, and green innovation: evidence from China's provincial panel data. *J. Clean. Prod.* 279, 123598. doi:10.1016/j.jclepro.2020.123598

Zhao, J., Dong, X., and Dong, K. (2021). How does producer services' agglomeration promote carbon reduction? the case of China. *Econ. Model.* 104, 105624. doi:10.1016/j.econmod.2021.105624

Zhao, J., Jiang, Q., Dong, X., Dong, K., and Jiang, H. (2022). Industrial structure adjustment and CO_2 emissions reduction: a spatial and mediation effects analysis for China. *Energy Econ.* 105, 105704. doi:10.1016/j.eneco.2021.105704

Zhu, X. (2022). Have carbon emissions been reduced due to the upgrading of industrial structure? Analysis of the mediating effect based on technological innovation. *Environ. Sci. Pollut. Res.* 29 (36), 54890–54901. doi:10.1007/s11356-022-19722-w

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 23 August 2024
DOI 10.3389/fenvs.2024.1452791

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Alessia Spada,
University of Foggia, Italy
Pasquale Giungato,
University of Bari Aldo Moro, Italy

*CORRESPONDENCE
Maoguo Wu,
wumaoguo@shu.edu.cn

RECEIVED 21 June 2024
ACCEPTED 01 August 2024
PUBLISHED 23 August 2024

CITATION
Jiang J and Wu M (2024) Does the Belt and Road Initiative reduce smog pollution in key provinces along the route?
Front. Environ. Sci. 12:1452791.
doi: 10.3389/fenvs.2024.1452791

COPYRIGHT
© 2024 Jiang and Wu. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Does the Belt and Road Initiative reduce smog pollution in key provinces along the route?

Jingao Jiang and Maoguo Wu*

SILC Business School, Shanghai University, Shanghai, China

This study investigated the impact of the Belt and Road Initiative (BRI) on reducing smog pollution in key provinces along the route. Utilizing data from 284 prefecture-level cities in China from 2007 to 2018, this study adopted a propensity score matching-difference-in-differences approach, and conducted a series of robustness checks. The results indicate that the BRI has overall reduced particulate matter with aerodynamic diameter less than 2.5 μm (PM2.5) levels in key provinces along the route, and robustness checks find consistent results. Dynamic effect tests reveal a significant reduction in the annual average PM2.5 levels in key provinces along the route after the BRI was implemented in 2014. Tests on underlying mechanism find that the BRI mainly reduced PM2.5 levels in key provinces along the route by promoting technological innovation and optimizing industrial structure. Furthermore, heterogeneity tests find that the BRI significantly reduced PM2.5 levels only in cities of key provinces along the Silk Road Economic Belt, with variations in significance due to regional differences, city administrative levels, and marketization. In addition, the BRI has enhanced green total factor productivity in key provinces along the route by reducing PM2.5 levels. This study enriches research on the economic consequences of the BRI in terms of environmental protection, and also provides empirical support for the construction of the green "Belt and Road."

KEYWORDS

The Belt and Road Initiative, key provinces along the route, smog pollution, PM2.5, China

1 Introduction

The Belt and Road Initiative (BRI) was proposed in 2013. The initiative aims at promoting policy coordination and the connectivity of facilities, unimpeded trade, financial integration, and a people-to-people bond in the international community (The State Council Information Office of China, 2020). The BRI aims to forge new paths of win-win cooperation and mutual development through enhanced bilateral and multilateral relations among participating countries (Huang, 2016). Despite its ambitious goals, the BRI has been met with skepticism, due to concerns over its potential motives behind China's increasing foreign investment and the extensive relocation of China's production capacities to participating countries. Critics are concerned that the BRI might result in transfer of high-polluting, high-carbon-dioxide-emission, and energy-intensive industries to less developed participating countries along the route, exacerbating environmental pollution (Li S. et al., 2022; Liu and Ma, 2023).

A great deal of research pertains to the BRI's effect on economic development in various aspects of trade, overseas direct investment, financing, industry upgrading, corporate innovation, and economic growth (Du and Zhang, 2018; Ramasamy and Yeung, 2019;

Wang and Lu, 2019; Xu S. et al., 2019). However, there have been few attempts to evaluate the effect of the BRI on China's environment, particularly on smog pollution, a severe air pollution problem in China. Several questions loom especially large. As a developing country, China have suffered from environmental pollution during its fast-economic growth. Can the BRI bring about a mitigative effect on smog pollution and unleash new opportunities for environmental protection? What is the channel through which the BRI could reduce smog pollution? Which factors impact the effectiveness of this initiative? Very little progress has been made in addressing these issues.

Based on an evaluation of the BRI, this study provides new evidence of the positive causal link between the BRI and environmental protection. Specifically, this study evaluates the BRI's impact on key provinces along the route, with a focus on smog pollution. Utilizing a panel dataset of 284 prefectural-level cities from 2007 to 2018, we examined the causal relationship between the BRI and smog pollution in a difference-in-differences (DID) framework. We used the particulate matter with aerodynamic diameter less than 2.5 μm (PM2.5) levels for measuring smog pollution. Besides, we investigated technological innovation and optimization of industrial structure to explore the underlying mechanism and examined heterogeneity in the effect. We found that the BRI significantly reduced PM2.5 levels in key provinces; it reduced PM2.5 levels through promoting technological innovation and optimizing industrial structure. The BRI's effect on reducing PM2.5 levels is more pronounced in key provinces belonging to the Silk Road Economic Belt, key provinces in central and western regions, cities of low administrative levels, and cities of low marketization.

This study's contributions are reflected in three aspects. First of all, it enriches research on the impact of the BRI on environment. This study provides new evidence for the discussion on the link between the BRI and environmental protection. Besides, we exploit the underlying path of how the BRI can reduce smog pollution from the perspective of technological innovation and optimization of industrial structure, which has not been fully discussed in previous studies. In addition, we further exploit the economic consequence of the BRI in reducing smog pollution by examining how promoting the BRI affects green total factor productivity (GTFP).

The remainder of this paper is organized as follows. Section 2 reviews related literature, introduces the BRI's institutional background, and develops the hypothesis. Section 3 describes the empirical framework, and Section 4 reports the baseline empirical results and robustness checks. Section 5 is devoted to tests on underlying mechanism, heterogeneity tests, and further economic consequences. Section 6 concludes and discusses policy implications.

2 Related literature and hypothesis development

2.1 Related literature

Previous research has focused on two main contradicting viewpoints regarding the impact of the BRI on environment. Some studies argued that the BRI has a positive impact on environment. Cao et al. (2021) found that the BRI has a certain positive impact on environmental improvement for participating countries of the BRI, but the extent of the impact depends on environmental quality. Su et al. (2022) found that the BRI promotes environmentally friendly practices and lowers carbon footprints of participating countries of the BRI. Xin and Wang (2022) found that the BRI has significantly reduced carbon intensity in participating countries of the BRI by promoting green economic growth, enhancing green technology, and upgrading industrial structure. Besides, Yu et al. (2021) found that the BRI has a reducing effect on environmental pollution in key provinces along the route, using three industrial pollutants, industrial wastewater, soot, and sulfur dioxide as the proxy of environmental pollution. Mahadevan and Sun (2020) found that the BRI has led to a reduction in pollution through China's foreign direct investment efforts, particularly benefiting the western and eastern regions of China. Yin and Wang (2020) found that the atmospheric environmental efficiency[1] in key provinces along the route has remained relatively low over a span of 6 years since the implementation of the BRI. Increasing GDP *per capita* and promoting technological progress are potential mechanism of enhancing atmospheric environmental efficiency in key provinces, while energy consumption structure has a negative effect. Cao et al. (2022) found that with the implementation of the BRI, this is a gradual improvement with considerable potential for energy conservation and emission reduction. Furthermore, Zhao and Liu (2020) found that green financial policies can significantly reduce carbon emissions in key provinces along the route. Moreover, Du et al. (2022) argued that the BRI aims to balance economic development with eco-environmental protection, focusing on reducing environmental pollution through sustainable practices.

On the contrary, some studies found a negative impact of the BRI on environment or an ambiguous relationship between the BRI and environmental quality. Using a multi-regional input–output model, Tang et al. (2021) found that the BRI significantly increased *per capita* consumption-based carbon dioxide emission. Besides, Li B. et al. (2022) found that developing countries participating in the BRI suffer the heaviest smog pollution by having the highest PM2.5 levels and the highest population-weighted exposure level, with the fastest increases observed in the least developed countries. High-risk areas are identified primarily in South Asia, the Arabian Peninsula, and parts of China, thus providing a basis for targeted air pollution control policies. Furthermore, some studies found a negative relationship between the initiative and PM2.5 levels. The BRI promotes urbanization, and urbanization and PM2.5 levels exhibit a coordinated increase in fast developing regions of China (Li et al., 2016). However, within the key provinces along the route, the correlation between urbanization and PM2.5 levels vary. For instance, urbanization led to increased energy pollution emissions and caused dynamic changes in PM2.5 concentrations (Wei et al., 2021). Meanwhile, Fang et al. (2020) found that energy intensity and *per capita* electricity consumption are the main drivers of PM2.5 concentrations by analyzing the spatio-temporal

1 Atmospheric environmental efficiency generally refers to the reduction of atmospheric pollution for the same economic output.

distribution of PM2.5 concentrations in participating countries of the BRI.

Regarding the issue of pollution transfer, Cai et al. (2018) argued that China has become a pollution haven for many developed countries, with 19 developing countries acting as China's pollution havens. Regarding pollution emission levels, Lin (2016) found that there are significant disparities in environmental pollution and green development levels among key provinces along the route; eastern regions have relatively advanced green development and higher economic development levels than central and western regions, but eastern regions also have higher pollution emissions. Huo and Li (2018) found that compared with neighboring countries, China's border provinces have higher carbon emission levels. Additionally, the green development levels in these border provinces vary substantially. Zhang et al. (2022) found that there is a spatial spillover of air pollution in key provinces along the route. In terms of economic development and environmental pollution, Xu W. et al. (2019) found that the overall economic growth has a positive effect on reducing air pollution. However, increases in the number of vehicles, energy consumption, and the secondary industry activities have a negative impact on the environment. Omri and Hadj (2020) found that GDP *per capita*, the number of permanent residents, and foreign direct investment significantly affect the growth of urban carbon emissions, while the increase in *per capita* disposable income of urban residents reduces urban carbon emissions. Regarding the distribution of PM2.5 levels, Mu et al. (2021) found remarkable regional differences in PM2.5 concentrations, with high concentrations in plain and densely populated areas like the North China Plain and low concentrations in Qinghai-Tibet Plateau. Regarding policy recommendations, Wang et al. (2022) examined the relationship between material footprint (MF) and economic growth in participating countries of the BRI. They found that while economic growth has led to increased MF, the coupling varies across regions and income levels. High-income countries experienced better decoupling, and economic growth was achieved with relatively lower increases in MF. The study emphasizes the need for strategic policies and industrial restructuring to promote sustainable development of participating countries of the BRI, as green industries play a crucial role in minimizing environmental impact during economic expansion.

2.2 Institutional background

China's opening up and economic reforms in the past three decades have achieved remarkable success. However, when describing the next period of economic growth, President Xi claimed that China's economic development entered a "new normal" stage in 2014 (China Daily, 2014). This concept is widely used to describe the fact that annual GDP growth has slowed to 7.0–7.5 percent from the double-digit levels of the high-growth period. This is attributed to the now weakened traditional driving forces of growth; that is, the output growth rates of the labor and capital factors that were originally relied on have decreased (Li and Zhang, 2015). Nonetheless, during this long-term extensive development, more attention was paid to quantitative growth, ignoring qualitative economic development and creating bottleneck problems such as overcapacity and inefficient resource allocation (Wang and Johansson, 2013). Under this new normal, opening up further to international trade and strengthening economic cooperation have become important ways to promote economic development. In the Chinese government's 2014 work report, Premier Li proposed that facilitating opening up to force domestic economic reform and structural transformation would be a focus in the 2014 work deployment (The State Council of the People's Republic of China, 2014).

In September and October 2013, China put forward the major initiatives of jointly constructing the Silk Road Economic Belt and the 21st Century Maritime Silk Road, which have attracted great attention. As of 2017, in the 4 years since China put forward the BRI, it has signed production capacity cooperation agreements with 37 countries, and a total of more than 5,000 trains have traveled between China and countries along the European route, connecting two-thirds of the provinces along the route, and flights to countries along the route have been organized. Flights to countries along the route are also distributed in 26 provinces along the route, and 29 provinces have set up industrial parks.

By capitalizing on the synergies of participating countries along the expanding route, the BRI bifurcates into two corridors: the Silk Road Economic Belt, which spans eight Chinese provinces (Xinjiang, Shaanxi, Gansu, Ningxia, Qinghai, Chongqing, Yunnan, and Guangxi), and the 21st Century Maritime Silk Road, encompassing five provinces (Shanghai, Fujian, Guangdong, Zhejiang, and Hainan). The other five key provinces are Inner Mongolia, Heilongjiang, Jilin, Liaoning, and Tibet. (Lam et al., 2018). These key provinces, with their unique geographical location and developed transportation infrastructure, are highly concentrated in business, people, logistics, capital, and information flows, and are responsible for promoting the transformation of China's industries and the construction of the green Belt and Road. Figure 1 visualizes the key provinces along the route in China.

2.3 Hypothesis development

Enhancing technological innovation helps enterprises reduce pollution emissions, and the BRI provides a platform for enterprises to invest overseas and enhance technological innovation, especially in high-end industries, such as transportation, energy, and communications (Du and Zhang, 2018). Lv et al. (2019) found that the BRI contributes to the development of multilateral trade and promotes the outward foreign direct investment (OFDI) of Chinese enterprises. Dunning (1993) and Pradhan and Singh (2009) argued that OFDI is conducive to the improvement of technological innovation. First of all, Chinese enterprises use the BRI platform to invest in factories and set up subsidiaries, joint ventures, and research and development (R&D) centers in participating countries or regions along the route. By doing so they can better participate in the international competitive market, acquire more cutting-edge technological innovations, and give back to parent companies through reversed technology transfer. This will improve the technological innovation capacity of Chinese enterprises through digestion, absorption, and secondary innovation (Pradhan and

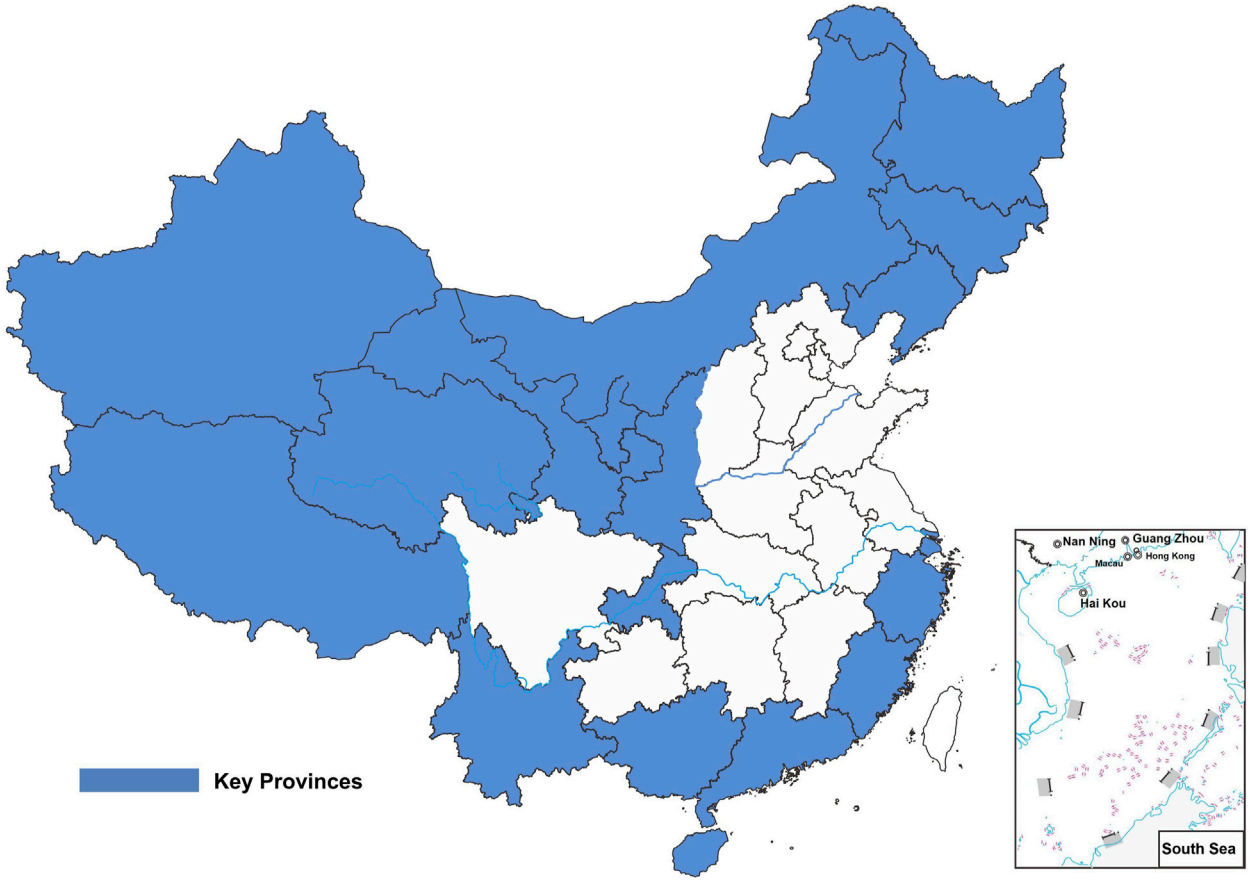


FIGURE 1
Key provinces along the route.

Singh, 2009), thus reducing the pollution emissions of Chinese enterprises. Dunning (1993) found that the number and percentage of patent applications of parent companies were lower than those of foreign subsidiaries, and OFDI promoted the technological innovation capacity of parent companies. Pradhan and Singh (2009) found that OFDI by Indian automobile companies has brought about technology and knowledge spillovers and promoted technological innovation capacities of parent companies. Besides, technological innovation requires enterprises to invest a great deal of money, and overseas subsidiaries can take over part of the peripheral and repetitive production work, so that parent companies can save the production costs and concentrate their financial resources on the R&D of the core technology, the introduction of high-end talents, and the purchase of R&D technology and products, so as to enhance the overall R&D and technological innovation capacities. Moreover, OFDI enterprises are generally given priority to take the privilege of the country's customs services, tax incentives, and foreign exchange support policies, which can also save some of the R&D costs for OFDI enterprises (Xu and Wang, 2018) and indirectly promote technological innovation.

Under the policy background of the BRI, more and more countries are investing in China. Factor resources continue to flow and cluster in Chinese cities along the route. Resource allocation gradually tends to be rationalized, energy consumption is gradually reduced, and corporate pollution emissions are gradually reduced. The Digital Belt and Road (DBAR) integrates cloud computing, big data platform, Internet of Things, mobile Internet, and other high-tech information technology. It can promote the flow and agglomeration of factors such as labor, capital, network, and technology to Chinese cities along the route, improve the efficiency of resource allocation, and optimize the industrial structure (Shi et al., 2018), and reduce pollution emissions. Ma and Cao (2022) found that the optimization of industrial structure reduces levels of atmospheric haze. Chen and Wang (2022) found that the BRI can help upgrade and optimize the industrial structures of key provinces along the route, mainly through optimization of the investment environment and the adjustment of the relationship between supply and demand. The information technology in the DBAR can timely and efficiently coordinate and allocate labor, transportation, logistics, information, and other resources in cities along the route. It therefore reduces the transaction costs of enterprises, and promotes the flow of factor resources to low-energy consumption and low-polluting enterprises, eliminating high-energy-consumption and high-polluting enterprises. It consequently realizes the reasonable and effective allocation among industries and sectors, thus reducing the pollution emission of the whole industry (Ryzhenkov, 2016). Besides, the information technology industry in the DBAR is characterized by high technology and low pollution, which can bring competitive pressure to the traditional polluting industries in cities along the route. Not only can it force these traditional polluting industries to carry out technological innovation and R&D on clean technology, but also eliminate those traditional polluting industries and

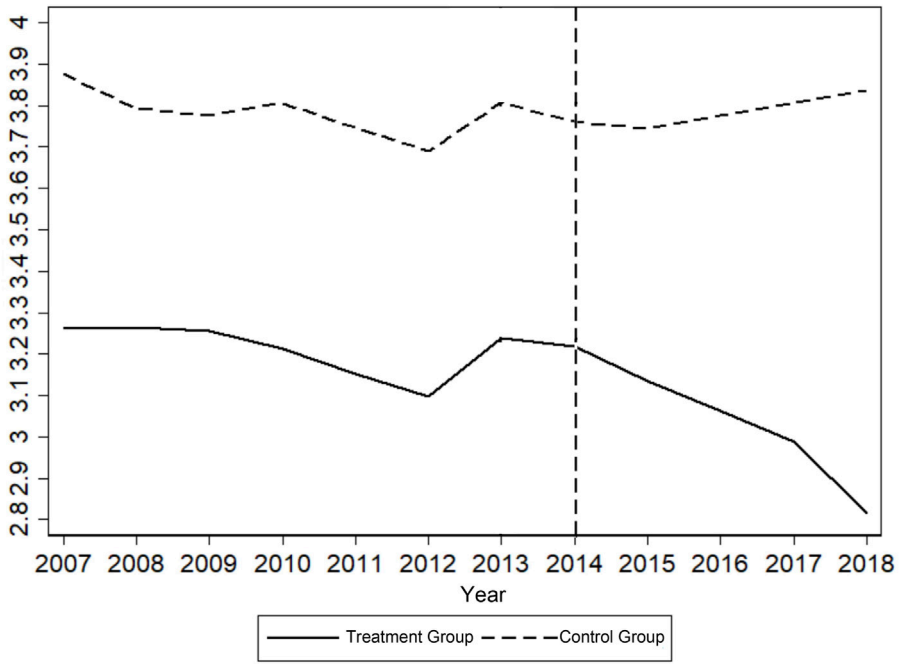


FIGURE 2
Parallel trend test.

TABLE 1 Variable definitions.

Variables	Denotation	Definition and calculation method
Explained variable	PM2.5	Logarithm of annual average PM2.5 levels of each prefecture-level cities
Main explanatory variable	Key provinces	Equals 1 if a prefecture-level city is in a key province, and otherwise, 0
	Post	Before or after the initiation: post equals 0 before 2014 and 1 after 2014
Control variables	Fixed asset investment	Log value of regional fixed asset investment
	Human capital	Number of students in general higher education
	Employment	Urban employment: proportion of employees in an urban area to the region's total population
	Secondary	The secondary industry: output value of the secondary industry accounts for the proportion of regional GDP
	Tertiary	The tertiary industry: output value of the tertiary industry accounts for the proportion of regional GDP
	Income	Average income *per capita*: log value of *per capita* real wage in a prefecture-level city
	Technology	Government spending on science and technology as a percentage of regional GDP
	Intervention	Government intervention: proportion of government budget expenditures to regional GDP

enterprises (Shi et al., 2018), thus reducing environmental pollution. Moreover, the information technology in the DBAR can timely grasp the market demand and market demand preferences of cities along the route. Once changes occur, it can quickly adjust and change the business strategy of enterprises, flexibly dispatch production factors such as labor, capital, and energy, so as to meet the real demand of the market in the cities along the route. DBAR can scientifically, accurately, and efficiently carry out product production, and reduce resource consumption.

Based on the above analysis, we propose the following hypothesis.

H1. The BRI reduces PM2.5 levels by promoting technological innovation and optimizing industrial structure.

3 Empirical framework

3.1 Explained variable

This study examines whether the BRI can reduce smog pollution in key provinces along the route. This study adopts PM2.5 levels as the measure of smog pollution. The annual data of average

TABLE 2 Descriptive statistics.

Variables	Sample size	Mean	Std	Min	Max
PM2.5	3,221	3.512	0.510	1.543	4.471
Fixed asset investment	3,281	7.596	1.0560	4.629	10.722
Human capital	3,281	54.630	80.369	5.490	986.870
Employment	3,281	12.411	11.772	0.260	147.310
Secondary	3,281	48.403	10.616	0.000	90.970
Tertiary	3,281	39.937	72.216	0.000	4,139
Income	3,281	5.506	0.351	3.360	7.580
Technology	3,281	7.694	0.810	4.120	10.920
Intervention	3,281	21.332	22.822	1.540	604.060

PM2.5 levels of 284 prefecture-level cities in China from 2007 to 2018 were gathered. The choice of the 2007–2018 period allows for a comprehensive before-and after comparison while mitigating the confounding variables introduced by a series of "Coordinated Regional Development" policies in 2019 and the pandemic in 2020. This time frame enables an accurate depiction of the evolution of PM2.5 levels, untainted by the extraordinary circumstances post-2018.

3.2 Main explanatory variables

As described earlier, we focus on the explanatory variable BRI, which is assigned according to the list of key provinces established in China. Treat equals 1 if a prefecture-level city belongs to a key designated province; otherwise, it equals 0. Post indicates whether the BRI has been launched and equals 0 before 2014 and 1 in or after 2014.

For the underlying mechanism analysis, following Kou and Liu (2017), we measure technological innovation (TO) using the average value of authorized invention patents and calculating the innovation index of 284 cities from 2007 to 2018. The city innovation index includes not only R&D investment and patents, but also innovation output, patent value, innovation and entrepreneurship, etc. It is based on the synthesis of multiple indicators, which is a more comprehensive assessment of a city's innovation capacity.

We use the Theil index (Theil, 1967) to measure industrial structure optimization (ISO) with Equation 1:

$$ISO = \sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right) ln\left(\frac{Y_i}{L_i}\Big/\frac{Y}{L}\right), \quad (1)$$

where Y is the industrial added value, L is the number of employees in the industry, i represents the industry, and n represents the number of industrial sectors. As Y/L expresses labor productivity, the ratio between Y_i/L_i and Y/L measures the deviation between the current industrial structure and the equilibrium. The greater the Theil index, the less rationalized the industrial structure.

TABLE 3 BRI impact on the PM2.5 levels of key provinces.

	(1)	(2)
	PM2.5	PM2.5
BRI	−0.529***	−0.407***
	(−3.69)	(−3.42)
Fixed asset investment		0.299***
		(3.38)
Human capital		0.000424
		(0.68)
Employment		−0.00442
		(−1.38)
Secondary		0.00234
		(0.83)
Tertiary		0.000104**
		(2.39)
Income		−0.513***
		(−2.78)
Technology		−0.0450
		(−0.50)
Intervention		−0.00212*
		(−1.92)
_cons	3.566***	4.495***
	(39.79)	(4.92)
N	3,221	3,221
adj. R^2	0.140	0.314
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

3.3 Control variables

A series of control variables are incorporated, including fixed-asset investment, human capital, urban employment rate, industrialization level, industrial structure, *per capita* income, technology, and government intervention. Table 1 presents the detailed definitions. All continuous variables are winsorized at the 1% and 99% percentiles to limit the influence of extreme values.

3.4 Empirical specification

Following existing literature on the impact of the BRI on environment in participating countries of the BRI (Cao et al., 2021) and studies on the effect of China's domestic audit policy on improving air quality (Li et al., 2022), this study uses the DID

TABLE 4 Parallel trend test and the dynamic effect.

	(1)
	PM2.5
key_provinces × before5	0.0355
	(0.29)
key_provinces × before4	0.0450
	(0.36)
key_provinces × before3	0.0204
	(0.39)
key_provinces × before2	0.0488
	(0.12)
key_provinces × before1	0.0445
	(0.10)
key_provinces × after1	−0.0522**
	(−2.18)
key_provinces × after2	−0.0816**
	(−2.44)
key_provinces × after3	−0.0736**
	(−2.36)
key_provinces × after4	−0.0621**
	(−2.22)
key_provinces × after5	−0.0543**
	(−2.11)
Fixed asset investment	−0.0730
	(−1.12)
Human capital	−0.000111
	(−0.98)
Employment	−0.00164**
	(−2.17)
Secondary	−0.00194
	(−1.02)
Tertiary	0.0000235
	(1.49)
Income	−0.0676
	(−1.08)
Technology	−0.168***
	(−3.29)
Intervention	0.000357
	(1.33)
_cons	5.663***
	(9.56)
N	3,221
adj. R^2	0.348
City FE	Yes
Year FE	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

method to explore the impact of the BRI on PM2.5 levels in prefecture-level cities along the route. This study divides the prefecture-level cities into four sub-samples: the treatment group (key provinces) and control group (other provinces) before and after implementing the BRI. The DID approach has two key advantages. First, the DID methodology rules out omitted time trends that are correlated with establishment of key provinces along the route and PM2.5 levels in both the treatment group and the control group. Second, the DID approach controls for constant unobserved differences between the treatment and the control groups that may bias our estimation. Accordingly, the benchmark regression specification of the DID model can be defined as Equation 2. Equation 3 specifies the term *BRI*.

$$\boldsymbol{PM2.5_{it}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 BRI_{it}} + \boldsymbol{\alpha X_{it}} + \boldsymbol{\delta_t} + \boldsymbol{\mu_i} + \boldsymbol{\varepsilon_{it}}, \quad (2)$$

$$\boldsymbol{BRI_{it}} = \boldsymbol{key_provinces_i} \times \boldsymbol{post_{it}}. \quad (3)$$

Here, i and t represent cities and years, respectively. *PM2.5* is the dependent variable, explaining the PM2.5 levels of city i in year t. *BRI* = 1 if city i belongs to a designed key provinces in year t; otherwise, it equals 0. X is a vector of control variables that vary with time. δ and μ represent the time fixed effect and city fixed effect, respectively, and ε is the random disturbance. *BRI* is the main explanatory variable of this study. It measures the difference in PM2.5 levels between cities in key provinces and cities not in key provinces after the implementation of the BRI, thereby identifying the net effect of the BRI controlling other factors that affect PM2.5 levels. If the BRI truly reduces PM2.5 levels, the coefficient β_1 of *BRI* should be lower than zero.

To test the underlying mechanism, we adding the interaction of BRI and the indexes that measure the technological innovation and industrial structure into the regression of Equation 4. The empirical specification is as follows.

$$\boldsymbol{PM2.5_{it}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 BRI_{it}} + \boldsymbol{\beta_2 TO_{it}/ISO_{it}} + \boldsymbol{\beta_3 BRI_{it}} \times \boldsymbol{TO_{it}/ISO_{it}} + \boldsymbol{\alpha X_{it}} + \boldsymbol{\delta_t} + \boldsymbol{\mu_i} + \boldsymbol{\varepsilon_{it}}. \quad (4)$$

Here, *TO* is technological innovation, and *ISO* is industrial structure optimization. If BRI truly reduces PM2.5 levels through technological innovation and optimization of the industrial structure, the coefficient β_3 of $BRI_{it} \times TO_{it}/ISO_{it}$ should be lower than zero.

TABLE 5 PSM balance test results.

Variable	Unmatched matched	Mean		%Bias	%Reduct |bias|	T	p > t
		Treated	Control				
Fixed asset investment	U	7.804	7.388	0.416	16.79	8.57	0.000
	M	7.608	7.584	0.024		0.45	0.655
Human capital	U	55.29	53.97	1.32	6.41	4.55	0.000
	M	54.72	54.54	0.18		1.39	0.163
Employment	U	12.141	12.681	−0.54	3.03	−8.98	0.000
	M	12.345	12.477	−0.132		−0.65	0.518
Secondary	U	50.264	46.542	3.722	2.07	6.48	0.000
	M	49.025	47.781	1.244		0.13	0.897
Tertiary	U	38.026	41.848	−3.822	4.67	−5.02	0.000
	M	39.613	40.261	−0.648		−1.37	0.171
Income	U	5.258	5.754	−0.496	3.61	−7.91	0.000
	M	5.454	5.558	−0.104		−0.33	0.739
Technology	U	7.347	8.041	−0.694	0.97	−8.98	0.000
	M	7.522	7.866	−0.344		−0.65	0.518
Intervention	U	24.046	18.618	5.428	2.88	16.48	0.000
	M	22.105	20.559	1.546		0.13	0.897

4 Materials and methods

4.1 The data

The data are gathered from the China City Statistical Yearbook, China Regional Economic Statistical Yearbook, CSMAR Database, and WIND Economic Database. The data are merged according to city and year to create the sample for the empirical analysis; there are 3,281 total observations. Although the study accounts for some of the missing data via interpolation to maintain a high degree of data consistency, areas with a significant number of missing observations are excluded. Table 2 reports the descriptive statistics of all variables.

4.2 Baseline estimates

Equation 2 is first employed to evaluate the net BRI effect on PM2.5 levels of key provinces. Table 3 reports the baseline estimation results. Column (1) shows the estimation results without incorporating the control variables. Columns (2) show the results after adding the control variables. As the results in Table 3 show, the coefficients of the policy variables are significant in both regressions. Thus, the BRI reduces the PM2.5 levels of key provinces.

4.3 Testing the parallel trend and the dynamic effect

The DID method assumes that the treatment and control groups have a parallel trend before the event. As shown in Figure 2, the TFP trend of the treatment and control groups is similar before the official BRI launch in 2014.

We exploit the exact timing of policy implementation to test whether the decrease in PM2.5 levels corresponds with the implementation, or if it precedes it. For this purpose, we estimate Equation 5 by substituting the BRI variable BRI_{it} with a full set of dummies ranging from 5 years before the implementation of the BRI to 5 years after. In particular, we estimate:

$$\begin{aligned} PM2.5_{it} = {} & \beta_0 + \beta_1 key_provinces_i \times before5_t + \ldots \\ & + \beta_5 key_provinces_i \times before1_t \\ & + \beta_6 key_provinces_i \times after1_t + \ldots \\ & + \beta_{10} key_provinces_i \times after5_t + \alpha X_{it} \\ & + \delta_t + \mu_i + \varepsilon_{it}. \end{aligned} \tag{5}$$

We replace the regressor BRI_{it} in Equation 2 with $key_province_{it} \times before/after$, where $before/after$ represents the year dummies from 2007 to 2018, with 2013 as the reference group. Table 4 shows the corresponding results.

In the years before the BRI launch, none of the coefficients of the lagged policy variables are significant, indicating no difference in PM2.5 levels between the treatment and control groups. The interaction terms of 2007–2012 are insignificant and are consistent with Figure 1, which confirms the parallel trend before the BRI was implemented. After implementation, the average PM2.5 levels of the treatment group decreased faster than that of the control group. The effect of the BRI is affected by local government participation and other supporting policies. With successive publicity and the implementation of the BRI, local governments have gradually deepened their understanding of the initiative, their relevant policies have improved, and their

TABLE 6 Propensity score matching-difference-in-differences results.

	(1)	(2)	(3)
	Radius matching	Kernel density matching	Nearest neighbor matching
	PM2.5	PM2.5	PM2.5
BRI	−0.390***	−0.392***	−0.407***
	(−3.29)	(−3.31)	(−3.42)
Fixed asset investment	0.319***	0.295***	0.299***
	(3.60)	(3.35)	(3.38)
Human capital	0.00138*	0.000942	0.000424
	(2.04)	(1.41)	(0.68)
Employment	−0.0119***	−0.00586	−0.00442
	(−3.21)	(−1.69)	(−1.38)
Secondary	0.00337	0.00310	0.00234
	(1.25)	(1.10)	(0.83)
Tertiary	0.000130***	0.000103**	0.000104**
	(3.18)	(2.33)	(2.39)
Income	−0.493**	−0.539***	−0.513***
	(−2.60)	(−2.90)	(−2.78)
Technology	−0.0978	−0.0567	−0.0450
	(−1.07)	(−0.63)	(−0.50)
Intervention	−0.00210*	−0.00205*	−0.00212*
	(−1.94)	(−1.89)	(−1.92)
_cons	4.621***	4.689***	4.495***
	(4.87)	(5.00)	(4.92)
N	3,186	3,212	3,212
adj. R^2	0.333	0.322	0.314
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

execution capabilities have increased. As seen in Table 4, after the BRI was fully launched in 2014, the significance of the coefficient increases year by year from 2015 to 2018, and its value increases gradually, that is, there are dynamic effects. The BRI policy effect increases gradually after implementation, with various regions responding to the state's call. As the implementation deepens, policies and related support facilities in various regions gradually improve, and detailed guidance plans are implemented; hence, the BRI impact on PM2.5 reduction in key provinces exhibits a dynamic effect.

4.4 Testing policy endogeneity

A suitable control group is essential for the accuracy and credibility of the DID method. This study sets non-key provinces as the control group, ignoring the inherent differences in PM2.5 levels and other aspects between cities in the treatment and control groups, which may cause the DID method's estimation results to be unreliable. We employ the propensity score matching (PSM) method to match cities in the treatment group with those in the control group to reduce the systemic bias and other endogeneity problems of the DID method; we thus overcome the systematic differences in the PM2.5 trends between the treatment and control groups. We conduct logit regressions on the control variables to obtain the PSM. We adopt the balance test to ensure the PSM matching is satisfactory. Table 5 shows the PSM balance test results.

The results show the standardized deviations (% bias) of variables after matching are significantly reduced, and the standardized deviations of all variables are less than 1%. Moreover, the t-test results show the differences between the

TABLE 7 Instrumental variables.

	(1)	(2)
	BRI	PM2.5
IV	0.256***	
	(3.60)	
BRI		−0.1580***
		(−3.70)
Fixed asset investment	0.0338	0.300***
	(0.38)	(3.10)
Human capital	−0.000235	0.000126
	(−0.46)	(0.17)
Employment	0.00490***	0.00161
	(2.97)	(0.50)
Secondary	−0.00707***	−0.00540
	(−3.24)	(−1.31)
Tertiary	0.0000786**	0.000203***
	(2.20)	(3.84)
Income	0.135	−0.285
	(1.00)	(−1.15)
Technology	−0.108	−0.157
	(−1.15)	(−1.46)
Intervention	0.000638	−0.000873
	(0.73)	(−0.63)
_cons	0.123	4.430***
	(0.17)	(4.44)
N	3,281	3,221
adj. R^2	0.405	0.292
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 8 GMM.

	(1)	(2)
	Difference GMM	System GMM
	PM2.5	PM2.5
L.PM2.5	0.420***	0.727***
	(22.56)	(57.18)
BRI	−0.128***	−0.102***
	(−14.19)	(−9.97)
Fixed asset investment	−0.0111	0.0246**
	(−1.04)	(2.08)
Human capital	0.0000335	0.000569***
	(0.27)	(3.93)
Employment	−0.00150**	−0.00314***
	(−2.57)	(−4.67)
Secondary	−0.00615***	−0.00475***
	(−9.94)	(−6.97)
Tertiary	0.0000487	0.0000504
	(1.52)	(1.33)
Income	0.0670***	−0.00740
	(3.26)	(−0.32)
Technology	−0.114***	−0.0662***
	(−8.58)	(−4.46)
Intervention	0.000200**	0.000235**
	(1.99)	(2.11)
_cons	2.907***	1.532***
	(24.64)	(13.74)
N	2,950	3,012
Wald χ^2	1763.25	5140.07
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

treated and the control samples after matching are all insignificant. All the above indicates that the matching effect is effective.

Three common matching methods (radius, kernel density, and nearest neighbor matching) are employed to perform a robustness check. Table 6 presents the results.

From Table 6, radius, kernel density, and nearest neighbor matching generate the same results. The coefficients of the *BRI* term are significantly positive at the 5% level. Therefore, the BRI significantly reduces the PM2.5 levels of key provinces, further verifying the main findings.

An important premise of the DID method is that the treatment and control group selection is random, which may not be the case in this study. Unobservable factors might have influenced designation of key BRI provinces. Provinces with a higher level of economic development may first be used as key provinces to further promote BRI implementation. However, provinces with lower economic development may also be selected. Therefore, the choice of the treatment group may be susceptible to endogeneity. Given the potential endogeneity of the policy variable, an instrumental variable (IV) is determined under two conditions: an IV is (1) related to the endogenous variable and (2) unrelated to the random error term. The two-stage least squares method is adopted for the estimation. The BRI concept is inspired by the ancient Silk Road, which witnessed hundreds of years of booming trade and cultural exchanges in the Eurasian continent; we therefore select the ancient Silk Road route provinces as IVs following Duranton et al. (2014). Although the BRI aims to revive the ancient Silk Road, they are far apart in time, and the latter does not influence the PM2.5 levels of

TABLE 9 Placebo tests falsifying the BRI launch year.

	(1)	(2)
	Assuming the BRI was implemented in 2011	Assuming the BRI was implemented in 2012
	PM2.5	PM2.5
BRI_falsified	−0.0188	−0.00569
	(−0.52)	(−0.17)
Fixed asset investment	−0.0805	−0.0792
	(−1.28)	(−1.23)
Human capital	−0.000144	−0.000141
	(−0.95)	(−0.96)
Employment	−0.00146*	−0.00147*
	(−2.04)	(−2.04)
Secondary	−0.00202	−0.00201
	(−1.04)	(−1.04)
Tertiary	0.0000245*	0.0000244*
	(1.93)	(1.93)
Income	−0.0625	−0.0605
	(−0.95)	(−0.95)
Technology	−0.173***	−0.171***
	(−3.14)	(−3.15)
Intervention	0.000391	0.000386
	(1.29)	(1.29)
_cons	5.722***	5.693***
	(9.07)	(9.07)
N	3,221	3,221
adj. R^2	0.347	0.347
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

key provinces along the route. Thus, the ancient Silk Road satisfies the two conditions of an IV. The specific setting is that if a key province is among the ancient Silk Road provinces (Shaanxi, Ningxia, Gansu, Qinghai, Xinjiang, Tibet), IV = 1; otherwise, IV = 0. Meanwhile, IV × Post is selected as the IV for the term BRI. Table 7 shows the corresponding results after the IV adoption.

The regression results in Column (1) confirm the rationality of using the ancient Silk Road route provinces as IVs. The F value from the Cragg-Donald test is greater than 10, indicating that the IVs are highly correlated with the endogenous variable in the first stage regression. Column (2) shows the regression results for the second stage. The coefficient of BRI is −0.158, significant at the 1% level. Thus, after alleviating potential endogeneity problems, the basic findings remain unchanged.

Following Zhang et al. (2012), this study utilizes the generalized method of moments (GMM) in two estimations for a robustness check to further control for potential endogeneity by unobserved variables. Table 8 reports the test results of Equation 2. BRI coefficients in the two regressions remain significant.

4.5 Placebo tests

There might be policies or influencing factors other than the BRI that may induce PM2.5 abatement during the same period. To rule out the possibility that PM2.5 levels might have been reduced by other contemporaneous policies, following Liu and Zhao (2015), we perform a placebo test by falsifying the year the policy was initiated. We assume that the BRI was proposed two or 3 years before the actual date and observe the coefficient and significance of the policy variable. If the estimated coefficient of the policy variable is insignificant under the two placebo tests, the BRI reduces the PM2.5 levels in key provinces. If the two falsified policy variables are significant, BRI implementation does not necessarily cause PM2.5 abatement in key provinces. Table 9 presents the results; when assuming the BRI was proposed in 2011 or 2012, the estimated coefficient of the BRI term is not significant. Thus, BRI implementation reduces the PM2.5 levels of key provinces without interference from other policies or factors.

4.6 Testing alternative samples

This study modifies Equation 2 by incorporating lagged control variables for a robustness check to mitigate the influence of the current data. Moreover, it removes observations from 2013, when the BRI was proposed. Column (1) and (2) of Table 10 reports the regression results; BRI coefficients in both regressions remain significant.

4.7 Testing the removal of confounding effects

During the implementation of the BRI, the global financial crisis occurred in 2008. The financial crisis reduced production activities, which may have influenced PM2.5 levels. Therefore, observations before 2009 are also removed to control for confounding effects. In addition, the confounding impact of the supply-side reform (proposed in November 2015 and implemented afterward) on PM2.5 levels is then removed by removing observations after 2016. Table 11 reports the regression results; BRI coefficients in both regressions remain significant.

This study also controls contemporaneous disturbances. It removed cities that have implemented the Low-Carbon City Pilot Policy and cities in two-control zones (acid rain control zone and sulfur dioxide pollution control zone). Table 12 shows the regression results, with the BRI term being significantly negative at the 1% level. This verifies that the BRI has a significant reduction effect on PM2.5 levels in key provinces along the route, yielding robust results.

4.8 Testing alternative regression methods

We further verify robustness by conducting a simultaneous quantile regression with 1,000 bootstraps. Specifically, we perform regression analysis on the 20th, 50th, and 80th PM2.5 quantiles using Equation 2. The advantage of using this estimate is that it allows us to test how the BRI affects the PM2.5 levels of cities with different PM2.5 levels. The results in Table 13 are consistent with the baseline results in Table 3: there is a pronounced negative relationship between the BRI and PM2.5. For cities with low PM2.5 levels, the BRI further reduces PM2.5, while for cities with high PM2.5 levels, the BRI provides timely assistance regarding PM2.5 abatement. The BRI also exhibits a negative impact for regions with intermediate PM2.5 levels.

Given that province- and prefecture-level variables are included in the regression, we utilize a hierarchical mixed model to re-estimate Equation 2. Martin et al. (2007) note that a hierarchical mixed model is more suitable for separating provincial- from prefecture-level impacts. Table 14 presents the results.

TABLE 10 Tests on alternative samples.

	(1)	(2)
	Lagged control variables	Remove 2013
	PM2.5	PM2.5
BRI	−0.408***	−0.393***
	(−3.25)	(−3.14)
Fixed asset investment	0.340***	0.309***
	(3.87)	(3.42)
Human capital	0.000410	0.000493
	(0.63)	(0.76)
Employment	−0.00331	−0.00500
	(−1.08)	(−1.47)
Secondary	−0.00333	0.00231
	(−0.78)	(0.79)
Tertiary	−0.00800	0.000103**
	(−1.46)	(2.40)
Income	−0.411*	−0.514***
	(−1.91)	(−2.80)
Technology	−0.0745	−0.0573
	(−0.80)	(−0.61)
Intervention	−0.00232**	−0.00206*
	(−2.18)	(−1.93)
_cons	4.437***	4.525***
	(4.73)	(4.92)
N	2,951	2,952
adj. R^2	0.308	0.303
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

5 Further tests

5.1 Underlying mechanism

As noted, the BRI significantly reduces the PM2.5 levels. From the hypothesis and model setup, we create interaction terms ($BRI_{it} \times TO_{it}$ and $BRI_{it} \times ISO_{it}$) to explore the possible influencing mechanism. Table 15 presents the regression results.

The results in Table 15 show that the regression coefficients on the interaction terms are significantly negative at the 1% level, indicating that the BRI can reduce PM2.5 levels by promoting technological innovation and optimizing industrial structure. From the perspective of technological innovation, the BRI provides a platform for enterprises to invest overseas and enhance technological innovation, which in turn helps enterprises reduce pollution emissions. Chinese enterprises use the platform of BRI to invest in factories and set up subsidiaries, joint ventures and R&D centers in participating countries or regions along the route. The reversed technology transfer helps improve the technological innovation capacity of Chinese enterprises, thus reducing the pollution emissions of Chinese enterprises. The relatively lower production costs in overseas subsidiaries can facilitate parent firms to concentrate its financial resources on the R&D and therefore enhance the overall R&D and innovation ability. Favorable policies for firms actively participating in the BRI also indirectly promote technological innovation. From the industrial structure perspective, under the policy background of the BRI, factor resources continue to flow and cluster in Chinese cities along the route as more countries are investing in China. DBAR integrates high-tech information technology and promotes the flow and agglomeration of production factors to Chinese cities along the route, improve the efficiency of resource allocation and optimize the industrial structure, and reduce pollution emissions. The information technology in the DBAR can timely and efficiently coordinate and allocate resources in cities along the route, and promotes the flow of factor resources to low-energy consumption, low-pollution enterprises, eliminating high-energy-consumption and high-pollution enterprises. The information technology industry in the DBAR is characterized by high technology and low pollution, which induces traditional heavy polluting industries to develop technological innovation and R&D on clean technology, thus reducing environmental pollution.

5.2 Heterogeneity tests

In terms of initiative layout and mode of transportation, the BRI can be divided into the Silk Road Economic Belt and the 21st Century Maritime Silk Road. According to the description of the regional opening plans of the Vision and Actions, we regard

TABLE 11 Removing confounding effects.

	(1)	(2)
	Remove the impact of the global financial crisis	Remove the impact of the supply-side reform
	PM2.5	PM2.5
BRI	−0.418***	−0.423***
	(−3.45)	(−4.10)
Fixed asset investment	0.301***	0.231**
	(3.20)	(2.39)
Human capital	0.000317	0.000484
	(0.54)	(0.73)
Employment	−0.00302	−0.00496
	(−1.15)	(−1.24)
Secondary	0.00137	−0.00367
	(0.50)	(−0.63)
Tertiary	0.000110***	−0.00906
	(2.86)	(−1.42)
Income	−0.519**	−0.329
	(−2.68)	(−1.54)
Technology	−0.0478	0.0193
	(−0.51)	(0.22)
Intervention	−0.00180*	−0.0107**
	(−1.92)	(−2.11)
_cons	4.433***	4.284***
	(4.27)	(4.22)
N	2,420	2,414
adj. R^2	0.340	0.313
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

Shanghai, Fujian, Guangdong, Zhejiang, and Hainan as belonging to the 21st Century Maritime Silk Road and other provinces as belonging to the Silk Road Economic Belt. We believe that although these provinces are all designated as key provinces, there are significant differences in the implementation priorities, development levels, and historical factors among the provinces. By contrast, the provinces belonging to the 21st century Maritime Silk Road are relatively more developed areas along the eastern coast of China, with relatively higher levels of initial economic development. Therefore, it is necessary to distinguish in the analysis the key provinces belonging to the two Roads. The grouping regression results are listed in Table 16.

The control group in column (1) includes cities of key provinces along the 21st Century Maritime Silk Road, while the control group in column (2) excludes cities of key provinces along the 21st Century Maritime Silk Road. The control group in column (3) includes cities of key provinces along the Silk Road Economic Belt, and the control group in column (4) excludes cities of key provinces along the Silk Road Economic Belt. The BRI estimation coefficients in Column (1) and (2) are significantly negative; by contrast, the results in Column (3) and (4) show that the BRI plays a relatively limited role in reducing PM2.5 levels in the provinces of the 21st century Maritime Silk Road, although they are also designated as key provinces. This result indicates that the BRI mainly improves TFP in the eight key provinces belonging to the Silk Road Economic Belt. This can be attributed to the relatively worse economic conditions of these regions, higher polluting levels, lower technological innovation, and underdeveloped industrial infrastructure. These late-development advantage help these provinces outperform the coastal provinces of the 21st century Maritime Silk Road in reducing pollution, thereby making the BRI's effect on reducing PM2.5 levels more significant.

As China is a vast country, the resource endowment, economic base, and infrastructure level of cities differs across regions. We separate the samples into eastern and central and western regions. As shown in Table 17, BRI is more significant in the central and western region.

The central region plays an important role in China's regional development by undertaking industrial transfer from the east and promoting the development of the west, it mainly focuses on domestic trade (Bai et al., 2020). The economic foundation of the western region is relatively weaker, and the implementation of the BRI can effectively mitigate its lack of economic growth power (Zhang et al., 2018). The impact of BRI will be further expanded through ethnic policies and resource endowment toward the western region. Moreover, the central and western regions have taken up the Silk Road Economic Belt, which has led to considerable trade among the countries along the route. The eastern coastal area has the natural advantage for developing an export-oriented economy, however, due to insufficient preferential policies for economic growth, the marginal effect of the implementation of the BRI is smaller.

Cities with different administrative levels have different resource levels, institutional arrangements, and management powers, so that they can provide different preferential and policies for implementing the BRI; thus, they have heterogeneous effects. The regression results for the subsamples of sub-provincial cities (high administrative level), and municipalities and prefecture-level cities (low administrative level) are shown in Table 18.

We find that the mitigating effect of the BRI on PM2.5 levels is significant in both regressions, with the effect being more pronounced in cities of low administrative level. Municipals and prefecture-level cities have a higher BRI impact than sub-provincial cities because of their lower economic development and higher pollution levels. Specifically, the initiative can bring about more marginal effect to late-development regions, and the local government has utilized BRI policy resources and benefits, significantly reducing the area's PM2.5 levels.

The OFDI of China in the BRI participating countries has surpassed US$50 billion. The target of unimpeded trade is promoting trade and investment facilitation and improving the business environment (The State Council Information Office of

TABLE 12 Controlling for contemporaneous disturbances.

	(1)	(2)
	PM2.5	PM2.5
BRI	−0.409***	−0.406***
	(−3.45)	(−3.42)
Low-carbon pilot city	−0.0954*	
	(−1.70)	
Two-control zones		−0.121*
		(−1.81)
Fixed asset investment	0.297***	0.298***
	(3.37)	(3.36)
Human capital	0.000502	0.000443
	(0.80)	(0.71)
Employment	−0.00426	−0.00449
	(−1.36)	(−1.43)
Secondary	0.00216	0.00238
	(0.77)	(0.85)
Tertiary	0.000103**	0.000106**
	(2.39)	(2.43)
Income	−0.502**	−0.511***
	(−2.75)	(−2.79)
Technology	−0.0411	−0.0441
	(−0.45)	(−0.48)
Intervention	−0.00214*	−0.00203*
	(−1.93)	(−1.78)
_cons	4.428***	4.598***
	(4.92)	(4.92)
N	3,221	3,221
adj. R^2	0.316	0.315
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 13 Simultaneous quantile regression.

	(1)	(2)	(3)
	20th Quant	50th Quant	80th Quant
	PM2.5	PM2.5	PM2.5
BRI	−0.388***	−0.409***	−0.438***
	(−10.42)	(−14.59)	(−14.16)
Fixed asset investment	0.281***	0.367***	0.349***
	(8.60)	(12.71)	(9.95)
Human capital	−0.000156	0.000410*	0.000295
	(−0.33)	(1.73)	(0.89)
Employment	−0.00207	−0.00309**	−0.00321***
	(−0.67)	(−2.03)	(−2.67)
Secondary	0.00244	−0.000842	0.00223
	(1.07)	(−0.21)	(0.52)
Tertiary	0.000246	0.0000824	0.0000137
	(0.10)	(0.01)	(0.00)
Income	−0.612***	−0.555***	−0.446***
	(−5.79)	(−4.46)	(−4.64)
Technology	0.105***	−0.147***	−0.155***
	(2.82)	(−5.50)	(−3.96)
Intervention	−0.00268*	−0.00272***	−0.00182**
	(−1.84)	(−2.94)	(−2.51)
_cons	3.713***	5.182***	4.975***
	(7.58)	(13.76)	(22.38)
N	3,221	3,221	3,221
adj. R^2	0.1754	0.2039	0.2150
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

China, 2019), which would be finally reflected in improved market mechanisms. Market mechanism creates a competition and investment effect among enterprises. Therefore, whether the local market operation mechanism is complete could partially determine the impact of the BRI on PM2.5 levels. Here, we introduce the marketization index of China's provinces (Wang et al., 2021). Based on the marketization index mean, cities are grouped into high marketization degree and low marketization degree. The results of the separate regressions are presented in Table 19.

The mitigating effect of the BRI on PM2.5 levels is significant in both regressions, with a more pronounced effect in low-marketization cities. The market operation mechanism in high-marketization cities is relatively complete. For cities with a high degree of marketization, local governments have taken measures to effectively improve the market mechanism and business environment to promote economic growth and reduce pollution. In comparison, the market operation mechanism of low-marketization cities is not complete, and local enterprises lack awareness of R&D and improving efficiency. The implementation of the BRI could encourage the implementation of operational and post-operational oversight systems by local governments in low-marketization cities, which could stimulate market vitality and, in turn, improve marketization. Through improving marketization in regions with a low degree of marketization can establish a sound legal system and intellectual property protection measures, which will promote enterprises to increase R&D investment. Besides,

TABLE 14 Hierarchical mixed regression.

	(1)
	PM2.5
BRI	−0.0501***
	(−2.67)
Fixed asset investment	0.104***
	(7.22)
Human capital	0.000358**
	(2.40)
Employment	−0.00160***
	(−2.65)
Secondary	0.000232
	(0.38)
Tertiary	0.0000747
	(1.15)
Income	−0.0743**
	(−2.15)
Technology	−0.00184
	(−0.12)
Intervention	−0.000722***
	(−2.67)
_cons	3.173***
	(16.80)
N	3,221
Wald χ^2	352.81
City FE	Yes
Year FE	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 15 Underlying mechanism of the policy effect on PM2.5 levels.

	(1)	(2)
	PM2.5	PM2.5
BRI	−0.410***	−0.391***
	(−3.38)	(−3.06)
TO	−0.00238**	
	(−2.39)	
BRI × TO	−0.000548**	
	(−2.12)	
ISO		−2.906**
		(−2.15)
BRI × ISO		−0.349**
		(−2.23)
Fixed asset investment	0.303***	0.271***
	(3.52)	(3.14)
Human capital	−0.000141	0.00119*
	(−.27)	(1.72)
Employment	−0.00553*	−0.00488*
	(−1.72)	(−1.95)
Secondary	0.00296	0.00303
	(1.08)	(1.14)
Tertiary	0.000114**	0.000260***
	(2.56)	(4.03)
Income	−0.548***	−0.394**
	(−2.92)	(−2.10)
Technology	−0.0538	−0.0803
	(−0.61)	(−0.89)
Intervention	−0.00183*	−0.00202*
	(−1.75)	(−1.89)
_cons	4.702***	4.315***
	(5.09)	(4.80)
N	3,221	3,221
adj. R^2	0.322	0.336
City FE	Yes	Yes
Year FE	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

through improving marketization in regions with a low degree of marketization, a fierce market competition and a more optimized price transfer mechanism will be established. It helps reduce the uncertainty of enterprise innovation returns, enhance the R&D and innovation vitality of the private science and technology enterprises with a strong preference for innovation, and increase the play of innovation to treat pollution and reduce smog pollution.

5.3 Economic consequences

Using micro-level data, Gu and Yan (2021) found that air pollution control policies reduce PM2.5 levels and promote total factor productivity in listed firms in China. This study further assessed whether the BRI promotes the GTFP of key provinces along the route by reducing PM2.5 levels. We adopted the epsilon-based measure to calculate radical and non-radial distance (Tone and Tsutsui, 2010), which is beyond the ability of traditional non-parametric methods (e.g., data envelopment analysis and slacks-based measure distance function model). Table 20 reports the DID estimation results of Equation 6.

TABLE 16 Silk Road Economic Belt versus the 21st Century Maritime Silk Road.

	(1)	(2)	(3)	(4)
	Silk Road Economic Belt		21st Century Maritime Silk Road	
	PM2.5	PM2.5	PM2.5	PM2.5
BRI	−0.123*	−0.123*	−0.0137	−0.00216
	(−1.90)	(−1.88)	(−0.45)	(−0.06)
Fixed asset investment	−0.101	−0.0973	−0.0785	−0.0178
	(−1.52)	(−1.40)	(−1.17)	(−0.28)
Human capital	−0.0000943	−0.000111	−0.000135	0.000186
	(−0.96)	(−1.04)	(−0.90)	(0.81)
Employment	−0.00127**	−0.00125*	−0.00148**	−0.00105***
	(−2.10)	(−1.99)	(−2.16)	(−3.40)
Secondary	−0.00121	−0.00127	−0.00198	0.000676
	(−0.78)	(−0.80)	(−1.02)	(0.43)
Tertiary	0.0000182	0.0000185	0.0000243*	0.00143
	(1.39)	(1.39)	(1.95)	(0.93)
Income	−0.0510	−0.0518	−0.0595	−0.0795
	(−0.89)	(−0.90)	(−0.97)	(−1.35)
Technology	−0.126***	−0.125***	−0.170***	−0.0246
	(−3.31)	(−3.30)	(−3.02)	(−1.24)
Intervention	0.000244	0.000250	0.000380	−0.000222
	(0.96)	(0.98)	(1.23)	(−1.21)
_cons	5.426***	5.416***	5.672***	4.377***
	(9.20)	(8.86)	(8.56)	(9.47)
N	3,221	2,302	3,221	2,309
adj. R^2	0.349	0.348	0.347	0.354
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

$$GTFP_{it} = \beta_0 + \beta_1 BRI_{it} + \beta_2 PM2.5_{it} + \beta_3 BRI_{it} \times PM2.5_{it} + \alpha X_{it} + \delta_t + \mu_i + \varepsilon_{it}. \quad (6)$$

From the regression results in Table 20, the interaction term *PM2.5* × *BRI* is significant at the 10% level. Thus, the BRI effectively promotes GTFP in key provinces along the route through reducing PM2.5 levels.

6 Conclusion and policy implications

This study adopts the PM2.5 levels as the measure of smog pollution of 284 prefecture-level cities in China. Utilizing the varying degree of different regions benefiting from the BRI, we conducted a quasi-natural experimental design for BRI to evaluate the impact of the BRI on the PM2.5 levels of key provinces using a DID framework. The empirical results show that the BRI has significantly reduced the PM2.5 levels in key provinces, and the promoting effect is consistent in various robustness checks. Moreover, the BRI demonstrates dynamic effects, characterized by stronger impact every year. Moreover, we found that the BRI can reduce PM2.5 levels through promoting technological innovation and optimizing industrial structure. Furthermore, the BRI's impact on PM2.5 levels also exhibits heterogeneous effects. Furthermore, through reducing PM2.5 levels, the BRI enhances GTFP of key provinces along the route.

Based on the empirical results, this study proposes the following policy implications. This study confirms the beneficial impact of the BRI on lowering PM2.5 levels in key

TABLE 17 East regions versus central and western regions.

	(1)	(2)
	Eastern	Central and western
	PM2.5	PM2.5
BRI	−0.289***	−0.467**
	(−4.39)	(−2.72)
Fixed asset investment	0.348***	0.263*
	(4.43)	(2.00)
Human capital	0.000643	0.000886
	(1.00)	(0.98)
Employment	−0.00317	−0.0143***
	(−1.33)	(−3.11)
Secondary	0.00706	0.00137
	(1.27)	(0.27)
Tertiary	0.0000545	−0.00491
	(1.16)	(−0.85)
Income	−0.263	−0.602*
	(−1.56)	(−1.84)
Technology	−0.190*	−0.0876
	(−1.91)	(−0.75)
Intervention	0.00157	−0.00209**
	(0.81)	(−2.22)
_cons	3.690***	5.697***
	(3.40)	(4.46)
N	1,306	1915
adj. R^2	0.457	0.299
City FE	Yes	Yes
Year FE	Yes	Yes
χ^2	0.178***	

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 18 High administrative level cities versus low administrative level cities.

	(1)	(2)
	High administrative level	Low administrative level
	PM2.5	PM2.5
BRI	−0.271**	−0.398***
	(−2.55)	(−3.22)
Fixed asset investment	0.211	0.284**
	(1.21)	(2.43)
Human capital	−0.000431	0.00200
	(−1.09)	(0.94)
Employment	−0.00468	−0.00923
	(−1.45)	(−1.47)
Secondary	0.0137	0.00380
	(0.60)	(1.23)
Tertiary	0.0198	0.000111**
	(0.82)	(2.31)
Income	0.195	−0.542***
	(0.60)	(−2.86)
Technology	−0.0450	−0.0948
	(−0.33)	(−1.04)
Intervention	−0.00588	−0.00197*
	(−0.39)	(−1.85)
_cons	0.0358	5.000***
	(0.02)	(4.57)
N	228	2,993
adj. R^2	0.365	0.310
City FE	Yes	Yes
Year FE	Yes	Yes
χ^2	0.127***	

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

provinces along the route, advocating for the continued implementation of the BRI. To further mitigate environmental and pollution transfer issues, it is advised to expand green industries and embrace sustainable development. Besides, the initiative is shown to enhance GTFP by reducing PM2.5 levels, thus underscoring the environmental and economic benefits of maintaining this initiative. Tests on the underlying mechanism detect a positive relationship between technological innovation and the reduction of PM2.5 levels in key provinces. We recommend governmental support through policy incentives, increased funding, and financial subsidies for innovation-driven enterprises. Furthermore, enhancing technological collaboration among the key provinces could bolster technological advancements and demonstrate the critical mechanism of innovation in environmental sustainability. The study also highlights the importance of optimizing industrial structure to further curtail PM2.5 pollution. The government is encouraged to expedite the transition towards a more service-oriented economy while diminishing the share of the secondary sector. Not only does such restructuring contribute to reduced PM2.5 levels, but also aligns with the broader environmental and economic objectives of the BRI. Heterogeneity tests found that the BRI's influence on PM2.5 reduction varies regionally. The disparity suggests a need for tailored environmental pollution control policies, particularly in regions where PM2.5 reduction is

TABLE 19 High marketization versus low marketization.

	(1)	(2)
	High marketization	Low marketization
	PM2.5	PM2.5
BRI	−0.300**	−0.500***
	(−2.31)	(−4.38)
Fixed Asset Investment	0.380***	0.314**
	(4.06)	(2.66)
Human Capital	0.00143	0.000286
	(0.87)	(0.48)
Employment	−0.0174*	−0.00227
	(−2.01)	(−0.94)
Secondary	0.00117	0.00725
	(0.38)	(0.65)
Tertiary	0.000165***	0.00183
	(3.34)	(0.17)
Income	−0.352	−0.571**
	(−1.50)	(−2.12)
Technology	−0.191**	−0.0176
	(−2.12)	(−0.12)
Intervention	−0.00239*	−0.00556
	(−1.99)	(−1.51)
_cons	4.338***	4.162***
	(3.62)	(4.12)
N	1,616	1,605
adj. R^2	0.304	0.355
City FE	Yes	Yes
Year FE	Yes	Yes
χ^2 test	0.200***	

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

TABLE 20 BRI impact on GTFP.

	(1)
	GTFP
PM2.5	−0.00309***
	(−3.11)
BRI	0.0139***
	(2.67)
PM2.5 × BRI	−0.00416*
	(−1.71)
Fixed asset investment	−0.00148
	(−1.16)
Human capital	0.000000372
	(0.10)
Employment	−0.0000498
	(−1.32)
Secondary	−0.0000270
	(−0.60)
Tertiary	0.00000421***
	(6.36)
Income	0.00352
	(1.47)
Technology	0.000723
	(0.47)
Intervention	0.0000227
	(0.63)
_cons	0.988***
	(91.75)
N	3,221
adj. R^2	0.12
City FE	Yes
Year FE	Yes

t values in brackets. *, **, *** indicate significance levels of 10%, 5%, and 1%, respectively.

less pronounced. This will allow more uniform environmental improvements across all areas involved in the initiative.

We conclude by outlining related questions that are beyond this study's scope. Despite the positive findings, our results cannot answer the broader questions of whether the BRI reduces other environmental pollution. Using PM2.5 as the sole parameter of environmental pollution may not fully reflect the complexity of the issue. Besides, while this study has investigated the role of technological innovation and the optimization of industrial structures as potential underlying mechanism, more underlying mechanism remains under researched. Furthermore, although this study conducts a battery of heterogeneity tests, expansion can be done on more heterogeneous effects on different dimensions, such as cities of different levels of economic development and different industrial structure. These issues warrant future research.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The data that support the findings of this study are in Chinese and available from the corresponding author upon reasonable request. Requests to

access these datasets should be directed to MW, wumaoguo@shu.edu.cn.

Author contributions

JJ: Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Writing–original draft. MW: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Validation, Writing–review and editing.

Funding

The author(s) declare that no financial support was received for the research, authorship, and/or publication of this article.

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Bai, Z. L., Sun, Y. H., and Wei, Z. (2020). Economic effect evaluation and location selection of the establishment policy of free trade area. *Int. Econ. Trade Res.* 36 (8), 4–22. doi:10.13687/j.cnki.gjjmts.2020.08.001

Cai, X., Che, X., Zhu, B., Zhao, J., and Xie, R. (2018). Will developing countries become pollution havens for developed countries? an empirical investigation in the belt and road. *J. Clean. Prod.* 198, 624–632. doi:10.1016/j.jclepro.2018.06.291

Cao, X., Teng, C., and Zhang, J. (2021). Impact of the belt and road initiative on environmental quality in countries along the routes. *Chin. J. Popul. Resour. Environ.* 19 (4), 344–351. doi:10.1016/j.cjpre.2022.01.007

Cao, X., Zhang, H., Huang, X., and Li, P. (2022). Can the belt and road initiative reduce pollution in enterprises? evidence from quasi-natural experiments. *Energy Rep.* 8, 11683–11694. doi:10.1016/j.egyr.2022.09.012

Chen, R. H., and Wang, F. (2022). Can the belt and road initiative promote the optimization of industrial structure of provinces and cities along the route?. *J. Nankai Univ. (Philosophy, Literature Soc.).* 2, 170–182.

China Daily (2014). New normal in economic development. Available at: https://www.chinadaily.com.cn/china/19thcpcnationalcongress/2017-10/05/content_32869258.htm (Accessed May 15, 2024).

Du, J., and Zhang, Y. (2018). Does one belt one road initiative promote Chinese overseas direct investment?. *China Econ. Rev.* 47, 189–205. doi:10.1016/j.chieco.2017.05.010

Du, X., Qin, Y., and Huang, C. (2022). Status and prospect of ecological environment in the belt and road initiative regions. *Int. J. Environ. Res. Public Health.* 19, 17091. doi:10.3390/ijerph192417091

Dunning, J. H. (Editor) (1993). *United nations library on transnational corporations. 1, the theory of transnational corporations*. London, UK: Routledge.

Duranton, G., Morrow, P. M., and Turner, M. A. (2014). Roads and trade: evidence from the US. *Rev. Econ. Stud.* 81 (2), 681–724. doi:10.1093/restud/rdt039

Fang, K., Wang, T., He, J., Wang, T., Xie, X., Tang, Y., et al. (2020). The distribution and drivers of PM2.5 in a rapidly urbanizing region: the belt and road initiative in focus. *Sci. Total Environ.* 716, 137010. doi:10.1016/j.scitotenv.2020.137010

Gu, H., and Yan, W. (2021). Impact of air pollution control on total factor productivity of firms: a quasi natural experiment based on the ambient air quality standards (2012). *China Population,Resources Environ.* 31 (11), 59–67.

Huang, Y. (2016). Understanding China's belt and road initiative: motivation, framework and assessment. *China Econ. Rev.* 40, 314–321. doi:10.1016/j.chieco.2016.07.007

Huo, Q., and Li, G. (2018). Green development index of border provinces under the belt and road initiative. *Ecol. Econ.* 34 (10), 52–56.

Kou, Z., and Liu, X. (2017). *FIND report on city and industrial innovation in China*. Shanghai, China: Fudan Institute of Industrial Development, School of Economics, Fudan University.

Lam, J. S. L., Cullinane, K. P. B., and Lee, P. T. W. (2018). The 21st-century maritime silk road: challenges and opportunities for transport management and practice. *Transp. Rev.* 38 (4), 413–415. doi:10.1080/01441647.2018.1453562

Li, B., Hu, J., Chen, G., Xiao, D., and Cheng, S. (2022). The environmental effects of regional economic cooperation: evidence from the Belt and Road Initiative. *Front. Environ. Sci.* 10. doi:10.3389/fenvs.2022.1020502

Li, G., Fang, C., Wang, S., and Sun, S. (2016). The effect of economic growth, urbanization, and industrialization on fine particulate matter (PM2.5) concentrations in China. *Environ. Sci. and Technol.* 50 (21), 11452–11459. doi:10.1021/acs.est.6b02562

Li, S., Shafi, S., Zou, B., Liu, J., Xiong, Y., and Muhammad, B. (2022). PM2.5 concentration exposure over the belt and road region from 2000 to 2020. *Int. J. Environ. Res. Public Health* 19 (5), 2852. doi:10.3390/ijerph19052852

Li, G., Wu, M., and Sun, R. (2022). Will China's audit of natural environmental resources promote green sustainable development? evidence from PSM-DID analysis based on substantial and strategic pollution reduction. *PLoS ONE* 17 (12), e0278985. doi:10.1371/journal.pone.0278985

Li, Y., and Zhang, X. (2015). The new normal: the logic and perspective of economic development. *Econ. Res. J.* 50 (5), 4–19.

Lin, Y. (2016). Green development in Chinese provinces under the background of the belt and road initiative: current situation, problems, and countermeasures. *Chin. J. Environ. Manag.* 8 (2), 42–46. doi:10.16868/j.cnki.1674-6252.2016.02.042

Liu, M., and Ma, H. (2023). Untangling the effects of the belt and road initiative on carbon dioxide emissions. *J. Environ. Manag.* 325, 116628. doi:10.1016/j.jenvman.2022.116628

Liu, R., and Zhao, R. (2015). Is the western development a growth drive or a policy trap? an analysis based on PSM-DID method. *China Ind. Econ.* 6, 32–43. doi:10.19581/j.cnki.ciejournal.2015.06.004

Lv, Y., Lu, Y., Wu, S., and Wang, Y. (2019). The effect of the belt and road initiative on firms' OFDI: evidence from China's greenfield investment. *Econ. Res. J.* 54 (9), 187–202.

Ma, T., and Cao, X. (2007). The effect of the industrial structure and haze pollution: spatial evidence for China. *Environ. Sci. Pollut. Res.* 29, 23578–23594. doi:10.1007/s11356-021-17477-4

Mahadevan, R., and Sun, Y. (2020). Effects of foreign direct investment on carbon emissions: evidence from China and its belt and road countries. *J. Environ. Manag.* 276, 111321. doi:10.1016/j.jenvman.2020.111321

Martin, K. D., Cullen, J. B., Johnson, J. L., and Parboteeah, K. P. (2007). Deciding to bribe: a cross-level analysis of firm and home country influences on bribery activity. *Acad. Manag. J.* 50 (6), 1401–1422. doi:10.5465/amj.2007.28179462

Mu, H., He, C., Nguyen, T. M., Wang, D., Zhou, X., Yang, L., et al. (2021). Spatiotemporal distribution characteristics and population exposure risks to PM2.5 in countries along the belt and road. *Acta Sci. Circumstantiae* 41 (6), 2229–2240. doi:10.13671/j.hjkxxb.2020.0488

Omri, A., and Hadj, T. B. (2020). Foreign investment and air pollution: do good governance and technological innovation matter?. *Environ. Res.* 185, 109469. doi:10.1016/j.envres.2020.109469

Pradhan, J. P., and Singh, N. (2009). Outward FDI and knowledge flows: a study of the indian automotive sector. *Int. J. Institutions Econ.* 1 (1), 156–187.

Ramasamy, B., and Yeung, M. C. H. (2019). China's one belt one road initiative: the impact of trade facilitation versus physical infrastructure on exports. *World Econ.* 42, 1673–1694. doi:10.1111/twec.12808

Ryzhenkov, M. (2016). Resource misallocation and manufacturing productivity: the case of Ukraine. *J. Comp. Econ.* 44 (1), 41–55. doi:10.1016/j.jce.2015.12.003

Shi, D., Ding, H., Wei, P., and Liu, J. (2018). Can smart city construction reduce environmental pollution?. *China Ind. Econ.* 6, 117–135. doi:10.19581/j.cnki.ciejournal.2018.06.008

Su, X., Li, Y., Fang, K., and Long, Y. (2022). Does China's direct investment in "Belt and Road Initiative" countries decrease their carbon dioxide emissions?. *J. Clean. Prod.* 339, 130543. doi:10.1016/j.jclepro.2022.130543

Tang, D., Li, X., Xu, X., Liu, X., Zhang, H., Shi, H., et al. (2021). Does the belt and road initiative really increase CO_2 emissions?. *Ann. Am. Assoc. Geogr.* 112 (4), 948–967. doi:10.1080/24694452.2021.1941747

Theil, H. (1967). *Economics and information theory*. Amsterdam: North Holland Publishing Company.

The State Council Information Office of China (2019). Unimpeded trade. *State Counc. Inf. Office China*, 182–185. Available at: http://english.scio.gov.cn/featured/chinakeywords/2019-07/11/content_74977490.htm (Accessed May 15, 2024).

The State Council Information Office of China (2020). What is five-pronged approach?. *State Counc. Inf. Office China*. Available at: http://english.scio.gov.cn/beltandroad/2020-08/04/content_76345571.htm (Accessed May 15, 2024).

The State Council of the People's Republic of China (2014). Report on the work of the government. Available at: http://english.www.gov.cn/archive/publications/2014/08/23/content_281474982987826.htm (Accessed May 15, 2024).

Tone, K., and Tsutsui, M. (2010). An epsilon-based measure of efficiency in DEA—a third pole of technical efficiency. *Eur. J. Oper. Res.* 207 (3), 1554–1563. doi:10.1016/j.ejor.2010.07.014

Wang, G., and Lu, X. (2019). The belt and road initiative and the upgrading of China's enterprises. *China Ind. Econ.* 3, 43–61. doi:10.19581/j.cnki.ciejournal.2019.03.013

Wang, H., Wang, X., Zhang, X., Liu, G., Chen, W., Chen, S., et al. (2022). The coupling between material footprint and economic growth in the "Belt and Road" countries. *J. Clean. Prod.* 359, 132110. doi:10.1016/j.jclepro.2022.132110

Wang, X., and Johansson, A. (2013). Financial repression and structural transformation. *Econ. Res. J.* 48 (1), 54–67.

Wang, X. L., Fan, G., and Hu, L. P. (2021). *Marketization index of China's provinces: neri report 2021*. Beijing: Social Sciences Academic Press.

Wei, G., Zhang, Z., Ouyang, X., Shen, Y., Jiang, S., Liu, B., et al. (2021). Delineating the spatial-temporal variation of air pollution with urbanization in the belt and road initiative area. *Environ. Impact Assess. Rev.* 91, 106646. doi:10.1016/j.eiar.2021.106646

Xin, L., and Wang, Y. (2022). Towards a green world: the impact of the belt and road initiative on the carbon intensity reduction of countries along the route. *Environ. Sci. Pollut. Res.* 29, 28510–28526. doi:10.1007/s11356-021-17575-3

Xu, H., and Wang, H. (2018). Will streamlining administration and delegating power improve export performance? a quasi-natural experiment based on decentralization of export tax rebates. *Econ. Res. J.* 53 (3), 157–170.

Xu, S., He, X., and Zhong, K. (2019). The belt and road initiative and Chinese firms' financial constraints. *China Ind. Econ.* 7, 155–173. doi:10.19581/j.cnki.ciejournal.2019.07.009

Xu, W., Sun, J., Liu, Y., Xiao, Y., Tian, Y., Zhao, B., et al. (2019). Spatiotemporal variation and socioeconomic drivers of air pollution in China during 2005–2016. *J. Environ. Manag.* 245, 66–75. doi:10.1016/j.jenvman.2019.05.041

Yin, N., and Wang, K. (2020). The air environmental efficiency of key provinces of the belt and road initiative. *J. Central South Univ. For. and Technol. Soc. Sci.* 14 (2), 44–52. doi:10.14067/j.cnki.1673-9272.2020.02.007

Yu, D., Li, X., and Li, H. (2021). Can the belt and road initiative reduce pollution in cities? Evidence from a quasi-natural experiment. *Stat. Res.* 38 (6), 44–56. doi:10.19343/j.cnki.11-1302/c.2021.06.004

Zhang, J., Wang, L., and Wang, S. (2012). Financial development and economic growth: recent evidence from China. *J. Comp. Econ.* 40, 393–412. doi:10.1016/j.jce.2012.01.001

Zhang, J., Yan, D. S., Feng, Z. X., and Li, C. (2018). Can the establishment of free trade zones effectively promote economic growth—a study from the dynamic perspective based on difference-in-differences method. *Inq. into Econ. Issues* 11, 125–133.

Zhang, M., Tan, S., Pan, Z., Hao, D., Zhang, X., and Chen, Z. (2022). The spatial spillover effect and nonlinear relationship analysis between land resource misallocation and environmental pollution: evidence from China. *J. Environ. Manag.* 321, 115873. doi:10.1016/j.jenvman.2022.115873

Zhao, J., and Liu, C. (2020). Does green financial policy promote low-carbon development?—evidence from key provinces along the Belt and Road. *Finance and Econ.* 5, 45–52. doi:10.19622/j.cnki.cn36-1005/f.2020.05.006

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 30 August 2024
DOI 10.3389/fenvs.2024.1432534

Check for updates

OPEN ACCESS

EDITED BY
Ji Zheng,
The University of Hong Kong, Hong Kong SAR, China

REVIEWED BY
Bingnan Guo,
Jiangsu University of Science and Technology, China
Diby Francois Kassi,
Henan University, China

*CORRESPONDENCE
Yang Liu,
yliu@nepu.edu.cn

RECEIVED 14 May 2024
ACCEPTED 19 August 2024
PUBLISHED 30 August 2024

CITATION
Liu Y, Wang Y, Yan B and Zhang H (2024) The impact of new infrastructure development on urban total factor carbon productivity-empirical evidence based on Chinese cities.
Front. Environ. Sci. 12:1432534.
doi: 10.3389/fenvs.2024.1432534

COPYRIGHT
© 2024 Liu, Wang, Yan and Zhang. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The impact of new infrastructure development on urban total factor carbon productivity-empirical evidence based on Chinese cities

Yang Liu[1]*, Yu Wang[1], Bing Yan[2] and Hengshuo Zhang[1]

[1]School of Economics and Management, Northeast Petroleum University, Daqing, China, [2]School of Humanities and Sciences, Northeast Petroleum University, Daqing, China

Digital technology plays a vital role in driving toward a zero-carbon future. This paper explores whether new infrastructure, serving as carriers for digital technology, contributes to carbon reduction and efficiency gains in cities. Drawing on panel data from 280 Chinese cities spanning 2011 to 2019, we establish a theoretical analytical framework to investigate how new infrastructure influences urban carbon performance through the perspectives of influence, threshold, and spatial spillover effects. The study reveals that new infrastructures development has a contributing effect on the total factor carbon productivity of cities, with consistent results across various testing methods. Additionally, the threshold effect test suggests that the dual threshold of regional energy consumption influences the enhancing effect of new infrastructure on total factor carbon productivity, exhibiting nonlinear characteristics. Furthermore, the spatial spillover effect test suggests that new infrastructure construction accelerates the local carbon emission performance, while having a positive spillover effect on neighboring cities. This study provides innovative ideas and experiences from China for the global realization of simultaneous promotion of digital economy development and energy conservation and emission reduction.

KEYWORDS

total factor carbon productivity, new infrastructure, carbon reduction, efficiency gains, energy consumption

1 Introduction

With the worldwide acknowledgement of the necessity to control greenhouse gas emissions, 151 countries have committed to carbon-neutral climate goals, encompassing 94% of the global economies and 86% of the world's population (Matthews et al., 2009; ICON, 2023). International green initiatives are expanding in scale and influence to achieve a sustainable global future (Arbolino et al., 2018). Major global economies have clarified their decarbonization schedules and are actively progressing toward a zero-carbon future.

Despite this, the tension between economic growth and carbon emissions persists globally. Any effective climate change policy must simultaneously aim to stabilize greenhouse gas levels in the atmosphere and promote sustained economic growth, thereby fostering the development decoupled from CO_2 emissions. Developing nations' economies, such as China, are shifting from high growth to high-quality development. Improvement in factor productivity serves as a core indicator for assessing the quality of

economic transformation (Solow, 1957; Khanna and Sharma, 2021). Compared with traditional productivity, total factor carbon productivity (TFCP) serves as a link between economic development and carbon emissions. It has become an important metric for reconciling economic growth with changes in carbon emissions. TFCP is also gaining traction in academic research. Studies have demonstrated that the advances in green technology advances, renewable energy innovations, and the opening of high-speed railways can serve as TFCP engines (Du and Li, 2019; Zhou and Tang, 2021; Lin and Jia, 2022).

In December 2018, the concept of "new infrastructure (NI) " was introduced at China's Central Economic Work Conference and included in the government's work report. NI is an infrastructure system based on the concept of new development, driven by technological innovation and supported by information networks. It can be instrumental to economic growth (Fernández-Portillo et al., 2020), technological innovation (Koutroumpis et al., 2020), industrial structure upgrading (Wu et al., 2023), and enhanced factor productivity (Mitra et al., 2016). Overall, NI has become a crucial indicator of national competitiveness in the digital economy age. However, there is an ongoing debate about the effectiveness of NI in promoting low carbon development. Numerous studies focusing on specific types of NI have suggested that digitization can lead to win-win situation for national prosperity and carbon reduction (Madlener et al., 2022; Kou and Xu, 2022). However, some scholars believe that the construction and operation of NI may promote energy-intensive production, leading to a rebound effect that exacerbates energy consumption and potentially decreases carbon efficiency (Wang et al., 2022). Consequently, the question of whether NI can enhance TFCP still needs to be answered in some instances.

This study utilizes data from city-level studies in China to investigate the impact of developing NI on TFCP. The motivation for this research stems from several factors. First, global carbon dioxide emissions reach a record high of 37.4 billion tons in 2023, according to the data of *CO_2 emission in 2023* releasing by the International Energy Agency (IEA). Among them, carbon emissions of China are 12.6 billion tons, and ranking first in the world. As the world's largest energy consumer, China is committed to achieving the highest reduction rate in carbon emission intensity globally and bears a significant responsibility to accelerate the adoption of low-carbon and green industries. Cities are the main geographical unit of carbon emissions in China, accounting for about 85% of the total carbon emissions (Mi et al., 2016), so improving carbon performance at the city level in China is the key to realize low carbon development. Second, unlike developed nations, developing countries face the dual challenges of environmental preservation and economic growth, which necessitates striking a balance between economic development and climate change. Third, as a rapidly emerging economy, China possesses considerable investment and consumption demands. Its NI construction has yielded substantial results through systematic development and large-scale deployment. According to the data provided by the Ministry of Industry and Information Technology (MIIT, 2024), as of 2023, China has 64.32 million km of fibre-optic cable lines, and over 3.377 million 5G base stations. Moreover, China is developing NI for the construction of the "Belt and Road." to promote deeper global integration.

In summary, with China as the research object, the present study seeks to address the following questions: How effective is the development of NI in reducing carbon at the city level? Is there a heterogeneous threshold effect for NI's lifting effect on TFCP? Are there spatial spillovers from NI influencing TFCP, and what is its regional radiative effect? The present study aims to address these question. The research results will provide additional empirical support for the rise of emerging economies, global responses to climate change, and the transition of development modes.

Compared with existing literature, this paper makes several distinct contributions. First, according to the connotation of NI, the paper assesses NI levels at the city level, employing a nuanced scale encompassing information, integration, and innovation dimensions. Second, it extends the dividend effect of NI from the economic realm to the low-carbon domain. By effectively integrating measures of economic growth and carbon emissions, it comprehensively examines the impact of NI on reducing carbon emissions through the TFCP indicator. Third, using a threshold econometric model, the paper reveals that the promotional effect of NI on urban TFCP is influenced by dual threshold of regional energy consumption, exhibiting nonlinear characteristics. As energy usage decreases, the positive promotional impact of NI on urban carbon performance gradually strengthens. Applying the Durbin spatial model, the study reveals that NI not only positively impacts the region's carbon performance improvement but also generates positive spillover impacts on neighboring cities in terms of relieving pressure on carbon emissions.

The rest of the paper is organized as follows: Section 2 reviews pertinent literature. Section 3 outlines the theoretical framework and necessary hypotheses. Section 4 delineates the research design, encompassing the econometric model, variables, and data. Section 5 presents empirical findings from the benchmark regression. Section 6 further examines threshold and spatial effects based on empirical results. The final section presents conclusions with policy recommendations.

2 Literature review

Currently, academics base their empirical analyses on the economic efficiency effects of new digital infrastructures, affirming their dual role in enhancing the speed and quality of economic advancement. At the macro level, Czernich et al. (2011) in their examination of a sample of OECD data, confirmed that broadband infrastructure enables high-speed Internet access, thereby positively influencing economic growth through increased penetration. Du et al. (2022) observed that new infrastructure investment can propel sustainable economic advancement by leveraging technological innovation, upgrading industrial structures, and increasing production efficiency as transmission pathways. At the micro level, Mitra et al. (2016) posited that information infrastructure offers novel avenues for firms to acquire and utilize information resources, consequently fostering technological efficiency and enhancing factor productivity.

In terms of environmental effects, studies at the macro level have found that the development of new digital infrastructures can enhance the efficient use of energy, thus leading to a reduction in pollution (Wu et al., 2021). At the micro level, studies have shown

that the development of digital infrastructure can promote green transformation of enterprises (Guo et al., 2024b).

As the emphasis on carbon neutrality in the digital age increases, scholars are beginning to discuss the carbon reduction effects of NI. Most studies have assessed the climate impact of specific types of NI on carbon emissions. Danish et al. (2018), Yang et al. (2022), and Ai and Yan, 2024 employed direct measures of NI, such as length of fiber-optic cable lines, the Broadband China Policy and capital stock. However, their findings regarding the influence of NI on the total carbon emissions of developing nations have been inconsistent. Some researchers have explored the impact of NI on urban *per capita* carbon emissions and carbon intensity by constructing an NI composite index (Tang and Yang, 2023; Zhang et al., 2023a).

The relation between economic development and zero-carbon targets is viewed as integrated and mutually reinforcing. Carbon performance has garnered scholarly attention because it connects enhanced economic performances with reduced carbon emissions. However, research on the impact of NI on carbon performance is still in its early stages. Given the limitations of assessing carbon performance by using a single metric (such as carbon productivity or carbon intensity), few scholars have initiated an exploratory investigation into the comprehensive effects of NI on ecological performance from the TFCP perspective. Hu et al. (2023) discovered that developing NI positively affects urban low-carbon development, demonstrating beneficial spatial spillover effects. This "low-carbon dividend" exhibits a Matthew effect and is prominent only in regions with abundant low-carbon endowments. Lan and Zhu (2023) argued that the impact of NI on TFCP exhibits nonlinear characteristics, and the rebound effect complicates the role of NI in carbon emission reduction.

Synthesizing the results of existing research, it can be inferred that NI is a new engine to promote high-quality economic development; however, there are limitations in the research on its low-carbon effect: First, much of the existing studies have either focused on NI's economic performance at national, regional, and enterprise levels or explored its environmental impact through single indicators such as total carbon emissions and carbon intensity. This approach makes it challenging to accurately assess NI's comprehensive effects on a city's carbon reduction and efficiency enhancement behaviors. Second, some studies have used specific proxies such as Internet penetration or policy dummy variables to represent NI, which may not accurately capture the level of developing NI at the city level. Due to limitations of previous studies regarding the relation between NI and carbon performance, the causal relation between the two remains to be clarified. There is a need to comprehensively characterize NI and its positive impact on urban green, low-carbon, and high-quality development. Third, the adverse effects of NI on carbon emission reduction have garnered more attention, and its positive impacts and the role of spatial spillovers in alleviating emission reduction pressures need further analysis.

In view of this, this paper links carbon emissions to economic development and measures the impact of NI on the efficiency of urban low-carbon economic development through TFCP indicator that considering multiple input and output factors. We innovatively constructed a system of indicators to measure the level of infrastructure development at the city level from the three dimensional layers of information, integration and innovation. The enhancement effect of NI on urban TFCP is also empirically examined, further revealing the positive spillover impact of NI on the low-carbon development of neighboring regions.

3 Theoretical analysis and research hypothesis

3.1 Direct effect of NI on TFCP

NI serves as the cornerstone of intelligent city construction and is fundamental for enabling the digital economy to bring about environmental improvements. Focusing on the connotation dimension of NI, we emphasize three aspects, namely information, integration, and innovation, which are aimed at promoting carbon reduction in cities.

First, information infrastructure lays the foundation for the comprehensive development of the urban digital economy. It bears the transmission of various information technologies such as big data, the Internet of things, artificial intelligence, and digital twins, establishing a collaborative network across the city. According to the resource-energy hypothesis, resources and energy are endogenously substitutable (Acemoglu et al., 2012). This implies that as the scale of information capital expands, information infrastructure can be dematerialized by high-tech information technologies, thereby optimizing and replacing enterprise production, processing, marketing, and management processes. Consequently, the result in reduced production costs and energy consumption reduce, thereby contributing to energy conservation and decarbonization (Zhong et al., 2022; Fu et al., 2023).

Second, the deep integration of digital technology into production and life scenarios plays a crucial role in fostering low-carbon urban development by reshaping industrial processes and promoting intelligent living. On one hand, the integration of digital technology within industries has effectively promoted specialized labor divisions in production. This integration has deeply permeated crucial carbon-emitting industries like petrochemicals, electricity, industry, construction, and transportation, facilitating whole-industry and whole-chain digital transformation and low-carbon industrial process re-engineering, concurrently leading to improvements in both carbon emissions and production efficiency (Dedrick et al., 2013). On the other hand, integrating NI into smart city frameworks encourages the gradual transformation of residents' lives toward paperless, advanced, and low-carbon alternatives. NI facilitates the realization of intelligent living, including digital payments, smart travel, and online healthcare, streamlining residents' daily behaviors and thereby reducing urban carbon emissions by improving travel efficiency and promoting low-carbon consumption (Mouratidis et al., 2021).

Third, innovation infrastructure with public goods attributes bolsters scientific research, technical advancement, and environmental protection, while furnishing technological dividends for urban units to engage in environmental governance. This enables environmental regulators to dynamically and promptly monitor production emissions, thereby achieving the process control of carbon emissions. Establishing a precise carbon information service platform through digital innovation lays the groundwork, which will work

together with energy-consuming rights trading policy and environmental information disclosure system, for enhancing governmental digital carbon management and the effectiveness of digital carbon reduction efforts (Guo et al., 2024a; Fang et al., 2022; Wang et al., 2024). In light of these observations, this study proposes Hypothesis 1.

H1: Developing NI can enhance urban TFCP.

3.2 Threshold effect of NI on TFCP

During the industrialization phase, developing countries have heavily relied on extensive resource consumption in exchange for GDP growth, leading to a steady rise in carbon emissions. This rough development model poses challenges to the sustainability of economic growth and may lead to "productivity paradox". Consequently, the efficacy of NI to promote TFCP is difficult to release. Additionally, developing countries often lack a robust foundation for advancing the digital economy, leading to increased energy consumption in pre-development stage of NI and a delay in carbon reduction efforts. In the early stages of development, the digital transformation of resource-dependent industries by NI, may boost their production efficiency, thereby stimulating higher energy consumption and impeding the Improvement in TFCP.

With dual-control constraints on the total amount and intensity of energy consumption, NI is propelled by digital advancements, instigating profound transformations within the energy sector, thereby diminishing the reliance of economic growth on energy consumption. Cities boasting larger economies, diverse industry types, and lower resource dependence, facilitating the scaling up of NI, are more prone to reap the benefits from the positive effects of NI on carbon performance (Du et al., 2023). Therefore, the impact of NI on TFCP may be constrained by the characteristics of regional energy consumption thresholds. The amalgamation of NI and energy constraints can effectively bolster TFCP.

H2: The effect of carbon emission reduction from new infrastructure development depends heterogeneously on regional energy consumption. NI's positive facilitating effect on enhancing urban carbon performance gradually increases as energy consumption decreases.

3.3 Spatial spillover effects of NI on TFCP

As the cornerstone of the digital economy, NI's roles in enhancing the efficiency of regional economic development have been validated. Drawing from Metcalfe's law of network technology development, NI effectively transcends the spatial and temporal constraints of information exchange, facilitating the cross-regional flow of high-value elements and generating spatial spillover effects (Du et al., 2023; Yan et al., 2022). With its universality and shareability, NI empowers the digital economy to break through geographical constraints, thereby unleashing the diffusion effect and influencing "local-neighborhood" economic activities (Bronzini and Piselli, 2009). Consequently, NI not only impacts the region's TFCP but also enhances the carbon performance of neighboring regions.

H3: Developing NI exhibits a spatial spillover effect on TFCP in the neighboring areas.

The theoretical framework is illustrated in Figure 1.

4 Research design

4.1 Modelling

This study establishes the following benchmark regression model to assess the direct impact of NI on TFCP. The detailed calculation is as Equation 1.

$$TFCP_{it} = \alpha_0 + \alpha_1 NI_{it} + \sum \alpha_2 Control_{it} + \lambda_i + \eta_i + \varepsilon_{it} \quad (1)$$

Where i denotes city; t denotes year; TFCP denotes total factor carbon productivity; NI denotes the level of new infrastructure development; $Control_{it}$ denotes a series of city-level control variables over time, including resourcing level (RAL), financial development level (FDL), level of investment in assets (IFA), economic development level (EDL), and degree of industrialization (IDD); λ denotes individual fixed effects; η denotes time fixed effect; and ε is the random perturbation term.

To further explore whether there are nonlinear effects and threshold conditions for the contribution of new infrastructure development to total factor carbon productivity in cities, this study established the threshold effect model on Model (1) as the Equation 2 (Hansen and Seo, 2002):

$$TFCP_{it} = \beta_0 + \beta_1 NI_{it} I(EC_{it} \le \gamma) + \beta_2 NI_{it} I(EC_{it} > \gamma) + \sum \beta_3 Control_{it} + \lambda_i + \eta_i + \varepsilon_{it} \quad (2)$$

In the equation, EC denotes the threshold variable energy consumption, γ denotes the threshold, and I denotes an indicator function that assumes the value 0 or 1.

Furthermore, to explore the spatial spillover effect of carbon emission reduction of new infrastructure construction, Model (1) has been expanded into a spatial panel model by adding a spatial interaction element as the Equation 3 (Elhorst, 2012):

$$TFCP_{it} = \delta_0 + \rho WTFCP_{it} + \delta_1 NI_{it} + \mu_1 WNI_{it} + \sum \mu_2 WControl_{it} + \lambda_i + \eta_i + \varepsilon_{it} \quad (3)$$

Here, W denotes the spatial weight matrix, ρ denotes spatial effect coefficients, and μ_1 and μ_2 denote the spatial lag terms' coefficients for the primary explanatory and controlling variables, respectively.

4.2 Variable settings

4.2.1 Explained variable: TFCP

Carbon productivity can link carbon emissions to economic development, and has emerged as a critical metric for gauging the efficiency of a country's (region's) low-carbon economic development. A single-indicator measurement approach emphasizes the direct correlation between carbon dioxide emissions and GDP. However, this method fails to capture the

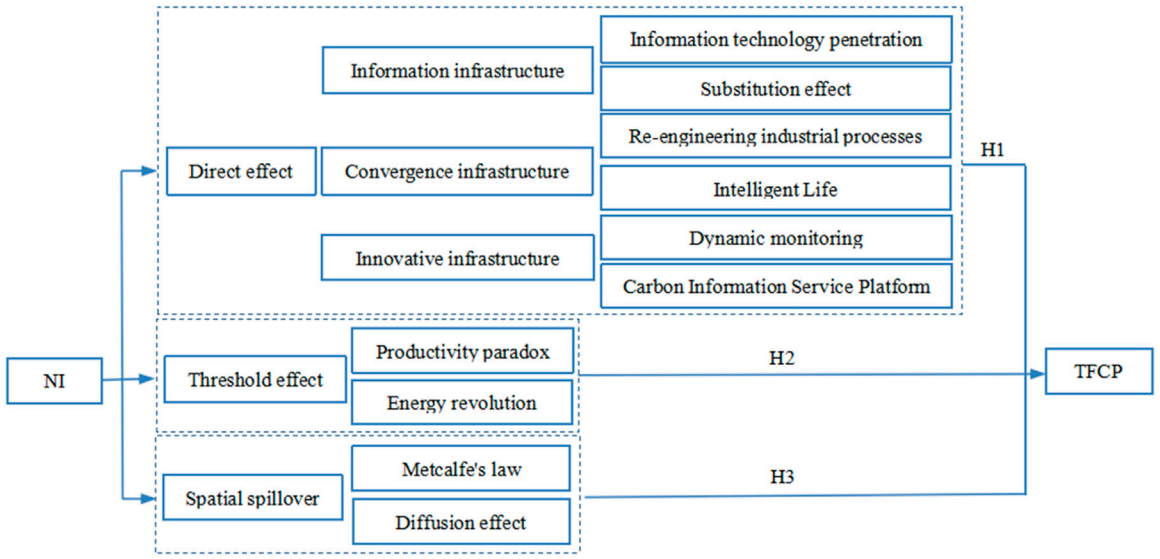


FIGURE 1
Theoretical framework.

intrinsic relations between CO_2 emissions and factors such as capital, labor, and energy, thereby hindering the comprehensive assessment of multiple inputs and outputs. The TFCP indicator, which integrates various relevant factors, considers offers account both economic efficiency gains and environmental carbon reductions (Li and Liao, 2022; Chen and Yao, 2024). It is more appropriate for evaluating the win-win performance of carbon reduction and efficiency gains.

Among the various methods for measuring TFCP, nonparametric data envelopment analysis (DEA) stands out for its ability to effectively address issues related to different scales and angular bias. DEA does not require the construction of production functions and has found widespread application in efficiency measurement studies (Zhou et al., 2017).

The present study employs a nonradial, nonangular Slacks-Based Measure (SBM) model to measure urban TFCP, drawing on the work of Tone and others (Tone, 2001). The indicator system comprises input and output components. The input component includes capital, labor, and energy. The fixed capital stock reflects the capital input and is processed using the perpetual inventory method (PIM) (Nehru et al., 1995). The formula of capital stock used for calculation is as follows: $K_{it} = K_{it-1}(1 - \delta_{it}) + I_{it}$. Utilizing 2000 as the base year, we consider an economic depreciation rate of 9.6% (Zhang et al., 2004). The practitioners in cities take on the dual role as both producers and consumers, intricately linked to carbon emissions, so the labor input factor is determined by the number of practitioners in cities (Chen and Yao, 2024). The energy input factor is gauged by the total amount of electricity consumed across various locations (Kong et al., 2024). The output element encompasses desired and undesired outputs. The desired output indicator is expressed in terms of gross regional product, and the undesired output is represented in terms of CO_2 emissions. The CO_2 emissions are calculated using the IPCC2006 methodology that involves applying data on the amount of energy consumed by electricity, natural gas, and liquefied petroleum gas, which are relatively easy to obtain in prefecture-level cities, and multiplying them by carbon emission coefficients, then summing to calculate total urban carbon emissions (Shan Y et al., 2018).

4.2.2 Explanatory variable: NI

Existing literature has mainly assessed NI development based on individual indicators such as the total volume of postal and telecommunication services, length of fiber-optic cable lines, Internet penetration rate, and the "Broadband China" strategy (Danish et al., 2018; Yang et al., 2022; Xiao et al., 2024). While these indicators provide insights into specific aspects of NI development, they may not offer a comprehensive measure of overall NI levels in a particular region.

Based on the definition of new infrastructure from the Commission on National Development and Reform of China, and according to the research ideas of Ndubuisi et al. (2021), Lan and Zhu (2023) and Chang et al. (2024). This research constructs an evaluation index system for China's city-level new infrastructure from three dimensions: information, convergence, and innovation, to thoroughly mirror the reality of China's urban new infrastructure development. Information infrastructure pertains to the communication network infrastructure reliant on new-generation information technology. Converged infrastructure combines information technology and traditional infrastructure to address deficiencies in the modern era. Innovation infrastructure empowers various sectors including science, education, and industry with digital innovation technology. By integrating the dimensions of information, convergence, and innovation, the level of NI development at the city level is determined using the entropy weight method. Table 1 reports the specific indicators.

4.2.3 Other variables

The threshold variable is energy consumption (EC), measured as electricity consumption *per capita* for society, which is calculated as

TABLE 1 Evaluation system for new infrastructure development.

Target level	Dimensionality layer	Indicator layer	Description of indicators
New infrastructure	Information infrastructure	Information infrastructure construction	Number of listed information and communications companies
		Information infrastructure users	Mobile phone subscribers per 100 population
			Internet users per 100 population
	Convergence infrastructure	Level of digital applications	Number of listed companies in digital technology applications
		Digital business models	Number of listed companies with digital business models
		Digital inclusive finance	Total Index of digital financial inclusion
	Innovative infrastructure	Technical elements	Number of companies listed on digital technology concepts
		Labour factor	Number of employees in the information, computer and software industry
		Capital element	Scale of development of telecommunication services

TABLE 2 Descriptive statistics.

	Variant	Observations	Average value	Standard deviation	Minimum value	Maximum values
Explained variable	TFCP	2,520	0.493	0.121	0.169	1.000
Explanatory variable	NI	2,520	0.049	0.066	0.011	0.929
Control variable	RAL	2,520	17.309	7.225	2.250	60.070
	FDL	2,520	0.988	0.613	0.118	9.623
	IFA	2,520	16.274	0.915	12.794	19.105
	IDD	2,520	1.133	0.469	0.007	14.211
	EDL	2,520	10.697	0.577	8.773	13.056
Threshold variable	EC	2,520	7.591	1.072	3.716	11.634

the ratio of total electricity consumption for the year to the number of people in the area (Khanna and Sharma, 2021).

The rest of the data are control variables for this paper. Drawing on the research methodology of Li et al., 2012, Rehman et al. (2019) and Fang et al. (2020), the main control variables are as follows: (1) Resource allocation level (RAL), represented by road space *per capita*; (2) financial development level (FDL), indicated by the year-end deposit and loan balances of the financial sector as a share of GDP; (3) level of asset investment (IFA), quantified as investment in fixed assets *per capita*; (4) economic advancement level (EDL), measured as regional GDP *per capita*; (5) degree of industrialization development (IDD), expressed as the share of output in the secondary sector to the share of employees in the secondary sector.

4.3 Data sources and descriptive statistics

To account for the missing data of some cities and ensure the continuity and availability of sample data, this study includes 280 prefecture-level cities in China from 2011 to 2019. A balanced panel of data from 2,520 cities is then formed. Data are sourced from the China Urban Statistical Yearbook, China Energy Statistical Yearbook, Statistical Yearbook of Urban Construction in China, Annual Development Report of China's Electric Power Industry, provincial and municipal statistical yearbooks and statistical bulletins, as well as the Juchao Information Network. We employed interpolation to manage data lacunae. Some variables are logarithmic to ensure scale uniformity. Descriptive statistics for each variable are presented in Table 2.

5 Empirical results and analyses

5.1 Benchmark regression results

Based on the theoretical analyses and hypotheses, first, this study explores the performance of the fundamental role of new infrastructure construction in carbon emission reduction. Table 3 presents the results of the benchmark regression of Model (1), controlling for the individual and time-fixed effects. Notably, the contribution of NI to urban TFCP appears relatively robust, with all impact coefficients being significant at 1% confidence level. Specifically, each 1% increase in the level of NI corresponds to an average 0.48% increase in TFCP. Although the effect decreases after incorporating control variables, it remains significant, affirming that developing NI bolster urban TFCP. This suggests that NI possess environmentally friendly

TABLE 3 Benchmark regression results of NI on TFCP.

	Benchmark regression		Lagging first order	Lagging second order	IV-2SLS
	(1)	(2)	(3)	(4)	(5)
	TFCP	TFCP	TFCP	TFCP	TFCP
NI	0.483*** (0.108)	0.432*** (0.081)	0.576*** (0.085)	0.679*** (0.113)	0.722*** (0.080)
RAL		0.000 (0.001)	0.0001 (0.001)	−0.0002 (0.001)	−0.0001 (0.001)
FDL		−0.014** (0.006)	−0.014** (0.007)	−0.015** (0.007)	−0.016** (0.006)
IFA		−0.053*** (0.009)	−0.053*** (0.008)	−0.060*** (0.009)	−0.060*** (0.006)
EDL		0.030*** (0.010)	0.041*** (0.015)	0.031 (0.030)	0.031* (0.018)
IDD		0.126*** (0.024)	0.127*** (0.024)	0.127*** (0.026)	0.124*** (0.019)
Individual fixation	Yes	Yes	Yes	Yes	Yes
Fixed time	Yes	Yes	Yes	Yes	Yes
Constant	0.469 (0.005)	−0.040 (0.211)	−0.067 (0.211)	0.054 (0.213)	−0.247 (0.184)
Observations	2,520	2,520	2,240	1,960	1,960
R^2		0.741	0.749	0.749	0.787
Kleibergen-Paap rk LM					[0.000]
Kleiberge-Paap rk Wald F					575.180
Hansen J					[0.289]

Note: Column (1) shows the benchmark regression results of NI, on TFCP, without addition of the control variable., and column (2) adds control variables. Columns (3) and (4) show regression test of lagged first and second order of NI, as instrumental variables. Columns (5) shows the regression results of two stage least square(2SLS). Clustering robustt standard errors in ( ), ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, P-values in [ ]. Endogeneity instrumental variable test using Kleibergen-Paap rk LM, statistic, Kleibergen-Paap rk Wald F statistic and Hansen J statistic to test for under-recognition, weak instrumental variables, and over-recognition problems, respectively.

characteristics and can support low-carbon sustainable development in cities (Vaka et al., 2020). These results verify Hypothesis 1 of this study.

Meanwhile, ecnonmic development level (EDL) and degree of industrialization development (IDD) also contribute to TFCP. Financial development level (FDL) and investment in assets (IFA) are negatively correlated with TFCP and both are significant at 1% level. This result suggests that the level of economic and industrialization development is an important factor in urban carbon reduction and efficiency, while controlling the level of financial development and asset investment is crucial.

Furthermore, this study employs lagged orders of NI for regression to mitigate possible causal inversion and endogenous disturbances stemming from unobservable factors in the benchmark regression (Hu et al., 2023; Lan and Zhu, 2023). As depicted in columns (3) and (4) of Table 3, the effect of lagged NI on TFCP remains significant. The robustness of the results is indicated by the positive and negative attributes of the coefficient values and the significance of the estimation outcomes, confirming the lagged effect of NI's influential role.

Lagged first and second orders of new infrastructure are employed as instrumental variables (IV) and estimated using two-stage least squares (2SLS) to further mitigate variable endogeneity (Li and Liu, 2022). The results in Column (5) of Table 3 indicate that the promotional effect of NI on TFCP persists under this approach.

5.2 Robustness check

5.2.1 Replace explained variables

This study recalculates explained variables (TFCP) by expanding the dimensions and reconducts regression tests by comprehensively considering the input and output performances of the production factors (Kong et al., 2024). In this context, two additional resource factors, water and land, are considered alongside the existing capital, labor, and energy input factors. In addition to the desired outputs of economic value, the wellbeing of life is considered, with the green space *per capita* in parks serving as a proxy for this aspect. The TFCP is recalculated using the super-efficient SBM model and labeled as TFCP1, and the parameters of the benchmark regression model are re-estimated. The results are displayed in column (1) of Table 4, which indicate that findings are stable and valid.

5.2.2 Replace explanatory variable evaluation methods

The informativeness method is employed as an alternative approach to evaluate the level of NI development, and further regression tests are conducted (Ndubuisi et al., 2021; Yang et al., 2021). The results are presented in Column (2) of Table 4. The positive effect of NI on TFCP remains significant. This finding reaffirms the beneficial role of NI in enhancing the city's TFCP.

TABLE 4 Robustness test.

	Replace explained variables	Replace explanatory variable evaluation methods	Excluding directly governed cities	Excluding coastal cities
	(1)	(2)	(3)	(4)
	$TFCP_1$	TFCP	TFCP	TFCP
NI	0.823*** (0.212)		0.363*** (0.129)	0.399*** (0.095)
RAL	−0.000 (0.001)	−0.000 (0.001)	3.84e-07 (0.001)	0.001 (0.001)
FDL	−0.020** (0.009)	−0.014** (0.007)	−0.013** (0.006)	−0.011** (0.005)
IFA	−0.051*** (0.012)	−0.053*** (0.009)	−0.053*** (0.009)	−0.061*** (0.010)
EDL	0.036*** (0.011)	0.030*** (0.010)	0.0305*** (0.010)	0.025*** (0.017)
IDD	0.091*** (0.024)	0.126*** (0.024)	0.1271*** (0.025)	0.169*** (0.023)
NI_1		0.425*** (0.083)		
Individual fixation	Yes	Yes	Yes	Yes
Fixed time	Yes	Yes	Yes	Yes
Constant	0.396 (0.255)	−0.032 (0.211)	0.0544 (0.2129)	−0.2472 (0.1844)
Observations	2,520	2,520	2,484	2,052
R^2	0.668	0.749	0.7494	0.7865

Note: Column (1) shows the regression results of the explanatory variable expands dimensions ($TFCP_1$). Columns (2) shows the regression results of replacing explanatory variable evaluation methods (NI_1). Columns (3) and (4) shows the regression results of excluding directly governed cities and excluding coastal cities. Clustering robust standard errors in ( ), ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5.2.3 Exclusion of special samples

Acknowledging the distinctive characteristics of directly governed cities, which fall under the direct administration of the central government, and coastal cities, which often benefit from preferential national policies, it is evident that their infrastructure configuration, economic development level, and degree of information differ from those of other prefecture-level cities. To enhance the generalizability of the research results, the sample data from directly governed and coastal cities are excluded. Regression tests are conducted again (Chang et al., 2024; Li et al., 2024). The positive and negative attributes of the coefficient values in columns (3) and (4) of Table 4 demonstrate the robustness of the findings of this study.

6 Further analysis

6.1 Analysis of threshold effects

This study empirically tests the threshold effect of regional energy consumption by using a panel threshold model to further explore whether NI affects TFCP nonlinearly. According to Model (2), a self-sampling threshold effect test (bootstrap) is initially conducted with 1,000 repeated samples to confirm the existence of a threshold. The results show that energy consumption has passed the single-threshold and double-threshold tests at 1% significance level. It indicates that the contribution of NI to TFCP exhibits heterogeneity under different levels of energy consumption. Graphs depicting changes in the likelihood ratio (LR) statistics of the threshold variables clearly illustrate the threshold estimates and their confidence intervals, as detailed in Table 5 and Figure 2.

The results presented in Table 6 indicate that NI contributes to urban TFCP, and energy consumption exhibits a double threshold effect on this relation, passing the 1% significance level test. Specifically, when the level of energy consumption is below 5.213, every 1% increase in the level of NI construction will lead to 10.643% increase in TFCP; when the level of energy consumption in the city exceeds the threshold, the impact coefficient of NI decreases to 3.888; and when the level of energy consumption exceeds the second threshold, the estimated coefficient of the impact index of NI decreases to 0.354. It indicates that the impact of NI on urban carbon performance is affected by the regional energy consumption threshold. The effect is obvious in cities with low energy consumption, while in cities with strong resource dependence, the carbon reduction effectiveness of NI is difficult to be realized.

Many cities characterized by high levels of energy consumption are in a rough development mode, relying heavily on industries with high energy consumption and emissions for economic growth. This situation leads to significant contradictions concerning resources, environment, climate, and security. The convergence of new infrastructures and resource-dependent industries plays a limited role in such cities. Even if the manufacturing efficiency of traditional resource-based industries improves through digital technology, it often results in further driving regional energy consumption, with a minimal pull effect on the city's carbon performance or even exacerbating low-carbon hazards (Hu et al., 2023). However, cities with a low level of energy consumption usually have a

TABLE 5 Threshold effect tests.

Threshold variables	Threshold type	F value	*P*-value	Boundary value			Threshold value	Confidence intervals
				10%	5%	1%		
Energy consumption (full sample)	Single threshold	504.08	0.000	84.513	100.293	125.313	5.213	[5.085, 5.281]
	Double threshold	155.89	0.000	59.423	84.424	115.275	6.059	[6.053, 6.073]
Energy consumption (nonresource-based cities)	Single threshold	469.71	0.000	98.715	115.376	146.695	5.689	[5.636, 5.717]
	Double threshold	85.94	0.000	18.717	22.111	31.136	6.900	[6.867, 6.910]
Energy consumption (resource-based cities)	None	—	—	—	—	—	—	—

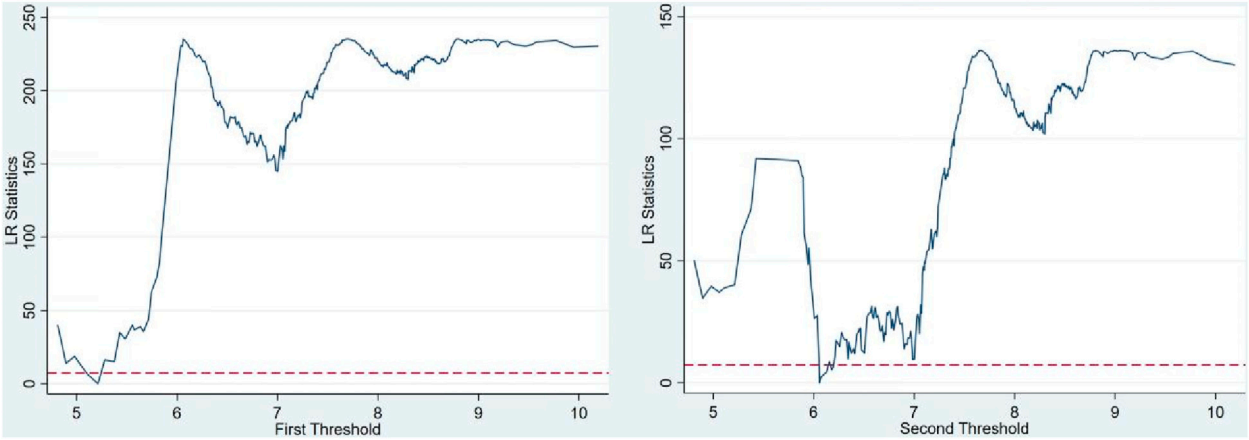


FIGURE 2
Plot of change in LR statistic for the whole sample.

larger scale of national innovation investment and a higher level of digital technology application and innovation. Therefore, the investment in digital infrastructure construction in low-energy cities is more massive, and providing richer application scenarios for them to promote the transformation and upgrading of energy structure and the green and low-carbon development of industries (Zhang et al., 2023a).

In the traditional theory of economic growth, abundant natural resources are the basis for the start of industrialization and the guarantee of sustainable economic development. Resource dependent cities and Resource undependent cities differ in terms of resource endowment and energy use efficiency. Thus, the sample has been divided into 109 resource-based cities and 171 nonresource-based cities to verify the energy consumption threshold effect for both types of cities. The findings demonstrate that in the sample of resource-based cities, the threshold effect of regional energy consumption fails the significance test. The industrial structure of resource cities is mostly high energy consumption and high pollution. Their reliance on traditional resources is characterized by typical "path dependence" and "lock-in effect". The persistence of their high-energy consumption pattern hinders the green transformation of traditional industries and the development of new energy industries, thus weakening the carbon-reducing effect of new infrastructures (Du et al., 2023).

A sample test of non-resource cities shows that new infrastructure development has a positive impact on the increase of total factor carbon productivity in cities, and that energy consumption has a double-threshold effect on this positive impact. With the rapid progress of industrialization, the demand for coal, electricity and other energy consumption of the whole society remains high in the early stage of urban development. At this stage, the digitalization level of cities is relatively backward, and the new infrastructure construction fails to follow up, which makes it difficult to release its effect on carbon performance. Industrial change promotes the diversification of the development mode of non-resource cities, and the level of energy consumption of the whole society is gradually reduced. At this stage, as the level of digital technology application in cities gradually increases, it creates more favorable conditions for the integration and penetration of new infrastructures (Pan et al., 2022; Peng et al., 2024). This has also led to digital infrastructure and digital platforms even better in cities, which makes it easier to upgrade industrial structure and green technological innovation, and strive to improve the efficiency of energy utilization, thus curbing carbon emissions (Liao and Liu, 2024).

TABLE 6 Threshold regression and robustness test results.

Variant	Full sample	Nonresource-based cities	Robustness check	
	(1)	(2)	(3)	(4)
	TFCP	TFCP	$TFCP_2$	TFCP
NI (EC ≤ 5.213)	10.643*** (1.118)			
NI (5.213<EC ≤ 6.059)	3.888*** (0.462)			
NI (EC > 6.059)	0.354*** (0.077)			
NI (EC ≤ 5.689)		9.036*** (0.809)		
NI (5.689<EC ≤ 6.900)		1.782*** (0.225)		
NI (EC > 6.900)		0.277*** (0.083)		
NI (EC ≤ 4.895)			13.819*** (1.097)	
NI (4.895<EC ≤ 6.059)			4.474*** (0.527)	
NI (EC > 6.059)			0.346*** (0.077)	
NI2 (EC ≤ 5.213)				14.391*** (2.336)
NI2 (5.213<EC ≤ 6.059)				5.570*** (0.745)
NI_2 (EC > 6.059)				0.381*** (0.080)
Control	yes	Yes	yes	yes
Constant	−0.289 (0.206)	0.441 (0.271)	−0.329 (0.211)	−0.183 (0.204)
Observations	2,520	1,539	2,520	2,520
R^2	0.461	0.501	0.470	0.433

Note: Column (1) and (2) shows the threshold regression results of full sample and nonresource-based cities. Columns (3) and (4) shows the robustness test results of replacing explained variables($TFCP_2$) and explanatory variable(NI_2). Clustering robust standard errors in ( ), ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

In addition, this paper also replaces the explained and explanatory variables during the threshold test and the robustness test shows that the research conclusions are still valid. In addition, this paper also replaces the explained and explanatory variables in threshold test during the threshold test. The robustness test shows that the research conclusions are still valid.

6.2 Analysis of spatial effects

To examine the existence of a spatial influence and linkage between NI and urban TFCP changes, first, we assess the spatial correlation of the core variables by calculating the global Moran's Index (Moran' I). The Moran' I index is calculated using the Formula 4 (Tiefelsdorf and Boots, 1997):

$$\text{Moran}'\text{I} = \frac{n\sum_{i-1}^{n}\sum_{j-1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i - x)^2} \quad (4)$$

Where n denotes the number of sample cities; x_i, x_j are TFCPs of cities i and j; $\bar{X}$ is the sample mean value of x; w_{ij} denotes the constructed spatial weight matrix. When i and j are not neighboring, $w_{ij} = 0$, and *vice versa* is 1. The global Moran' I index takes the value range of [-1, 1], and if Moran' I > 0, it indicates the existence of spatial positive correlation of TFCP, and if Moran' I < 0, it indicates the existence of spatial negative correlation (Hao and Liu, 2016).

The construction of spatial weight matrix is the basis for spatial measurement correlation analysis. In order to reflect the degree of spatial correlation between cities and the spatial effect of NI on the impact of TFCP (Elhorst, 2012). Considering that the research content and explanatory variables in this paper are related to environmental pollution and energy consumption, and therefore related to spatial distance. So this paper chooses to construct the weight matrix based on the spatial neighboring of cities (W_1) and geographic distance (W_2). The detailed calculation is as Equation 5 and Equation 6.

$$W_1 = \begin{Bmatrix} 1, \text{When city i and city j share a common boundary or node} \\ 0, \text{When city i and city j do not share a common boundary or node} \end{Bmatrix} \quad (5)$$

$$W_2 = \begin{cases} 1/d_{ij} (i \neq j) \\ 0 (i = j) \end{cases} \quad (6)$$

Here, d_{ij} denotes the surface distance between cities calculated by longitudinal and latitudinal position, with greater weighting given to closer geographic proximity.

The results are presented in Table 7. The values of global Moran's I index for both NI and TFCP are positive, indicating significant spatial autocorrelation between the two variables. To further explore the spatial effects, this study selects the spatial

TABLE 7 NI, TFCP global Moran's index.

Vintages	TFCP				NI			
	W1 - spatial neighbourhood		W2 - geographical distance		W1 - spatial neighbourhood		W2 - geographical distance	
	Moran' I	P	Moran' I	P	Moran' I	P	Moran' I	P
2011	0.084	0.029	0.017	0.001	0.090	0.009	0.021	0.000
2012	0.149	0.000	0.025	0.000	0.086	0.011	0.021	0.000
2013	0.097	0.012	0.012	0.014	0.123	0.000	0.029	0.000
2014	0.078	0.041	0.016	0.003	0.080	0.019	0.021	0.000
2015	0.152	0.000	0.038	0.000	0.091	0.008	0.022	0.000
2016	0.169	0.000	0.036	0.000	0.087	0.012	0.022	0.000
2017	0.329	0.000	0.063	0.000	0.093	0.008	0.025	0.000
2018	0.322	0.000	0.055	0.000	0.094	0.008	0.025	0.000
2019	0.280	0.000	0.055	0.000	0.092	0.008	0.025	0.000

Durbin model (SDM) with double fixed effects based on the LM, LR, Wald and Hausmann tests (Elhorst, 2014).

Table 8 displays the spatial autocorrelation regression coefficients ρ of the two models, which are 0.141 and 0.541, respectively. Both coefficients pass the 1% significance level test, indicating that the city's TFCP is affected by the NI levels in geospatially proximate cities. This finding confirms that NI exhibits a radiative effect on regional carbon emission performance, consistent with the findings of selected scholars (Zhang et al., 2023b). The positive effect persists in the regression coefficients of the spatial interaction terms. The coefficient of the interaction term with geographical distance is even more significant, indicating that NI enhances the TFCP of neighboring cities, and this cross-regional spillover effect is closely related to geographical distance.

NI enables the continuous adaptation of a city's internal space through the aggregation of multiple functions and the transmission of massive amounts of information, effectively connecting the city's external space. While some studies have suggested a spatial-geographical decay law of knowledge spillover (Fischer et al., 2009), the high permeability of NI determines its role in blurring the traditional geographic boundaries and facilitating knowledge sharing. NI breaks through the limitations of geospatial distance; promote flow of knowledge, information, data, and other innovation factors across regions; and reduce information asymmetry caused by geographic distance (Raghupathi et al., 2014). This strengthens the correlation between a city's carbon emission performance and the level of NI development in neighboring cities. In that case the NI of neighboring cities significantly contributes to local low carbon development through elemental correlation.

Because of a significant and nonzero ρvalue, the direct use of regression coefficients cannot adequately explain the effects of the two variables. Therefore, the total marginal effect should be divided into direct and indirect effects to more comprehensively analyze the effects of each factor on urban TFCP (Lesage and Pace, 2009).

Regarding the total effect (see Table 9), NI facilitates the improvement of the TFCP index in the region and neighboring cities under two spatial weight matrices of neighborhood and geography. The deployment and utilization of new infrastructure in the region radiate the integration and development of digital industries in neighboring regions. The application of information technology enhances productivity by reducing energy loss, while reducing emissions of pollutants such as CO_2, thereby promoting low-carbon development in the local area and neighboring regions (Khan et al., 2018).

From the results reflecting by the direct and indirect effects, the direct and spillover impact coefficients of NI on urban TFCP are significantly positive at 1% confidence level. This indicates that NI significantly positively affects carbon reduction and improve efficiency in the region. Its diffusion effect surpasses the echo effect, enhancing the green, low-carbon, and high-quality development of neighboring regions. Notably, the spatial spillover effect under the geographic weighting matrix is substantially more pronounced than the direct effect, with a difference in the coefficient of influence of NI being 3.408. This suggests that the geographic distance significantly amplifies the promotional effect of NI on TFCP of neighboring regions.

TABLE 8 Spatial measurement model regression results.

Variant	(1)	(2)	Variant	(3)	(4)
	W_1	W_2		W_1	W_2
	TFCP	TFCP		TFCP	TFCP
NI	0.403*** (0.060)	0.381*** (0.061)	WNI	0.333*** (0.124)	1.510*** (0.574)
Control	yes	Yes	Control	yes	yes
ρ	0.141*** (0.028)	0.541*** (0.105)	ρ	0.141*** (0.0281)	0.541*** (0.105)
sigma2_e	0.003*** (9.34e-05)	0.003*** (9.27e-05)	sigma2_e	0.003*** (9.34e-05)	0.003*** (9.27e-05)
Observations	2,466	2,466	Observations	2,466	2,466
R^2	0.182	0.242	R^2	0.182	0.242

Note: Column (1) and (3) shows the results of the spatial effects test under spatial adjacency matrix. Columns (3) and (4) shows the results of the spatial effects test under geographic distance matrix. Clustering robust standard errors in ( ), ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 9 Spatial measurement model regression results.

Spatial weighting matrix	Type of effect	Ratio
W_1	Direct effect	0.415*** (0.059)
	Indirect effect	0.439*** (0.139)
	Total effect	0.855*** (0.135)
W_2	Direct effect	0.395*** (0.060)
	Indirect effect	3.803** (1.510)
	Total effect	4.199*** (1.501)

Note: Clustering robust standard errors in ( ), ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Moreover, NI promotes high-efficiency concentration and diffusion of information technology factors between regions through spatial clustering and production networking. It also drives the greening, digitalization, and energy-saving upgrading of production processes and techniques. The accelerated establishment of a wide-coverage intelligent transport and fast-track system, along with the rapid flow of production factors across regions and the continuous reduction of logistics and transaction costs, contribute to the formation of an organic community among cities (Hepburn et al., 2021).

7 Conclusions and policy implications

Digital technologies play a crucial role in driving towards a zero-carbon future. This paper explores whether new infrastructures as vehicles for digital technologies can play a role in carbon reduction and efficiency enhancement in cities. Drawing on panel data from 280 Chinese cities spanning 2011–2019, this study investigates the effect of NI on urban TFCP, offering insights to complement existing literature and create policy rationale toward low-carbon development through digitization. The main findings of the study are as follows: (1) The fundamental role analysis shows that NI positively influences urban TFCP, with robustness of the result affirmed through various testing methodologies. (2) As the level of energy consumption decreases, the positive contribution of NI to TFCP gradually increases. This effect is obvious in non-resource cities, while the carbon reduction effect of new infrastructure is difficult to realize in cities with strong resource dependence. (3) The spatial spillover effect analysis indicates that NI can accelerate local carbon performance and exerts a positive spillover effect on neighboring cities through emission reduction and pressure reduction, thereby promoting large-scale urban integration.

Based on the empirical tests provided above, we present the following policy recommendations:

In view of the significant impact of NI on the improvement of urban carbon performance, On one hand, it is recommended to advance the layout of NI appropriately, increase the penetration rate of information infrastructure such as 5G base stations, data centers, and the Internet of Things, so as to enhance the new energy level of the digital pedestal. The "NI" should be emphasized the effectiveness of investment, and localities make a prediction of investment prospects. It is necessary to design the profit model rationally and arrange the financing method. It should be made feasible for commercial investment, enhance development momentum and form high-quality assets that can be reused in the long term. Meanwhile, it is necessary to increase financial support to support the relevant fields of universities, research institutes and enterprises to carry out common technology research jointly and solve technical problems of industries involved in NI. On the other hand, strengthening the innovation infrastructure that supports scientific research and promoting the application of digital technology in urban low-carbon management. Carbon emissions are monitored and analyzed through big data, and the effects of environmental policy implementation are assessed. This improves the efficiency and responsiveness of urban governance and creates conditions for enhancing the effectiveness of digital carbon management and digital carbon reduction by the government.

Furthermore, considering that the carbon emission reduction effect of NI is affected by regional energy consumption thresholds, cities should strengthen energy constraints and other key supporting factors and seize energy consumption's "threshold point" in NI development. On one hand, accelerate the deep integration of information technology and resource-based industries, and lead the transformation and upgrading of traditional energy industries with digital technology. Cities introduce

policies and norms to promote the synergistic development of digital infrastructure and green energy actively. promote the rational distribution of green energy, and improve the energy utilization efficiency of the digital industry. On the other hand, the Government has scientifically designed and deployed an accurate energy control mechanism, built a modern smart grid and promoted the digitalization of energy control. Through real-time monitoring and analysis of energy use data, the visualization of energy use is realized, ultimately improving energy use efficiency and reducing energy consumption.

Finally, NI has spatial spillover effects on neighboring cities in terms of carbon reduction and efficiency, and contributes to the construction of ecological civilization in urban agglomerations by upgrading innovation capacity and accelerating urban-rural integration. However, the prevalence of information silos and the lack of effective integrated planning have led to different cities promoting NI projects independently without unified coordination, resulting in scattered resources and duplication of construction. At the starting line of the construction of smart city clusters, a top-level design with a far-reaching orientation is crucial. The Government should strengthen interregional cooperation in the development of the digital economy and coordinate the construction layout of interregional data centers, arithmetic algorithms, industrial Internet and other infrastructures to maximize their effectiveness. The carbon-reducing effects of new infrastructure can cross traditional urban governance boundaries by industrial integration, corporate cooperation and factor sharing. This creates a green and intensive regional integration pattern and improves the overall green economy efficiency among cities.

Although this study uses 280 cities in China as the sample, the findings are equally helpful for other emerging countries. Like China, most developing economies are still in the early stages of NI. Expanding effective investment and advancing the layout of NI will significantly impact the economic growth of these countries.

This study also has some limitations. On the one hand, we focus on the fundamental role, nonlinear effect and spatial spillover effect of NI impact on TFCP. This research line of thought weakens the differences manifested under different city characteristics. Future research can further explore the impact, such as different city sizes, factor endowments, and geographic locations. On the other hand, in the complex relationship of NI affecting urban TFCP, whether there are other factors that play a moderating role besides being constrained by the threshold characteristics of energy consumption. Which can be further explored at a later stage to explore the role of technological accumulation, human capital, and so on, in enhancing the empowering effect of digital investment.

Data availability statement

This data can be found here: Data are sourced from the China Urban Statistical Yearbook, China Energy Statistical Yearbook, provincial and municipal statistical yearbooks and statistical bulletins. Available at: "https://data.cnki.net/" and "https://www.stats.gov.cn/sj/ndsj/".

Author contributions

YL: Conceptualization, Methodology, Writing–original draft. YW: Data curation, Software, Writing–original draft. BY: Writing–review and editing. HZ: Data curation, Writing–original draft.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by Ministry of Education, Humanities and social science projects of China (No. 22YJC790086), as well as High-level Talent Cultivation Project of Heilongjiang Provincial Undergraduate Colleges and Universities with Central Support for the Reform and Development Funds of Local Colleges and Universities (No. 14011202101).

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The environment and directed technical change. *Am. Econ. Rev.* 102, 131–166. doi:10.1257/aer.102.1.131

Ai, K., and Yan, X. (2024). Can green infrastructure investment reduce urban carbon emissions:empirical evidence from China. *Land* 13 (2), 226. doi:10.3390/land13020226

Arbolino, R., Carlucci, F., Cirà, A., Yigitcanlar, T., and Ioppolo, G. (2018). Mitigating regional disparities through microfinancing: an analysis of microcredit as a sustainability tool for territorial development in Italy. *Land Use Policy* 70, 281–288. doi:10.1016/j.landusepol.2017.10.042

Bronzini, R., and Piselli, P. (2009). Determinants of long-run regional productivity with geographical spillovers: the role of R&D, human capital and public infrastructure. *Reg. Sci. Urban Econ.* 39, 187–199. doi:10.1016/j.regsciurbeco.2008.07.002

Chang, X., Li, J., and Zheng, Q. (2024). Does new-type infrastructure improve total factor carbon productivity? Experimental evidence from China. *J. Clean. Prod.* 460, 142620. doi:10.1016/j.jclepro.2024.142620

Chen, W., and Yao, L. (2024). The impact of digital economy on carbon total factor productivity: a spatial analysis of major urban agglomerations in China. *J. Environ. Manag.* 351, 119765. doi:10.1016/j.jenvman.2023.119765

Czernich, N., Falck, O., Kretschmer, T., and Woessmann, L. (2011). Broadband infrastructure and economic growth. *Econ. J.* 121, 505–532. doi:10.1111/j.1468-0297.2011.02420.x

Danish, N. K., Baloch, M. A., Shah Saud, T. F., Saud, S., and Fatima, T. (2018). The effect of ICT on CO_2 emissions in emerging economies: does the level of income matters? *Environ. Sci. Pollut. Res.* 25, 22850–22860. doi:10.1007/s11356-018-2379-2

Dedrick, J., Kraemer, K. L., and Shih, E. (2013). Information technology and productivity in developed and developing countries. *J. Manage. Inf. Syst.* 30, 97–122. doi:10.2753/MIS0742-1222300103

Du, K., and Li, J. (2019). Towards a green world: how do green technology innovations affect total-factor carbon productivity. *Energy Policy* 131, 240–250. doi:10.1016/j.enpol.2019.04.033

Du, X., Zhang, H., and Han, Y. (2022). How does new infrastructure investment affect economic growth quality? Empirical evidence from China. *Sustainability* 14, 3511. doi:10.3390/su14063511

Du, Y., Zhou, J., Bai, J., and Cao, Y. (2023). Breaking the resource curse: the perspective of improving carbon emission efficiency based on digital infrastructure construction. *Resour. Policy* 85, 103842. doi:10.1016/j.resourpol.2023.103842

Elhorst, J. P. (2012). Dynamic spatial panels: models, methods, and inferences. *J. Geogr. Syst.* 14 (1), 95–119. doi:10.1007/978-3-642-40340-8_4

Elhorst, J. P. (2014). Matlab software for spatial panels. *Int. Reg. Sci. Rev.* 37, 389–405. doi:10.1177/0160017612452429

Fang, Z., Gao, X., and Sun, C. (2020). Do financial development, urbanization and trade affect environmental quality? Evidence from China. *J. Clean. Prod.* 259, 120892. doi:10.1016/j.jclepro.2020.120892

Fang, Z., Razzaq, A., Mohsin, M., and Irfan, M. (2022). Spatial spillovers and threshold effects of internet development and entrepreneurship on green innovation efficiency in China. *Technol. Soc.* 68, 101844. doi:10.1016/j.techsoc.2021.101844

Fernández-Portillo, A., Almodóvar-González, M., and Hernández-Mogollón, R. (2020). Impact of ICT development on economic growth. A study of OECD European Union countries. *Technol. Soc.* 63, 101420. doi:10.1016/j.techsoc.2020.101420

Fischer, M. M., Scherngell, T., and Reismann, M. (2009). Knowledge spillovers and total factor productivity: evidence using a spatial panel data model. *Geogr. Anal.* 41, 204–220. doi:10.1111/j.1538-4632.2009.00752.x

Fu, L., Zhang, L., and Zhang, Z. (2023). The impact of information infrastructure construction on carbon emissions. *Sustainability* 15, 7693. doi:10.3390/su15097693

Guo, B., Feng, Y., and Wang, X. (2024b). The effect of environmental information disclosure on carbon emission. *Pol. J. Environ. Stud.* 33, 1681–1691. doi:10.15244/pjoes/173106

Guo, B., Hu, P., and Lin, J. (2024a). The effect of digital infrastructure development on enterprise green transformation. *Int. Rev. Financial Analysis* 92, 103085. doi:10.1016/j.irfa.2024.103085

Hansen, B. E., and Seo, B. (2002). Testing for two-regime threshold cointegration in vector error-correction models. *J. Econ.* 110, 293–318. doi:10.1016/S0304-4076(02)00097-0

Hao, Y., and Liu, Y. (2016). The influential factors of urban PM2.5concentrations in China: a spatial econometric analysis. *J. Clean. Prod.* 112, 1443–1453. doi:10.1016/j.jclepro.2015.05.005

Hepburn, C., Qi, Y., Stern, N., Ward, B., Xie, C., and Zenghelis, D. (2021). Towards carbon neutrality and China's 14th Five-Year Plan: clean energy transition, sustainable urban development, and investment priorities. *Environ. Sci. Ecotechnology* 8, 100130. doi:10.1016/j.ese.2021.100130

Hu, J., Zhang, H., and Irfan, M. (2023). How does digital infrastructure construction affect low-carbon development? A multidimensional interpretation of evidence from China. *J. Clean. Prod.* 396, 136467. doi:10.1016/j.jclepro.2023.136467

ICON (2023). *Annual progress report on global carbon neutrality 2023*. Beijing: Institute for Carbon Neutrality (Accessed September 23, 2023).

Khan, Z., Linares, P., Rutten, M., Parkinson, S., Johnson, N., and García-González, J. (2018). Spatial and temporal synchronization of water and energy systems: towards a single integrated optimization model for long-term resource planning. *Appl. Energy* 210, 499–517. doi:10.1016/j.apenergy.2017.05.003

Khanna, R., and Sharma, C. (2021). Does infrastructure stimulate total factor productivity? A dynamic heterogeneous panel analysis for Indian manufacturing industries. *Quart. Rev. Econ. Finance* 79, 59–73. doi:10.1016/j.qref.2020.08.003

Kong, L., Li, Z., Liu, B., and Xu, K. (2024). The impact of environmental protection tax reform on low-carbon total factor productivity: evidence from China's fee-to-tax reform. *Energy* 290, 130216. doi:10.1016/j.energy.2023.130216

Kou, J., and Xu, X. (2022). Does internet infrastructure improve or reduce carbon emission performance?A dual perspective based on local government intervention and market segmentation. *J. Clean. Prod.* 379, 134789. doi:10.1016/j.jclepro.2022.134789

Koutroumpis, P., Leiponen, A., and Thomas, L. D. W. (2020). Small is big in ICT: the impact of R&D on productivity. *Telecommun. Policy* 44, 101833. doi:10.1016/j.telpol.2019.101833

Lan, M., and Zhu, Y. (2023). Digital infrastructure construction, carbon total factor productivity, and carbon rebound effect. *Environ. Sci. Pollut. Res.* 30, 88968–88985. doi:10.1007/s11356-023-28738-9

LeSage, J. P., and Pace, R. K. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC. doi:10.1201/9781420064254

Li, G., and Liao, F. (2022). Input digitalization and green total factor productivity under the constraint of carbon emissions. *J. Clean. Prod.* 377, 134403. doi:10.1016/j.jclepro.2022.134403

Li, H., Wang, L., Shen, L., and Chen, F. (2012). Study of the potential of low carbon energy development and its contribution to realize the reduction target of carbon intensity in China. *Energy Policy* 41, 393–401. doi:10.1016/j.enpol.2011.10.061

Li, J., and Liu, A. (2022). Impact of urbanization on total factor carbon productivity in Central Asia. *Sustainability* 14, 15379. doi:10.3390/su142215379

Li, X., Yang, G., Shao, T., Yang, D., and Liu, Z. (2024). Does digital infrastructure promote individual entrepreneurship? Evidence from a quasi-natural experiment on the "Broadband China" strategy. *Tech Fore & Soci Chan* 206, 123555. doi:10.1016/j.techfore.2024.123555

Liao, K., and Liu, J. (2024). Digital infrastructure empowerment and urban carbon emissions: evidence from China. *Telec Policy* 48, 102764. doi:10.1016/j.telpol.2024.102764

Lin, B., and Jia, H. (2022). Does the development of China's high-speed rail improve the total-factor carbon productivity of cities? *Transp. Res. Part D. Transp. Environ.* 105, 103230. doi:10.1016/j.trd.2022.103230

Madlener, R., Sheykhha, S., and Briglauer, W. (2022). The electricity-and CO_2-saving potentials offered by regulation of European video-streaming services. *Energy Policy* 161, 112716. doi:10.1016/j.enpol.2021.112716

Matthews, H. D., Gillett, N. P., Stott, P. A., and Zickfeld, K. (2009). The proportionality of global warming to cumulative carbon emissions. *Nature* 459, 829–832. doi:10.1038/nature08047

Mi, Z., Zhang, Y., Guan, D., Shan, Y., Liu, Z., Cong, R., et al. (2016). Consumption-based emission accounting for Chinese cities. *Appl. Energy* 184, 1073–1081. doi:10.1016/j.apenergy.2016.06.094

MIIT (2024). *Launch of China's industrial and informatisation development in 2023*. Beijing: Ministry of Industry and Information Technology.

Mitra, A., Sharma, C., and Véganzonès-Varoudakis, M. A. (2016). Infrastructure, information & communication technology and firms' productive performance of the Indian manufacturing. *J. Policy Model.* 38, 353–371. doi:10.1016/j.jpolmod.2016.02.013

Mouratidis, K., Peters, S., and van Wee, B. (2021). Transportation technologies, sharing economy, and teleactivities: implications for built environment and travel. *Transp. Res. Part D. Transp. Environ.* 92, 102716. doi:10.1016/j.trd.2021.102716

Ndubuisi, G., Otioma, C., and Tetteh, G. K. (2021). Digital infrastructure and employment in services: evidence from Sub-Saharan African countries. *Tele. Pol.* 45 (8), 102153. doi:10.1016/j.telpol.2021.102153

Nehru, V., Swanson, E., and Dubey, A. (1995). A new database on human capital stock in developing and industrial countries: sources, methodology, and results. *J. Dev. Econ.* 46, 379–401. doi:10.1016/0304-3878(94)00054-G

Pan, W., Xie, T., Wang, Z., and Ma, L. (2022). Digital economy: an innovation driver for total factor productivity. *J. Bus. Res.* 139, 303–311. doi:10.1016/j.jbusres.2021.09.061

Peng, H., Ling, K., and Zhang, Y. (2024). The carbon emission reduction effect of digital infrastructure development: evidence from the broadband China policy. *J. Clean. Prod.* 434, 140060. doi:10.1016/j.jclepro.2023.140060

Raghupathi, W., Wu, S. J., and Raghupathi, V. (2014). The role of information and communication technologies in global sustainability: a review. *J. Manage. Glob. Sustain.* 2, 123–145. doi:10.13185/JM2014.02106

Rehman, A., Rauf, A., Ahmad, M., Chandio, A. A., and Deyuan, Z. (2019). The effect of carbon dioxide emission and the consumption of electrical energy, fossil fuel energy, and renewable energy, on economic performance: evidence from Pakistan. *Environ. Sci. Pollut. Res.* 26 (21), 21760–21773. doi:10.1007/s11356-019-05550-y

Shan, Y., Guan, D., Zheng, H., Ou, J., Li, Y., Meng, J., et al. (2018). China CO_2 emission accounts: 1997-2015. *Sci. Data* 5, 170201. doi:10.1038/sdata.2017.201

Solow, R. M. (1957). Technical change and the aggregate production function. *Rev. Econ. Stat.* 39, 312–320. doi:10.2307/1926047

Tang, K., and Yang, G. (2023). Does digital infrastructure cut carbon emissions in Chinese cities? *Sustain. Prod. Consum.* 35, 431–443. doi:10.1016/j.spc.2022.11.022

Tiefelsdorf, M., and Boots, B. (1997). A note on the extremities of local Moran's I(i)s and their impact on global Moran's I. *Geogr. Anal.* 29 (3), 248–257. doi:10.1111/j.1538-4632.1997.tb00960.x

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* 130, 498–509. doi:10.1016/S0377-2217(99)00407-5

Vaka, M., Walvekar, R., Rasheed, A. K., and Khalid, M. (2020). A review on Malaysia's solar energy pathway towards carbon-neutral Malaysia beyond Covid'19 pandemic. *J. Clean. Prod.* 273, 122834. doi:10.1016/j.jclepro.2020.122834

Wang, K., Sun, T., Xu, R., Miao, Z., and Cheng, Y. (2022). How does internet development promote urban green innovation efficiency? Evidence from China. *Technol. Forecast. Soc. Change* 184, 122017. doi:10.1016/j.techfore.2022.122017

Wang, M., Wang, Y., Yang, Z., and Guo, B. (2024). Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? A quasi-natural experiment from China. *Front. Environ. Sci.* 12, 1430031. doi:10.3389/fenvs.2024.1430031

Wu, H., Hao, Y., Ren, S., Yang, X., and Xie, G. (2021). Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* 153, 112247. doi:10.1016/j.enpol.2021.112247

Wu, W., Ji, Z., and Liang, H. (2023). The impact of new infrastructure construction on optimization and upgrading of industrial structure. *Buildings* 13, 2580. doi:10.3390/buildings13102580

Xiao, X., Liu, C., and Li, S. (2024). How the digital infrastructure construction affects urban carbon emissions—a quasi-natural experiment from the "Broadband China" policy. *Sci. Total Environ.* 912, 169284. doi:10.1016/j.scitotenv.2023.169284

Yan, X., Bai, J., Zhang, Y., and Hu, S. (2022). Can the ecological environment reverse feed renewable energy technology innovation?Heterogeneity test from the Yangtze River Economic Belt. *Renew. Energy* 195, 1381–1392. doi:10.1016/j.renene.2022.06.124

Yang, Y., Chen, W., and Gu, R. (2021). How does digital infrastructure affect industrial eco-efficiency? Considering the threshold effect of regional collaborative innovation. *J. Clean. Prod.* 427, 139248. doi:10.1016/j.jclepro.2023.139248

Yang, Z., Gao, W., Han, Q., Qi, L., Cui, Y., and Chen, Y. (2022). Digitalization and carbon emissions: how does digital city construction affect China's carbon emission reduction? *Sustain. Cities Soc.* 87, 104201. doi:10.1016/j.scs.2022.104201

Zhang, J., Wu, G., and Zhang, J. (2004). Estimation of provincial physical capital stocks in China: 1952–2000. *Econ. Res.* 10, 35–44.

Zhang, W., Fan, H., and Zhao, Q. (2023a). Seeing green: how does digital infrastructure affect carbon emission intensity? *Energy Econ.* 127, 107085. doi:10.1016/j.eneco.2023.107085

Zhang, W., Zeng, M., Zhang, Y., and Su, C. W. (2023b). Reducing carbon emissions: can high-speed railway contribute? *J. Clean. Prod.* 413, 137524. doi:10.1016/j.jclepro.2023.137524

Zhong, M. R., Cao, M. Y., and Zou, H. (2022). The carbon reduction effect of ICT: a perspective of factor substitution. *Technol. Forecast. Soc. Change* 181, 121754. doi:10.1016/j.techfore.2022.121754

Zhou, L., and Tang, L. (2021). Environmental regulation and the growth of the total-factor carbon productivity of China's industries: evidence from the implementation of action plan of air pollution prevention and control. *J. Environ. Manage.* 296, 113078. doi:10.1016/j.jenvman.2021.113078

Zhou, P., Delmas, M. A., and Kohli, A. (2017). Constructing meaningful environmental indices: a nonparametric frontier approach. *J. Environ. Econ. Manage.* 85, 21–34. doi:10.1016/j.jeem.2017.04.003

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 10 September 2024
DOI 10.3389/fenvs.2024.1419720

Check for updates

OPEN ACCESS

EDITED BY
Ji Zheng,
The University of Hong Kong, Hong Kong SAR, China

REVIEWED BY
Bingnan Guo,
Jiangsu University of Science and Technology, China
Fang Qu,
Xihua University, China

*CORRESPONDENCE
Duanqiang Zhai,
zhaiduanqiang@tongji.edu.cn

RECEIVED 19 April 2024
ACCEPTED 27 August 2024
PUBLISHED 10 September 2024

CITATION
Tian K, Zhai D and Han S (2024) Impact of carbon emission trading on urban green innovation: empirical evidence from China's carbon emission trading pilot policy. *Front. Environ. Sci.* 12:1419720. doi: 10.3389/fenvs.2024.1419720

COPYRIGHT
© 2024 Tian, Zhai and Han. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Impact of carbon emission trading on urban green innovation: empirical evidence from China's carbon emission trading pilot policy

Kun Tian[1], Duanqiang Zhai[2,3]* and Shuo Han[2]

[1]Archiland (Tianjin) Architectural Design Co., Ltd., Tianjin, China, [2]College of Architecture and Urban Planning, Tongji University, Shanghai, China, [3]Innovation and Research Center, Shanghai Tongji Urban Planning and Design Institute Co., Ltd., Shanghai, China

In the face of global climate change challenges, China's implementation of the carbon emission trading (CET) pilot policy has provided new empirical research opportunities. Based on a dataset covering 281 Chinese cities from 2005 to 2021, this paper employs econometric models to conduct an in-depth analysis of the policy's impact on urban green innovation (UGI). The findings indicate that the CET pilot policy has significantly promoted green innovation activities in affected cities, with positive effects observed both directly in pilot cities and indirectly in non-pilot cities through spatial spillover effects. In addition, the policy has been found to encourage technological investment and enhance public environmental awareness (PEA), further advancing green innovation. The paper also unveils comprehensive policy effects, indicating that the Big Data Comprehensive Test Zone policy and the New Energy Demonstration City policy work synergistically with the CET pilot policy in advancing green innovation. These findings provide valuable experiences and insights for designing environmental policy tools at the national level, promoting green development, and constructing climate change response strategies.

KEYWORDS

carbon emission trading, urban green innovation, technological investment, public awareness, spatial spillover effect

1 Introduction

Global climate change has emerged as one of the most pressing environmental challenges facing the world today. Greenhouse gases released by human activities, particularly carbon dioxide (CO_2), are the primary drivers of global temperature rise. Climate change poses significant threats to natural ecosystems, economic activities, and societal wellbeing, necessitating urgent action from the international community to reduce carbon emissions and mitigate its impacts. Carbon emissions trading, as a market-based mechanism, aims to reduce the overall volume of greenhouse gas emissions by establishing a cap on carbon emissions and allowing the trading of emission allowances. This mechanism is predicated on the "polluter pays" principle, incentivizing emission reductions by putting a price on carbon emissions (Zhang et al., 2020). Globally, the European Union Emissions Trading System (EU ETS) stands as one of the earliest implemented and largest carbon markets. Other regions, such as California, Quebec, and New Zealand, have also established

their own carbon trading systems (Narassimhan et al., 2018). These practices demonstrate that carbon markets can serve as effective tools for reducing greenhouse gas emissions and promoting the development of green, low-carbon technologies.

Emissions trading, originating in the 1970s, has emerged as a pivotal ecological and environmental economic policy in market-oriented economies. Nations such as the United States, Germany, Australia, and the United Kingdom have successively implemented emissions trading policy measures. In 2006, at the Sixth National Environmental Protection Conference, China announced its intention to collaborate with relevant departments to promote reforms in the paid acquisition and trading of emission rights. The following year, seven provinces and municipalities were selected to initiate pilot programs for total emission control and trading of pollutants such as sulfur dioxide. Faced with the challenges of climate change and international pressure to reduce greenhouse gas emissions, the Chinese government formally launched carbon emissions trading pilot programs in 2011. Concurrently, pilot regions were instructed to research and formulate management measures for carbon emissions trading pilots, elucidate fundamental rules, calculate and establish regional greenhouse gas emission control targets, and develop allocation schemes for greenhouse gas emission quotas. Beginning in 2013, seven provinces and municipalities, including Beijing, Shanghai, and Guangdong, officially commenced carbon emissions trading operations. China's carbon emissions trading pilot program comprises two main components: the carbon emission allowance trading market and the Chinese Certified Emission Reduction market. These pilots encompass multiple high-carbon-emitting industries such as electricity, steel, and chemical sectors, accumulating valuable experience for the construction of China's national carbon market. Furthermore, these policies reflect China's increasingly proactive role in global climate governance and its determination to transition towards a green, low-carbon economy. On one hand, carbon emissions trading requires pilot regions to enhance the quality of development in high-carbon industries, continuously adjust economic structures, eliminate polluting processes, equipment, and enterprises, and implement stringent emission standards for all enterprises, thereby raising entry barriers for heavily polluting industries such as steel, non-ferrous metals, traditional construction, and electricity. On the other hand, considering local industrial characteristics and development strategies, pilot regions are expected to accelerate low-carbon technological innovation and promote low-carbon development and industrialization. Through the implementation of these pilot policies, China aims not only to effectively control and reduce domestic carbon emissions but also to stimulate technological innovation and green low-carbon development through market mechanisms, thereby advancing the optimization and upgrading of its economic structure. Consequently, studying the impact of China's carbon emissions trading pilot policy on UGI is significant not only for understanding the practices and challenges of the carbon market in China but also for providing important references and insights for the implementation of similar policies in other regions globally.

CET has been recognized as an important environmental regulatory tool for reducing CO_2 emissions and mitigating climate change (Zhang et al., 2023). Since its implementation, China's CET pilot policy has attracted widespread attention. Existing literature has discussed the policy's effects on emission reduction (Sun et al., 2020) and socioeconomic impacts (Wei, 2015), among other aspects. For instance, Lu and Luo (2020), based on panel data from 30 provinces and municipalities in China and employing the difference-in-differences approach, analyzed the policy's impact on CO_2 emission volume and intensity, finding that the carbon trading policy has produced significant and sustained positive effects on the reduction of both regional CO_2 emission volumes and intensities. Additionally, Shi et al. (2015), using a computable general equilibrium model (CGE) to build a simulation CGE model of the carbon trading mechanism, quantitatively estimated the impact of the carbon trading mechanism on China's economic and social system, finding that it can effectively reduce carbon and energy intensity, promoting energy conservation and emission reduction processes, but at the same time having a certain negative impact on economic output.

Furthermore, an increasing number of scholars have begun to focus on the impact of CET on green innovation (Yu et al., 2022; Zhang W. et al., 2022). Most studies have found that CET effectively promotes green innovation. For instance, Chen et al. (2021), based on a quasi-natural experiment from China's carbon trading pilot, used a difference-in-differences model and patent data to discover that carbon trading significantly reduced the proportion of green patents in pilot regions. Similarly, Liu and Li (2022) also used a difference-in-differences model and demonstrated that China's carbon trading pilot policy induced green innovation in pilot regions, with a more pronounced effect on invention patents. Zhou and Wang (2022) employed a mediation effect model and found that carbon trading improved urban carbon emission efficiency through two pathways: corporate innovation and resource allocation. Zhang M. et al. (2022) utilized a panel data model and concluded that while CET inhibited renewable energy development in the implementation areas, it promoted renewable energy development in surrounding areas through spatial spillover effects, resulting in an overall positive effect. However, a few studies have concluded that CET suppresses green innovation. Zhang W. et al. (2022), using a difference-in-differences method, found that CET hindered immediate green technology innovation, as firms opted to reduce output rather than increase green innovation to meet emission reduction targets. Du et al. (2021), based on empirical results from provincial panel data in China from 2008 to 2018, revealed that the carbon trading pilot policy significantly reduced the proportion of green patents in pilot regions. The primary reason was that carbon trading crowded out corporate R&D investment and increased carbon prices, thereby inhibiting green innovation. It is noteworthy that each of these conflicting conclusions has its theoretical origins. On one hand, following neoclassical theory, when technology, resource allocation, and consumer demand are fixed, enterprises have already made cost-minimizing decisions, and introducing environmental regulations only increases environmental capital expenditures, weakening competitiveness and inevitably exerting certain displacement effects on technological innovation. On the other hand, according to the "Porter Hypothesis," well-designed environmental regulations can lead to an "innovation compensation" effect on enterprises under changing constraints, thereby encouraging technological innovation.

Existing literature has also analyzed various factors influencing the effects of CET on green innovation. Liu and Li (2022) found significant differences in the sensitivity of state-owned enterprises and high-pollution industries to carbon trading policies. Xin-gang et al. (2023) identified that the success of the carbon trading pilots in Beijing and Guangdong was due to factors such as the refinement of quota accounting mechanisms, the use of compensated allocation methods, larger enterprise sizes, and increased R&D investments. Zhou and Wang (2022) indicated that the degree of marketization and the concept of green consumption positively moderated the impact of carbon trading on green innovation, with industrial structure upgrading playing a positive mediating role between the two. Yao et al. (2021) emphasized the importance of carbon market design, noting that active quota trading, ambitious auction mechanisms, and a focus on the largest emitting entities were key factors in the success of the Hubei pilot.

In summary, existing research primarily focuses on emerging economies such as China, employing quasi-natural experiments and econometric models. Most studies support the notion that CET promotes green innovation, though some have reached contrary conclusions. Factors influencing these effects include carbon market design, firm heterogeneity, and external environmental conditions. Overall, research on the relationship between CET and green innovation remains underdeveloped and unsystematic, with factors needing further refinement and empirical testing. Moreover, studies on the spatial spillover effects of carbon trading, its dynamic impact patterns, and its coupling and synergy with other emission reduction policy tools are still relatively weak and require further investigation. To advance research in this field and extend the analysis of the mechanisms involved, this study examines the relationship between China's CET pilot policies and UGI using data from 281 cities. The specific contributions of this research are as follows. Firstly, this study not only assesses the overall impact of CET policies on UGI but also delves into the mediating roles of technological investment and PEA, thereby expanding the understanding of the policy's impact pathways. Secondly, by employing various empirical methods such as difference-in-differences (DID) and spatial Durbin models (SDM), the study ensures the robustness and reliability of the findings while enriching the research on spatial spillover effects of carbon trading and providing new insights into the regional collaborative effects of the policy. Finally, the study explores the coupling and synergy effects of CET with other emission reduction policy tools, revealing the potential for multiple policy tools to jointly promote green innovation and offering references for future policy optimization.

2 Theoretical analysis

2.1 Economic incentive mechanisms

In global climate governance strategies, the CET system offers an innovative economic incentive mechanism, which achieves the goal of reducing greenhouse gas emissions through market means. By establishing a carbon market, this mechanism integrates the cost of carbon emissions into the operational expenses of companies, encouraging them to seek economically efficient ways to reduce emissions (Ellerman et al., 2007; Stavins, 2008). The core advantage of this system is its ability to stimulate market actors' innovative drive, fostering the research, development, and application of low-carbon technologies, thereby achieving environmental protection goals without sacrificing economic growth (Porter and Linde, 1995).

Through economic incentives, the carbon trading mechanism not only promotes green innovation at the enterprise level but also drives green development in cities. As hubs of population and industrial activity, cities are primary sources of carbon emissions. Implementing CET encourages city administrators to adopt measures to improve energy efficiency, develop public transportation, and promote green buildings to reduce overall carbon emissions (Bulkeley and Betsill, 2005). Additionally, the emergence of the carbon market fosters the development of green financial instruments, providing financial support for sustainable city projects (Kamal-Chaoui et al., 2009).

However, the successful implementation of a carbon trading system must overcome many challenges, such as ensuring the stability of carbon prices, enhancing market participation, optimizing policy design, and strengthening regulation (Zhang et al., 2014). This demands close cooperation between policymakers, businesses, and market participants to realize the long-term objectives of the CET system.

2.2 Analysis of the direct impact of China's CET pilot policy on UGI

The impact of China's CET pilot policy on UGI is a multidimensional issue. The economic incentive mechanism is one of the key theories explaining how environmental policies encourage enterprises to engage in green innovation (Liu et al., 2021). According to the Porter Hypothesis (Porter, 1991), well-designed environmental regulations can internalize external costs, providing innovation incentives that enable enterprises to achieve both environmental and economic benefits. Specifically, China's CET pilot policy exerts economic incentives in several ways. First, the CET mechanism internalizes the environmental costs of carbon emissions into the actual costs for enterprises, compelling them to consider the impact of carbon emissions on their operating costs (Zhao et al., 2022). To reduce carbon emission costs, enterprises are more inclined to adopt green technologies and processes, thereby promoting green innovation. Second, the CET mechanism increases the operating costs for high-carbon-emission enterprises, motivating them to invest in technology R&D to reduce emission intensity and thus lower carbon emission costs. Simultaneously, the carbon trading market provides new market opportunities for green technologies, encouraging enterprises and research institutions to invest more in the development of environmental technologies. Lastly, with the rising prominence of global climate change issues and the proliferation of green consumption concepts, enterprises with advanced green technologies will gain a competitive advantage in future markets (Li et al., 2022). The CET policy offers enterprises the opportunity to gain market share and brand reputation through green innovation, further enhancing their motivation to innovate.

When faced with institutional pressure, enterprises actively adjust their behavior to comply with external environmental requirements to gain legitimacy and resource support. China's

CET pilot policy exerts institutional pressure on enterprises through several mechanisms, promoting green innovation: The government enforces legal regulations and policy documents, mandating enterprises to participate in CET and meet corresponding emission reduction targets. This coercive pressure forces enterprises to adopt measures to reduce carbon emissions, promoting the application and innovation of green technologies. During the implementation of the CET pilot policy, leading enterprises that successfully adopt green technologies set an example for other enterprises. To remain competitive, other enterprises will imitate and learn from these leading enterprises' green innovation strategies, creating a diffusion effect of green innovation within the industry (Tian et al., 2022). The implementation of the CET policy is accompanied by the establishment of related standards and industry norms, which require enterprises to adhere to green development principles in their production and operations. Normative pressure drives enterprises to upgrade technologies and innovate in management practices to comply with industry standards and norms, thereby achieving green innovation (Liu et al., 2020).

In summary, the economic incentive mechanism motivates enterprises to innovate through cost internalization, technological R&D investment, and competitive market advantages, while institutional pressure forces enterprises to adjust their behavior through coercive, mimetic, and normative pressures. The combined forces of these two mechanisms propel enterprises from passively responding to environmental regulations to actively pursuing green development, thereby achieving the goal of UGI. Therefore, we propose the research hypothesis H1:

H1. China's CET pilot policy contributes to promoting UGI.

2.3 Analysis of the indirect impact of China's CET pilot policy on UGI

2.3.1 China's CET pilot policy, technological investment, and UGI

China's CET pilot policy not only directly promotes UGI but also drives green innovation through indirect mechanisms such as increased technological investment. Technological investment is a critical factor in promoting green innovation. By investing in the research and application of technology, enterprises can significantly enhance resource efficiency, reduce pollution emissions, and foster sustainable urban development. Through increased investment in green technology research and application, enterprises can develop more efficient and environmentally friendly production processes and products, thus achieving efficient energy use and effective pollution control (Zhao et al., 2022). Technological investment also facilitates iterative upgrades in technology, enabling enterprises to continuously improve their green innovation capabilities and gain a competitive edge in the market (Chen et al., 2021). As technological investment increases, the overall level of green technology and innovation capacity in cities will also rise, steering cities towards green and sustainable development.

China's CET pilot policy promotes technological investment in enterprises through various mechanisms, thereby indirectly fostering UGI. Firstly, the CET policy internalizes the cost of carbon emissions through market mechanisms, providing strong economic incentives. This compels enterprises to pay for their emissions, motivating them to invest more in green technology research and development to reduce carbon emission costs and enhance competitiveness (Feng et al., 2017). Secondly, the policy optimizes resource allocation, forcing enterprises to invest more in technological research and innovation to improve production efficiency and reduce emissions (Wu et al., 2021). Additionally, the policy stimulates external funding and resource investment, with the government and social capital increasing their investments in green technology projects, providing financial support and tax incentives, and attracting more enterprises and research institutions to participate in green technology research and development (Li et al., 2022; Wang et al., 2024). Lastly, the CET policy enhances the efficiency of technological investment by promoting collaboration and exchange. It encourages technical cooperation, joint research, and knowledge sharing between enterprises and research institutions, enabling quicker mastery of advanced green technologies and improving innovation efficiency.

In summary, China's CET pilot policy indirectly promotes UGI through increased technological investment. Driven by economic incentives and policy support, enterprises actively engage in the research and application of green technologies. This not only achieves environmental protection goals but also enhances their competitiveness, driving sustainable urban development and green transformation. Therefore, the following research hypothesis H2 is proposed:

H2. China's CET pilot policy promotes UGI through increased technological investment.

2.3.2 China's CET pilot policy, PEA, and UGI

In addition to technological investment, enhancing PEA is a crucial factor in promoting UGI. PEA refers to the public's understanding and concern about environmental issues, as well as their propensity to choose eco-friendly products and services in their daily lives and consumption habits (Yan et al., 2010). The enhancement of PEA can stimulate market demand for green products and technologies, thereby driving enterprises to engage in green innovation (Xu et al., 2021). As environmental problems become increasingly severe, public concern for environmental protection has risen, leading to a greater preference for eco-friendly products and services. This shift in market demand forces enterprises to continuously develop and provide products that meet environmental standards to satisfy consumer needs. Under this market pressure, enterprises actively pursue technological innovation and product improvement, thereby advancing the overall process of UGI. Additionally, the rise in PEA can also facilitate the enactment and implementation of environmental regulations and policies, creating external pressure on enterprises and further promoting green innovation (Zheng et al., 2014).

China's CET pilot policy enhances PEA through various mechanisms, thereby indirectly promoting UGI. Firstly, the policy raises public awareness of carbon emissions and environmental protection through extensive publicity and educational activities. During policy implementation, the government and environmental organizations utilize various

media channels to widely disseminate information and educate the public about CET and its significance. This dissemination of knowledge enhances public understanding and support for environmentally friendly technologies and products, thereby stimulating market demand for green products and technologies (Fan and Xiao, 2021). Secondly, the CET policy boosts public engagement in environmental actions through economic incentive mechanisms. During the policy's implementation, measures such as tax incentives and subsidies are used to encourage public participation in environmental protection activities. For example, the government may provide subsidies to consumers who purchase eco-friendly products or offer tax incentives to individuals participating in CET (Ji et al., 2017). These economic incentives not only directly promote public environmental behavior but also indirectly drive enterprises to innovate green products to meet market demands (Cai and Ye, 2022). Furthermore, the policy fosters cooperation between enterprises and communities, enhancing public participation in green innovation. During the implementation of the CET pilot policy, the government encourages enterprises to collaborate with communities on environmental projects and activities. This cooperation not only strengthens public recognition and involvement in environmental protection but also provides enterprises with opportunities for direct interaction with the public. This interaction helps enterprises better understand market needs, allowing them to conduct targeted technological innovations and product improvements.

In summary, China's CET pilot policy indirectly promotes UGI by enhancing PEA through various means. The policy leverages publicity and education, economic incentives, and community cooperation to strengthen public understanding and support for environmental protection. This, in turn, stimulates market demand for green products and technologies, driving enterprises to innovate and promoting sustainable urban development and green transformation. The following research hypothesis H3 is put forth:

H3. China's CET pilot policy promotes UGI by increasing PEA.

2.4 China's CET pilot policy, spatial spillover effects, and UGI

In addition to its direct and indirect impacts, China's CET pilot policy also exerts positive influences on green innovation in neighboring cities through spatial spillover effects. Spatial spillover effects refer to the phenomenon where policies or economic activities in one region affect the economic and innovation activities of surrounding regions through various channels such as technology diffusion, knowledge transfer, and market linkages (Du et al., 2021). This effect is particularly important in the realm of environmental policy and green innovation, as environmental issues and innovation activities often transcend regional boundaries (Guo et al., 2023).

China's CET pilot policy can generate positive spatial spillover effects on neighboring cities through technology diffusion and knowledge transfer. Following the implementation of the carbon trading policy, pilot cities actively develop and apply green technologies. These technologies and knowledge can then spread to neighboring cities through inter-firm cooperation, personnel mobility, and information exchange. For instance, enterprises in pilot cities may establish collaborative relationships with enterprises in neighboring cities to jointly develop and promote green technologies, thereby driving green innovation in those neighboring areas (Yang et al., 2022). Additionally, the movement of technical personnel and experts within the region facilitates the dissemination of knowledge and the application of technologies, enabling green innovation to be promoted and implemented over a broader area.

The CET policy also impacts neighboring cities through market linkage mechanisms. The establishment and operation of the carbon trading market not only affect the pilot cities but also have profound implications for the market environment and economic activities of the entire region. After implementing the carbon trading policy, pilot cities may develop more sophisticated green markets and industrial chains, attracting enterprises from surrounding cities to participate and fostering regional industrial collaboration. For example, enterprises in neighboring cities can engage in the carbon trading market to gain access to more green technologies and financial support, thereby enhancing their green innovation capabilities (Bai et al., 2023). Moreover, the increasing demand for green consumption within the region stimulates enterprises in neighboring cities to develop and promote eco-friendly products and services, further advancing regional green innovation.

In summary, China's CET pilot policy generates positive spatial spillover effects on green innovation in neighboring cities through mechanisms such as technology diffusion, market linkages, and policy demonstration. The successful implementation of the pilot policy not only aids the green development of the pilot cities themselves but also, through regional interaction and cooperation, drives green innovation and sustainable development across the entire region. This spatial spillover effect not only amplifies the overall impact of the policy but also provides valuable insights and lessons for other regions seeking to implement similar policies. Hence, the following research hypothesis H4 is proposed:

H4. China's CET pilot policy stimulates green innovation in neighboring cities.

3 Methodology

3.1 Model design

3.1.1 Baseline regression model

In this study, we use a dataset from 281 Chinese cities spanning the years 2005–2021 and treat the CET pilot policy as a quasi-natural experiment to explore its impact on UGI using the Difference-in-Differences (DID) method. The DID method is chosen for its effectiveness in leveraging the differences before and after the policy implementation as well as between pilot and non-pilot cities, allowing for an accurate estimation of the policy's causal effect by controlling for potential unobserved heterogeneity and time trends. Moreover, the introduction of a two-way fixed effects model further enhances the accuracy of the estimations by controlling for city-specific effects that do not change over time

TABLE 1 Variable definition table.

	Variable name	Variable symbol	Measure of variable
Dependent Variable	UGI	GIF	Number of green patent applications per 10,000 people in the city
Independent Variable	China's CET Pilot Policy	DID	Policy dummy variable
Control Variables	The level of economic development	agdp	Per capita GDP logarithm
	financial development level	fin	Balance of deposits and loans of financial institutions as a proportion of regional GDP at year-end
	Openness level	fdi	Ratio of actual utilization of foreign capital to regional GDP
	Infrastructure development	inf	Public library books per hundred people
	Degree of government intervention	gov	Government general expenditure as a proportion of regional GDP
	Environmental regulation	er	Comprehensive utilization rate of general industrial solid waste

and for time effects common to all cities, ensuring the robustness of the results. This methodological approach aims to provide a rigorous and scientific analytical framework to assess and interpret the specific role of China's CET pilot policy in promoting UGI, offering strong empirical support for the formulation and optimization of related policies.

$$GIF_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \delta X + \gamma_i + \omega_t + \varepsilon_{i,t} \quad (1)$$

Here, GIF represents urban-level green innovation, DID represents the dummy variable for China's CET pilot policy, and X represents various control variables, including economic development level (agdp), financial development level (fin), openness level (fdi), infrastructure development (inf), government intervention (gov), and environmental regulation (er). In addition, γ_i and ω_t represent the fixed effect of urban individuals and the fixed effect of time respectively.

3.1.2 Mechanism test model

To test the mechanisms through which the new energy demonstration city policy affects UGI capability, the study employed a mediation effect model and examined the mechanisms from two aspects: technology investment and PEA.

$$GIF_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \delta X + \gamma_i + \omega_t + \varepsilon_{i,t} \quad (2)$$

$$middle_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \delta X + \gamma_i + \omega_t + \varepsilon_{i,t} \quad (3)$$

$$GIF_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \alpha_2 middle_{i,t} + \delta X + \gamma_i + \omega_t + \varepsilon_{i,t} \quad (4)$$

Here, 'middle' represents technology investment (sci) and PEA (car) in Equation 3 and Equation 4, and Equation 2 is the same as Equation 1.

3.1.3 Spatial regression model

To delve into the spatial dimension of the impact of China's CET pilot policy, this study introduced the spatial Durbin model shown below to investigate the spatial spillover effects of this policy on UGI. This method allows us to evaluate not only the impact of the policy on the implementing cities themselves but also to examine whether this impact is transferred to neighboring cities through interregional economic connections, thus creating a spillover effect. A common spatial economic distance matrix was used for the analysis.

$$GIF_{i,t} = \alpha_0 + \alpha_1 DID_{i,t} + \beta_1 \sum_j w_{ij} DID_{i,t} + \alpha_2 X + \beta_2 \sum_j w_{ij} X + \rho \sum_j w_{ij} GIF_{i,t} + \gamma_i + \omega_t + \varepsilon_{it} \quad (5)$$

In Equation 5, ρ represents the spatial lag autoregressive coefficient, w_{ij} is the element of the spatial weight matrix.

3.2 Variable selection

3.2.1 Dependent variable

Urban Green Innovation (GIF). This study chooses the amount of green patent applications to measure UGI. First, as a forward-looking indicator of innovative activities, the number of green patent applications directly reflects the results of a city's R&D and innovative efforts, providing a timely perspective on the latest trends in innovative activities. Moreover, compared to granted patents, the number of applications reduces the interference of administrative approval processes, more accurately reflecting the dynamics of a city's green innovation. Data collection is based on the International Patent Classification (IPC) codes of the World Intellectual Property Organization (WIPO), ensuring the international standardization and reliability of the data. Meanwhile, to eliminate the influence of different city sizes, we adopted the method of dividing the number of green patent applications by city population for normalization. This practice enhances the accuracy and fairness in comparing the green innovation capabilities of different cities. Through this approach, we aim to ensure the robustness and credibility of the research results, providing strong data support for evaluating the green innovation effects of the CET pilot policy. For uniformity of measurement, borrowing the practice of Rao et al. (2024), the number of green patent applications is divided by the city population (in tens of thousands).

TABLE 2 Descriptive statistics.

VarName	Obs	Mean	SD	Median	Min	Max
GIF	4777	0.855	2.195	0.201	0.000	35.407
DID	4777	0.070	0.255	0.000	0.000	1.000
agdp	4777	10.435	0.760	10.483	4.595	13.056
fin	4777	2.316	1.217	1.974	0.508	21.302
fdi	4777	0.019	0.020	0.012	0.000	0.229
inf	4777	68.193	276.640	33.000	1.000	10426.000
gov	4777	0.181	0.121	0.154	0.043	2.349
er	4777	0.793	0.238	0.883	0.002	2.238

TABLE 3 Baseline regression results.

	(1)	(2)	(3)	(4)
	GIF	GIF	GIF	GIF
DID	2.587***	1.716***	1.810***	1.613***
	(0.119)	(0.112)	(0.101)	(0.109)
agdp			0.923***	−1.306***
			(0.037)	(0.111)
fin			0.538***	0.013
			(0.024)	(0.037)
fdi			1.121	−14.169***
			(1.301)	(1.464)
inf			0.001***	0.000***
			(0.000)	(0.000)
gov			−2.027***	−2.255***
			(0.234)	(0.272)
er			0.538***	0.239*
			(0.109)	(0.139)
_cons	0.674***	0.735***	−10.287***	14.808***
	(0.031)	(0.020)	(0.397)	(1.201)
Control	No	No	YES	YES
City_FE	No	YES	No	YES
Year_FE	No	YES	No	YES
Obs	4777	4777	4777	4777
r2	0.090	0.670	0.378	0.694

Note: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.2.2 Independent variable

China's CET Pilot Policy (DID). In 2013, seven local carbon markets in cities such as Beijing and Shanghai successively began trading. Following the approach of Zhang et al. (2023), the dummy variable of cities chosen as "carbon trading" pilot cities is used as the core explanatory variable. CET pilot cities are treated as the experimental group, assigning the policy dummy variable DID a value of 1 for the year of approval and subsequent years, and 0 before approval.

3.2.3 Control variables

This study uses economic development level (agdp), financial development level (fin), level of openness (fdi), infrastructure development (inf), degree of government intervention (gov), and environmental regulation (er) as control variables. These variables comprehensively account for other factors influencing UGI capabilities, allowing for a more accurate identification of the green innovation effects of China's CET pilot policy.

The variable definitions are shown in Table 1.

3.3 Data description

Considering the availability and continuity of urban data, this paper selects balanced panel data from 281 Chinese cities for the years 2005–2021 as the empirical research basis. Green patent application data are sourced from the China National Intellectual Property Administration, while other city data are from the China City Statistical Yearbook and the China Statistical Yearbook. Additionally, linear interpolation is used to fill in some missing values. A descriptive statistic of the variables is shown in Table 2.

4 Results

4.1 Baseline regression results

Table 3 presents the test results of the impact of China's CET pilot policy on UGI. Among them, columns (1)–(4) represent the regression results with gradually added control variables and fixed effects, respectively. We observe that the coefficient for DID is significantly positive, indicating that China's CET pilot policy has significantly promoted UGI, thus confirming research hypothesis H1. Specifically, the CET pilot policy in China, through the establishment of a carbon market, offers economic incentives for emissions reductions and encourages enterprises and cities to adopt more green innovation measures for reducing carbon emissions. This market-based incentive mechanism motivates firms to invest in

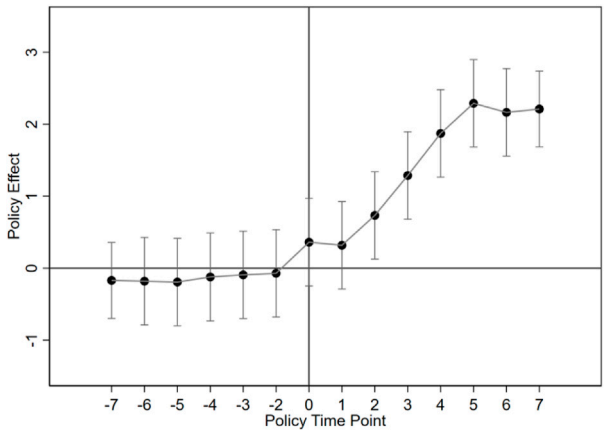


FIGURE 1
Parallel trends test.

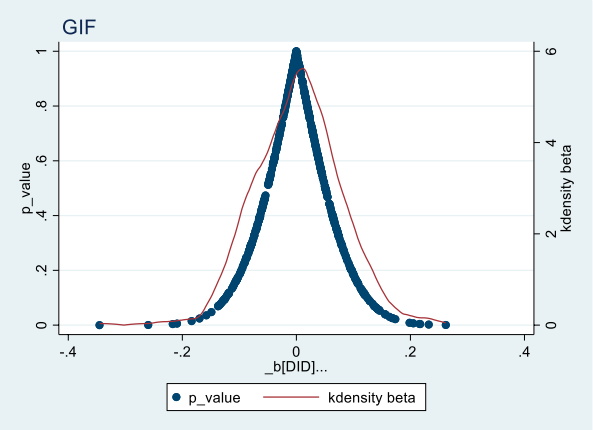


FIGURE 2
Placebo test.

green technology development, accelerating the application and promotion of environmental protection technologies, and thereby enhancing the overall level of UGI.

This discovery empirically strengthens the notion that the CET policy is an effective market mechanism capable of promoting technological innovation through economic incentives, especially in the field of environment-friendly technology. This finding not only aligns with theoretical expectations but also provides important empirical backing for policymakers, showing that facilitating green innovation through market-based approaches is feasible and efficient.

4.2 Robustness test results

4.2.1 Parallel trends test

To ensure the effectiveness of the Difference-in-Differences (DID) model and to enhance the robustness of the regression results, we conducted a parallel trends test, a key prerequisite for applying the DID method. The parallel trends assumption requires that the pre-policy green innovation capabilities of treated (pilot cities) and control (non-pilot cities) groups must follow a consistent trend. If the assumption holds, it can be inferred that other external factors influence both groups similarly, aside from the policy implementation, allowing the treatment effects to be attributed to the policy impact.

In this study, employing the event study approach and referencing Jacobson et al. (1993), the period immediately before the implementation of China's CET pilot policy was taken as the base period, and data from 7 years before and after the policy implementation were tested. By comparing the changes in green innovation capabilities of treated and control groups before and after the policy implementation, we can test the validity of the parallel trends assumption.

The test results are shown in Figure 1. The results indicate that, before the policy implementation, the differences in green innovation capabilities between the treatment group and the control group were not significant, meaning the trends between the two groups were parallel prior to the policy implementation. Notably, the policy effect in the immediate post-implementation period (the first time point after the policy implementation) is not significant. This can be attributed to several possible reasons. On one hand, the immediate period following the implementation of a new policy often involves an adjustment phase. During this phase, enterprises and local governments may be adapting to new regulations, setting up necessary infrastructure, and understanding compliance requirements. As stakeholders gradually align their operations with the new policy, this transition period can temporarily weaken the immediate effect of the policy. On the other hand, the introduction of the carbon trading mechanism may require significant initial investments and a learning curve for both enterprises and regulatory bodies. Firms may need time to invest in green technologies, train personnel, and optimize their operations to meet the new standards. This initial phase of investment and learning may delay the direct impact of the policy on green innovation. Additionally, there may be lags in effective communication and awareness of the policy among stakeholders. Comprehensive understanding and proactive engagement from all involved parties are crucial for the policy to have a significant impact. Any delays in these aspects can result in the immediate effect of the policy not being significant. These factors collectively suggest that while the policy did not show a significant impact immediately after implementation, this does not undermine the overall effectiveness of the CET pilot policy in promoting green innovation. The significant positive effects observed in subsequent periods affirm the policy's role in driving sustainable development and innovation.

4.2.2 Placebo test

To ensure that our estimated results are not affected by endogeneity problems such as unobservable omitted variables or reverse causality, we conducted a placebo test to strengthen the study's robustness and credibility. The placebo test evaluates the randomness of the empirical results by creating fictitious policy pilots and checking whether the model still shows similar significant effects in the absence of policy intervention.

For this procedure, we conducted 500 random samplings, randomly selecting a subset of cities as a "treated" group for each

TABLE 4 Robustness test results.

	(1)	(2)	(3)	(4)	(5)
	GIF	GIF2	GIF	GIF	GIF
DID	2.190***	0.917***		1.228***	1.467***
	(0.132)	(0.067)		(0.110)	(0.109)
LDID			1.680***		
			(0.111)		
dp					0.559***
					(0.137)
ul					−2.932***
					(0.374)
Control	YES	YES	YES	YES	YES
City_FE	YES	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES	YES
Obs	3878	4777	4496	4709	4691
r2	0.716	0.676	0.715	0.683	0.840

TABLE 5 Mechanism test results.

	(1)	(2)	(3)	(4)
	sci	GIF	car	GIF
DID	0.007***	1.234***	33.008***	1.465***
	(0.001)	(0.102)	(4.423)	(0.160)
sci		51.800***		
		(1.972)		
car				0.002**
				(0.001)
Control	YES	YES	YES	YES
City_FE	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES
Obs	4777	4777	3091	3091
r2	0.702	0.735	0.790	0.830

sample, when in fact these cities did not implement the CET pilot policy. Then, we re-estimated the regression for these 500 samples, observing the distribution of the estimated values.

Figure 2 displays the distribution of the placebo test estimated coefficients, where most coefficients are close to zero, and their p-values are mostly greater than 0.1, indicating a very low probability of obtaining significant estimates at random. This outcome is clearly different from the coefficient estimates of the baseline regression, which show significant statistical and practical significance. Therefore, the placebo test results suggest that our baseline regression outcomes are unlikely due to random chance factors or unobserved omitted variables, further confirming the robustness of our baseline conclusions.

4.2.3 PSM-DID test

To address any potential selection bias arising from the selection mechanism of China's CET pilot policy, we employed a combined propensity score matching (PSM) and difference-in-differences (DID) method (PSM-DID) for a more robust estimation. The PSM-DID method can effectively reduce systematic differences in observable variables between the treated and control groups, enhancing the credibility of causal inferences.

In the PSM step, the study used control variables such as economic size, industrial structure, population density as matching variables, and through radius matching, we matched each pilot city with non-pilot cities that have similar characteristics, thus constructing a new treated and control group. The balance test results after propensity score matching show that the differences in matching variables between the treated and control groups are effectively controlled, indicating a good match quality.

Next, we applied DID regression analysis on the matched sample, and the results are displayed in column (1) of Table 4. The results indicate that after controlling for selection bias, the coefficient for DID remains significantly positive, consistent with our baseline regression results. This finding reinforces our conclusion that China's CET pilot policy significantly promotes UGI.

4.2.4 Other robustness tests

To ensure the robustness and credibility of the research results, this study conducted a series of additional robustness checks, including replacing the dependent variable, adjusting the timing of the core explanatory variable, excluding specific samples, and adding control variables to mitigate the omitted variable bias.

First, to verify the robustness of the measurement of UGI capability, the study replaced the dependent variable with the amount of green patent grants per 10,000 people in the city as another measure of UGI capability. The regression results after replacing the variable (shown in column 2 of Table 4) reveal that the DID coefficient remains significantly positive, confirming that the positive impact of the CET pilot policy on UGI is consistent and robust regardless of the measure used—patent applications or grants.

Second, considering the potential lag effect of policy impact, the study processed the core explanatory variable and control variables with a one-period lag to explore the durability of the policy effect and to weaken potential reverse causality. The regression results after the lag processing (shown in column 3 of Table 4) still show a significantly positive coefficient for the policy effect, indicating a certain permanence of the carbon trading policy's positive impact on UGI.

In addition, as municipalities directly under the central government have special political and economic status, they may influence research results. To ensure the universality of the research findings, the study excluded samples of municipalities and performed the regression, and the results (shown in column 4 of Table 4) remain consistent, indicating that the research conclusions are not affected by the specificity of the municipality samples.

Lastly, to further mitigate possible omitted variable issues, the study added control variables such as population density, and urbanization level to the regression. These variables help control for the potential impact of city size, economic activity intensity, and urbanization level on green innovation. The regression results with these additional control variables (shown in column 5 of Table 4) indicate that the DID coefficient remains significantly positive, further affirming the robustness of the research conclusions.

4.3 Mechanism test results

4.3.1 Technology investment mechanism test

The study used the ratio of expenditures on science and technology to local government general public budget expenditures as a measure of the level of technology input and conducted regression on the mechanism test models (3) and (4). The regression results indicate that in model (3), the DID coefficient is significantly positive (shown in column 1 of Table 5), suggesting that cities implementing the CET pilot policy have experienced significantly higher growth in technology investment than cities without such a policy. These results show that the carbon trading pilot policy has not only a direct role in promoting green innovation but also a positive effect in encouraging local governments to increase spending on scientific research.

Additionally, in model (4), both the DID and technology investment (sci) coefficients are significantly positive (shown in column 2 of Table 5), pointing out that the increase in technology investment has a direct and positive impact on enhancing UGI capability. This finding not only highlights the role of technology investment as a key channel through which the carbon trading policy influences green innovation but also reveals that increasing technology investment is crucial for promoting UGI. Research hypothesis H2 is verified.

These results provide strong evidence on how the CET pilot policy promotes UGI by influencing technology investment. Theoretically, this finding supports the innovation-driven development theory that technology investment is an important driver for UGI. From a practical standpoint, these results offer insights to policymakers, suggesting that the policy's role in stimulating research investment should be considered to comprehensively promote green innovation and sustainable development. Such mechanism tests not only enrich existing research on CET policy but also provide an empirical basis for policy optimization.

4.3.2 PEA mechanism test

Drawing on the research of Wu et al. (2022), we explored how China's CET pilot policy promotes UGI by enhancing public awareness of environmental issues using the Baidu smog search index as a proxy for PEA. This internet search behavior data provides a timely and accurate reflection of public interest and is a powerful tool for understanding shifts in public consciousness.

Regression results show that the CET pilot policy significantly raised PEA (results in column 3 of Table 5), indicating that cities implementing the carbon trading policy have significantly higher public concern for air quality and environmental pollution compared to cities without the policy. This boost may be driven by policy-induced media coverage, public discussion, and educational activities, reflecting the policy's effectiveness in raising environmental consciousness.

TABLE 6 Spatial autocorrelation test results.

year	I	E(I)	Sd(I)	Z	P-value
2005	0.023	−0.004	0.004	7.275	0.000
2006	0.031	−0.004	0.004	9.563	0.000
2007	0.044	−0.004	0.004	11.769	0.000
2008	0.047	−0.004	0.004	12.055	0.000
2009	0.050	−0.004	0.004	12.746	0.000
2010	0.070	−0.004	0.004	16.380	0.000
2011	0.070	−0.004	0.005	15.960	0.000
2012	0.079	−0.004	0.005	17.170	0.000
2013	0.071	−0.004	0.005	15.384	0.000
2014	0.078	−0.004	0.005	16.643	0.000
2015	0.091	−0.004	0.005	19.097	0.000
2016	0.094	−0.004	0.005	19.987	0.000
2017	0.103	−0.004	0.005	21.814	0.000
2018	0.100	−0.004	0.005	21.484	0.000
2019	0.089	−0.004	0.005	18.755	0.000
2020	0.093	−0.004	0.005	19.317	0.000
2021	0.083	−0.004	0.005	17.427	0.000

TABLE 7 Spatial durbin model regression results.

	(1)	(2)	(3)	(4)
	GIF	GIF	GIF	GIF
DID	1.363***	1.360***	1.084***	0.923***
	(0.093)	(0.092)	(0.146)	(0.138)
Wx*DID	1.102***	1.077***	0.919	1.431**
	(0.219)	(0.215)	(0.597)	(0.625)
Direct*DID	1.657***	1.538***	1.098***	0.929***
	(0.107)	(0.098)	(0.148)	(0.137)
Indirect*DID	6.068***	3.763***	2.956***	2.336***
	(0.700)	(0.429)	(1.024)	(0.699)
Total*DID	7.725***	5.301***	4.054***	3.265***
	(0.757)	(0.477)	(0.939)	(0.619)
Control	NO	YES	NO	YES
City_FE	YES	YES	YES	YES
Year_FE	YES	YES	YES	YES
Obs	4777	4777	4777	4777
r2	0.143	0.165	0.135	0.112

TABLE 8 Extended analysis results.

	(1)	(2)
	GIF	GIF
DID	0.498***	1.006***
	(0.133)	(0.115)
DID2	−0.714***	
	(0.100)	
DID*DID2	2.961***	
	(0.178)	
DID3		0.260***
		(0.091)
DID*DID3		3.640***
		(0.258)
Control	YES	YES
City_FE	YES	YES
Year_FE	YES	YES
Obs	4215	4777
r2	0.750	0.711

Further, the positive association between PEA and UGI capability (results in column 4 of Table 5) reveals an important mechanism: heightened public environmental concern may encourage the government and enterprises to adopt more environmental and green innovation measures in response to public demand and expectations for the environment. This finding validates the route through which the policy promotes green innovation by raising public environmental consciousness, aligned with theoretical expectations. Research hypothesis H3 is verified.

These results not only deepen our theoretical understanding of the mechanisms by which the CET pilot policy works but also provide empirical evidence for policymakers, emphasizing the need to consider the impact on public consciousness and behavior when formulating and implementing environmental policies. Through such mechanism tests, this study further underscores a multi-dimensional perspective on policy assessment, offering valuable references and insights for subsequent research and policy optimization.

4.4 Spatial spillover effect results

First, a spatial autocorrelation test was conducted (using the global Moran's I, see Table 6) to confirm the spatial clustering of UGI. The significantly positive Moran's I value indicates a positive spatial correlation in UGI. This step is necessary as it sets the stage for further analysis of spatial spillover effects.

The further spatial Durbin model regression results are shown in Table 7, where columns (1)–(4) represent the regression results of the economic distance matrix and the nested economic geography matrix without and with control variables, respectively. The results reveal that the CET pilot policy has a significant direct effect on promoting green innovation in the cities where it is implemented, as well as a positive indirect effect or spillover effect on neighboring cities. The coefficients of the spatial Durbin term and indirect effects term are significantly positive, emphasizing the spatial transmission and diffusion of policy effects—that the policy not only impacts the implementation region but also positively influences surrounding areas through economic connections and geographic proximity. This finding validates research hypothesis H4.

This discovery holds important theoretical and practical implications. Theoretically, it enriches the spatial-economic analysis of the effects of CET policy, emphasizing the importance of considering interregional interactions when evaluating policy outcomes. Practically, it provides insights to policymakers, suggesting that the positive influence of CET policy may be propagated through interregional interactions, and therefore, the potential regional linkage effects should be considered when formulating and implementing related policies.

4.5 Extended analysis

4.5.1 Testing the incentive effects of the "National Big Data Comprehensive Pilot Zone" policy

Against the backdrop of the high-speed development of the digital economy, the Chinese government has established "National Big Data Comprehensive Pilot Zones" to promote the widespread application of big data technology across various industries and drive the digital transformation of the social economy. These pilot zones are not only hotspots for technological innovation but also important platforms for studying how big data can contribute to economic and social development. The "National Big Data Comprehensive Pilot Zone" policy has significant synergies with the CET policy in several key areas. The big data policy enhances data management and transparency, supports the development of green technologies, facilitates policy implementation and compliance, promotes smart city development, and encourages cross-sector collaboration. These elements provide a robust technical and data foundation for CET, helping to improve the operational efficiency of the carbon market, ensure accurate emissions monitoring and reporting, and promote the adoption and innovation of green technologies. With the support of big data, the CET policy can more effectively drive UGI and sustainable development, achieving broader environmental and economic benefits. Within this context, this study set out to explore whether the "National Big Data Comprehensive Pilot Zone" policies have enhanced the effect of China's CET pilot policy in promoting UGI.

Combining the lists of National Big Data Comprehensive Pilot Zones announced by the Chinese government in 2015 and 2016, the study designates the included provinces and municipalities as the experimental group and the rest as the control group to construct a multi-period difference-in-differences model. This analyzes the potential influence of the National Big Data Comprehensive Pilot Zone policy (DID2) on the effectiveness of the CET pilot policy in promoting UGI.

Regression results (column 1 of Table 8) show a significantly positive coefficient for the interaction term between DID and DID2, implying that the "National Big Data Comprehensive Pilot Zone" policy strengthens the effect of the CET pilot policy in promoting green urban transformation. This outcome indicates that big data technology integration and application provide new momentum and platforms for green innovation, enhancing the implementation effect of the CET policy.

Theoretically, this finding enriches our understanding of the mechanism through which big data technology affects environmental policy outcomes, suggesting that a combination of technological advancement and policy innovation can create a synergistic effect that further promotes green innovation. Practically, it offers valuable insights to policymakers, indicating that advanced technologies like big data should be fully utilized to enhance the comprehensive benefits of policies and more effectively drive green transformation and sustainable development.

4.5.2 Testing the incentive effects of the "new energy demonstration city" policy

Amid global environmental challenges and energy transition, the Chinese government has placed high importance on the development of new energy and environmental protection, elevating these tasks to a strategic national level. To accelerate the dissemination and application of new energy technologies and promote green economic restructuring, the Chinese government officially announced 81 new energy demonstration cities and eight new energy demonstration industrial parks in 2014. The establishment of these demonstration areas is crucial for exploring the application of new energy technologies across various sectors and for pushing forward the green transformation of social and economic systems (Guo et al., 2024).

Against this backdrop, this study further explores the potential impact of the "New Energy Demonstration Cities" pilot policy on the effectiveness of China's CET pilot policy in promoting urban green transformation. By including the new energy demonstration cities as an experimental group and comparing them with other provinces and cities, this study constructs a multi-period difference-in-differences (DID) model to reveal how the new energy demonstration cities policy (DID3) interacts with the CET policy to jointly promote urban green transformation. To further isolate the impact of the new energy demonstration cities on the study's results, this study incorporates the effect of the new energy demonstration cities as a control variable in the model analysis. Regression results show a significantly positive coefficient for the interaction term between DID and DID3 (column 2 of Table 8), indicating that the new energy demonstration city policy enhances the effect of the CET policy in promoting UGI and transformation.

This result is significant both theoretically and practically. Theoretically, it indicates the importance of policy synergy in driving green transformation and innovation, particularly how policies supporting the new energy sector actively contribute to accelerating carbon emission reduction and environmental improvement. Practically, it provides insights to policymakers, showing that integrating and coordinating different policy tools, such as new energy technology promotion and CET mechanisms, can enhance policy outcomes and achieve the goal of regional coordinated development.

5 Discussion

5.1 Direct promotion of green innovation by CET policy

Through the Difference-in-Differences (DID) method, this study thoroughly examined the impact of China's CET pilot policy on UGI. The empirical results showcase a significantly positive effect of the policy, which aligns not only with previous research indicating that market-based environmental policies can provide innovation incentives (Ambec and Lanoie, 2008; Johnstone et al., 2010) but also supports a series of hypotheses regarding China's environmental regulation and technology innovation incentives. The findings suggest that the policy implementation has created a positive economic incentive by internalizing the cost of carbon emissions, stimulating companies to adopt cleaner and more efficient new technologies or to improve existing ones to enhance energy efficiency and reduce emissions. This perfectly reflects the Porter Hypothesis (Porter, 1991), which posits that environmental regulations can drive technological innovation.

Concerning the mechanism between CET and technological innovation, a portion of the literature provides a theoretical foundation. Rennings (2000) argues that environmental policies can promote technological innovation through two major pathways: by providing pressure and incentives for innovation ("push" and "pull" effects) and by providing companies with resources to research and test new technologies. In this case, China's carbon market provides a direct financial "push" and "pull" through its pricing mechanism, altering the incentive structure for firms to shift from a focus on emissions to making investment decisions centered around green technology research and development.

5.1.1 Driving green innovation by increasing technology investment

The study demonstrates that the CET policy effectively promotes UGI through increasing technology investment. This outcome is in line with the research by Popp (2002), who found that environmental policies can encourage R&D activities by enhancing the market potential value of environmentally friendly technologies. Economic incentives of environmental policies such as tax breaks and subsidies directly affect the marginal cost and revenue associated with corporate R&D in environmental technologies, which can greatly stimulate the innovation motives of companies (Jaffe and Stavins, 1994).

The increase in technology investment by companies is not just a direct response to immediate cost savings but also a forward-looking investment in anticipation of future market opportunities. On one hand, the growing market demand for green technologies is accompanied by intensifying global climate change discussions; on the other hand, advances in clean technology offer new opportunities for businesses to enhance their competitiveness (Acemoglu et al., 2012). Consequently, in anticipation of stricter future government regulations on emissions, firms seek to adapt to market changes proactively by increasing their investment in green technologies, thereby securing a first-mover advantage.

5.1.2 Enhancing PEA to promote green innovation

Empirical results from this article indicate that besides the increase in technology investment, enhancing PEA is also crucial for achieving green innovation. This finding echoes the view of Kesidou and Demirel (2012), which suggests that environmental innovation is significantly driven by market demand changes. As concerns about the environment intensify, public interest in health and sustainable living quality spurs demand for green products and services. Therefore, society's willingness to understand and recognize environmental technologies rises, offering innovative commercial motivations for businesses (Oltra and Saint Jean, 2009). Moreover, economic incentives and social consciousness form a mutually reinforcing cycle where technology supply innovation and the steadily rising level of public awareness create a virtuous circle.

Policies significantly enhance societal understanding of environmentally friendly technologies and products through various means, such as education, knowledge dissemination, and media promotion. This spread of knowledge may change consumer purchasing behavior, thereby increasing market demand for such products and motivating companies to continue investing in green innovation (Frondel et al., 2007). The elevation of public awareness also offers value signals to companies, aiding them to identify which technologies and products can meet the market's future trajectory, which directly supports the CET policy's push for green innovation.

5.1.3 Spatial spillover effects of CET policy

Furthermore, the study reveals a significant spatial spillover effect of the CET policy. This effect means that the green innovation activities of pilot cities are not confined to their locality, but can also influence and propel the innovation dynamics of the entire region or neighboring cities through regional networks and collaborative relationships. This finding suggests that knowledge and innovation are not only shared within corporations but also spread across cities and regions through various channels (Jaffe et al., 1993; Audretsch and Feldman, 1996).

When inter-regional communication and competitive relationships are optimized, the effects of knowledge spillover play a decisive role in promoting a region's innovative environment. The theory of absorptive capacity by Cohen and Levinthal (1989) emphasized the role of knowledge spillovers as social capital in innovation and the role of corporate learning capacity in the chain of innovation. Such absorptive capacity enables firms to beneficially utilize both external and internal knowledge and convert it into concrete technological innovations. The spatial spillover effect found in this study indicates that by strengthening collaboration and knowledge exchange mechanisms between regions, the environmental innovation capacity of the entire area can be further enhanced. The CET policy, as a catalyst, plays an important role in forming such collaborative and learning networks.

5.1.4 Discussion on extended analysis

Our extended analysis focused on different aspects of the incentive effects of the "National Big Data Comprehensive Pilot Zone" policy and the "New Energy Demonstration City" policy as complements to the CET policy's incentives. The results show that these policies related to carbon market trading complement each other and play an active role in promoting UGI. The analysis of these integrated policies not only highlights the impact of single policies but also reveals the combined effects of policy portfolios in advancing technology investment and PEA.

The study discussed the synergistic effects of different policy stimulus measures, which is crucial for evaluating policy impacts. Similar to the complementary policy effects in environmental economics, a combination of multiple strategies may display non-linear synergistic enhancement (Lehmann, 2012). When considering strategies for promoting UGI, beyond the core CET mechanisms, the support of peripheral policies could be key to achieving comprehensive green transformation.

6 Conclusion

6.1 Research findings

This study focused on China's CET pilot policy, utilizing data from 281 Chinese cities from 2005 to 2021 to comprehensively assess the policy's impact on UGI. The empirical analysis consistently shows that CET policy significantly and positively incentivizes green innovation activities at the urban level, a conclusion confirmed in various robustness tests. By identifying the increase in technology investment and the rise in PEA as key intermediate channels, this research elucidates how the CET policy fosters the research and application of green technologies by businesses and cities. The policy's spatial spillover effect broadens its range of influence, allowing non-pilot cities to benefit indirectly. Furthermore, the extended analysis explored the National Big Data Comprehensive Pilot Zone policy and the New Energy Demonstration City policy, revealing the dual role of both individual policies and their combined application in incentivizing green innovation. These findings provide important references for future policy formulation.

6.1.1 Policy recommendations

Based on the conclusions of the research, we propose the following policy recommendations to further propel the effectiveness of the CET policy in terms of UGI:

Firstly, the government should continuously strengthen and refine market-based environmental policy tools, such as CET mechanisms, to ensure they provide sufficient incentives for green technology innovation. Moreover, the government should promote the successful experiences of pilot policies among different cities to build a network of knowledge sharing and technological cooperation between regions.

Secondly, policymakers should value the introduction and optimization of supporting policies, such as the National Big Data policy and the New Energy Demonstration City program. Through a combination of policy portfolios, a more comprehensive and effective green innovation incentive system can be formed.

Lastly, given the spatial spillover effect of incentive policies, local governments should promote cooperation and exchange between cities, enhancing regional environmental innovation capabilities through resource sharing, collaborative research, and development, and support for businesses to continue investing and researching in the green technology field.

6.1.2 Limitations and future directions

While this study provides new insights into how CET policy impacts UGI, it has certain limitations. The research focused on policy effects within Chinese cities, and the applicability may differ in other countries and regions. Also, due to the focus on quantitative analysis, it may not capture in-depth information on policy implementation details or individual corporate behavior changes. Future research could include comparative analyses of multiple countries or regions to verify the wider applicability of the Chinese experience. Additionally, qualitative research methods could provide a more detailed understanding of the actual feedback and suggestions from firms and policy implementers, further optimizing existing models and theoretical frameworks.

Data availability statement

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

Author contributions

KT: Conceptualization, Formal Analysis, Methodology, Writing–original draft, Writing–review and editing. DZ: Data curation, Methodology, Software, Writing–original draft, Writing–review and editing. SH: Formal Analysis, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by the Research Project of Shanghai Tongji Urban Planning & Design Institute Co., Ltd. and China Intelligent Urbanization Co-creation Center for High Density Region (KY-2023-YB-B04).

Conflict of interest

Author KT were employed by Archiland (Tianjin) Architectural Design Co., Ltd. Author DZ were employed by Innovation and Research Center, Shanghai Tongji Urban Planning and Design Institute Co., Ltd.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The environment and directed technical change. *Am. Econ. Rev.* 102 (1), 131–166. doi:10.1257/aer.102.1.131

Ambec, S., and Lanoie, P. (2008). Does it pay to be green? A systematic overview. *Acad. Manag. Perspect.* 22 (4), 45–62. doi:10.5465/amp.2008.35590353

Audretsch, D. B., and Feldman, M. P. (1996). Innovative clusters and the industry life cycle. *Rev. Industrial Organ.* 11, 253–273. doi:10.1007/bf00157670

Bai, T., Qi, Y., Li, Z., and Xu, D. (2023). Will carbon emission trading policy improve the synergistic reduction efficiency of pollution and carbon? Evidence from 216 Chinese cities. *Manag. Decis. Econ.* doi:10.1002/mde.4014

Bulkeley, H., and Betsill, M. (2005). Rethinking sustainable cities: multilevel governance and the'urban'politics of climate change. *Environ. Polit.* 14 (1), 42–63. doi:10.1080/0964401042000310178

Cai, W., and Ye, P. (2022). Local-neighborhood effects of different environmental regulations on green innovation: evidence from prefecture level cities of China. *Environ. Dev. Sustain.* 24, 4810–4834. doi:10.1007/s10668-021-01635-2

Chen, Z., Zhang, X., and Chen, F. (2021). Do carbon emission trading schemes stimulate green innovation in enterprises? Evidence from China. *Technol. Forecast. Soc. Change* 168, 120744. doi:10.1016/j.techfore.2021.120744

Cohen, W. M., and Levinthal, D. A. (1989). Innovation and learning: the two faces of R and D. *Econ. J.* 99 (397), 569–596. doi:10.2307/2233763

Du, G., Yu, M., Sun, C., and Han, Z. (2021). Green innovation effect of emission trading policy on pilot areas and neighboring areas: an analysis based on the spatial econometric model. *Energy Policy* 156, 112431. doi:10.1016/j.enpol.2021.112431

Ellerman, A. D., and Buchner, B. K. (2007). The European Union emissions trading scheme: origins, allocation, and early results. *Rev. Environ. Econ. Policy* 1, 66–87. doi:10.1093/reep/rem003

Fan, J., and Xiao, Z. (2021). Analysis of spatial correlation network of China's green innovation. *J. Clean. Prod.* 299, 126815. doi:10.1016/j.jclepro.2021.126815

Feng, C., Shi, B., and Kang, R. (2017). Does environmental policy reduce enterprise innovation? evidence from China. *Sustainability* 9 (6), 872. doi:10.3390/su9060872

Frondel, M., Horbach, J., and Rennings, K. (2007). End-of-Pipe or cleaner production? An empirical comparison of environmental innovation decisions across OECD countries. *Bus. Strategy Environ.* 16 (8), 571–584. doi:10.1002/bse.496

Guo, B., Feng, Y., and Hu, F. (2023). Have carbon emission trading pilot policy improved urban innovation capacity? Evidence from a quasi-natural experiment in China. *Environ. Sci. Pollut. Res.* 31, 10119–10132. doi:10.1007/s11356-023-25699-x

Guo, B., Feng, Y., Lin, J., and Wang, X. (2024). New energy demonstration city and urban pollutant emissions: an analysis based on a spatial difference-in-differences model. *Int. Rev. Econ. and Finance* 91, 287–298. doi:10.1016/j.iref.2024.01.048

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *Amer. Econ. Rev.*, 685–709.

Jaffe, A. B., and Stavins, R. N. (1994). The energy-efficiency gap what does it mean? *Energy Policy* 22 (10), 804–810. doi:10.1016/0301-4215(94)90138-4

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Q. J. Econ.* 108 (3), 577–598. doi:10.2307/2118401

Ji, Q., Li, C., and Jones, P. (2017). New green theories of urban development in China. *Sustain. cities Soc.* 30, 248–253. doi:10.1016/j.scs.2017.02.002

Johnstone, N., Haščič, I., and Popp, D. (2010). Renewable energy policies and technological innovation: evidence based on patent counts. *Environ. Resour. Econ.* 45 (1), 133–155. doi:10.1007/s10640-009-9309-1

Kamal-Chaoui, L., and Robert, A. (2009). Competitive cities and climate change.

Kesidou, E., and Demirel, P. (2012). On the drivers of eco-innovations: empirical evidence from the UK. *Res. Policy* 41 (5), 862–870. doi:10.1016/j.respol.2012.01.005

Lehmann, P. (2012). Justifying a policy mix for pollution control: a review of economic literature. *J. Econ. Surv.* 26 (1), 71–97. doi:10.1111/j.1467-6419.2010.00628.x

Li, X., Guo, D., and Feng, C. (2022). The carbon emissions trading policy of China: does it really promote the enterprises' green technology innovations? *Int. J. Environ. Res. Public Health* 19 (21), 14325. doi:10.3390/ijerph192114325

Liu, B., Sun, Z., and Li, H. (2021). Can carbon trading policies promote regional green innovation efficiency? Empirical data from pilot regions in China. *Sustainability* 13 (5), 2891. doi:10.3390/su13052891

Liu, C., Ma, C., and Xie, R. (2020). Structural, innovation and efficiency effects of environmental regulation: evidence from China's carbon emissions trading pilot. *Environ. Resour. Econ.* 75, 741–768. doi:10.1007/s10640-020-00406-3

Liu, M., and Li, Y. (2022). Environmental regulation and green innovation: evidence from China's carbon emissions trading policy. *Finance Res. Lett.* 48, 103051. doi:10.1016/j.frl.2022.103051

Lu, Z. N., and Luo, Y. S. (2020). Analysis of the emission reduction effectiveness of China's carbon trading policy—the application and test of the difference-in-differences method. *J. Arid Land Resour. Environ.* (04), 1–7. doi:10.13448/j.cnki.jalre.2020.087

Narassimhan, E., Gallagher, K. S., Koester, S., and Alejo, J. R. (2018). Carbon pricing in practice: a review of existing emissions trading systems. *Clim. Policy* 18 (8), 967–991. doi:10.1080/14693062.2018.1467827

Oltra, V., and Saint Jean, M. (2009). Sectoral systems of environmental innovation: an application to the French automotive industry. *Technol. Forecast. Soc. Change* 76 (4), 567–583. doi:10.1016/j.techfore.2008.03.025

Popp, D. (2002). Induced innovation and energy prices. *Am. Econ. Rev.* 92 (1), 160–180. doi:10.1257/000282802760015658

Porter, M. E. (1991). Essay. *Sci. Am.* 264 (4), 168. doi:10.1038/scientificamerican0491-168

Porter, M. E., and Linde, C. V. D. (1995). Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* 9 (4), 97–118. doi:10.1257/jep.9.4.97

Rao, J., Zhang, X., and Zhai, D. (2024). Does the upgrading of development zones improve land use efficiency under the net-zero carbon city goal? prefectural-level evidence from quasi-natural experiments in China. *Land* 13 (8), 1245.

Rennings, K. (2000). Redefining innovation — eco-innovation research and the contribution from ecological economics. *Ecol. Econ.* 32 (2), 319–332. doi:10.1016/s0921-8009(99)00112-3

Shi, J. R., Cai, H. L., Tang, L., and Yu, L. A. (2015). Study on the economic and environmental impact of carbon trading mechanism based on CGE model. *Chin. Manag. Sci.* (S1), 801–806.

Stavins, R. N. (2008). Addressing climate change with a comprehensive US cap-and-trade system. *Oxf. Rev. Econ. Policy* 24, 298–321. doi:10.1093/oxrep/grn017

Sun, Z. Q., Li, H. H., and Liu, B. L. (2020). Study on regional emission reduction potential under carbon trading policy—dual perspectives of industrial structure adjustment and technological innovation. *Sci. Technol. Prog. Countermeas.* (15), 28–35.

Tian, H., Lin, J., and Jiang, C. (2022). The impact of carbon emission trading policies on enterprises' green technology innovation—evidence from listed companies in China. *Sustainability* 14 (12), 7207. doi:10.3390/su14127207

Wang, M., Wang, Y., and Guo, B. (2024). Green credit policy and residents' health: quasi-natural experimental evidence from China. *Front. Public Health* 12, 1397450. doi:10.3389/fpubh.2024.1397450

Wei, Q. P. (2015). Analysis of the compatibility of carbon trading and carbon tax—also on China's emission reduction path choice. *China Popul. Resour. Environ.* (05), 35–43.

Wu, Q., Tambunlertchai, K., and Pornchaiwiseskul, P. (2021). Examining the impact and influencing channels of carbon emission trading pilot markets in China. *Sustainability* 13 (10), 5664. doi:10.3390/su13105664

Wu, L., Yang, M., and Sun, K. (2022). The impact of public environmental awareness on corporate and government environmental governance. *China Population, Resources and Environment* (02), 1–14.

Xin-gang, Z., Wenjie, L., Wei, W., and Shuran, H. (2023). The impact of carbon emission trading on green innovation of China's power industry. *Environ. Impact Assess. Rev.* 99, 107040. doi:10.1016/j.eiar.2023.107040

Xu, L., Fan, M., Yang, L., and Shao, S. (2021). Heterogeneous green innovations and carbon emission performance: evidence at China's city level. *Energy Econ.* 99, 105269. doi:10.1016/j.eneco.2021.105269

Yan, G., Kang, J., Xie, X., Wang, G., Zhang, J., and Zhu, W. (2010). Change trend of public environmental awareness in China. *China Popul. Resour. Environ.* 20, 55–60.

Yang, Z., Yuan, Y., and Zhang, Q. (2022). Carbon emission trading scheme, carbon emissions reduction and spatial spillover effects: quasi-experimental evidence from China. *Front. Environ. Sci.* 9, 824298. doi:10.3389/fenvs.2021.824298

Yao, S., Yu, X., Yan, S., and Wen, S. (2021). Heterogeneous emission trading schemes and green innovation. *Energy Policy* 155, 112367. doi:10.1016/j.enpol.2021.112367

Yu, H., Jiang, Y., Zhang, Z., Shang, W. L., Han, C., and Zhao, Y. (2022). The impact of carbon emission trading policy on firms' green innovation in China. *Financial Innovation* 8 (1), 55.

Zhang, D., Rausch, S., and Karplus, V. J. (2014). Regional emissions trading in China: an analysis of chongqing's carbon market pilot. *MIT Jt. Program Sci. Policy Glob. Change*. Report No. 264.

Zhang, J., Shen, J., and Xu, M. (2023). Does the carbon emission trading promote the transformation and upgrading of industrial structure? empirical evidence from China's carbon emission trading pilot policy. *Econ. Issues* (08), 84–91. doi:10.16011/j.cnki.jjwt.2023.08.010

Zhang, M., Ge, Y., Liu, L., and Zhou, D. (2022b). Impacts of carbon emission trading schemes on the development of renewable energy in China: spatial spillover and mediation paths. *Sustain. Prod. Consum.* 32, 306–317. doi:10.1016/j.spc.2022.04.021

Zhang, W., Li, G., and Guo, F. (2022a). Does carbon emissions trading promote green technology innovation in China? *Appl. Energy* 315, 119012. doi:10.1016/j.apenergy.2022.119012

Zhang, Y. J., Liang, T., Jin, Y. L., and Shen, B. (2020). The impact of carbon trading on economic output and carbon emissions reduction in China's industrial sectors. *Appl. Energy* 260, 114290. doi:10.1016/j.apenergy.2019.114290

Zhao, Z., Zhou, S., Wang, S., Ye, C., and Wu, T. (2022). The impact of carbon emissions trading pilot policy on industrial structure upgrading. *Sustainability* 14 (17), 10818. doi:10.3390/su141710818

Zheng, S., Kahn, M. E., Sun, W., and Luo, D. (2014). Incentives for China's urban mayors to mitigate pollution externalities: the role of the central government and public environmentalism. *Reg. Sci. Urban Econ.* 47, 61–71. doi:10.1016/j.regsciurbeco.2013.09.003

Zhou, F., and Wang, X. (2022). The carbon emissions trading scheme and green technology innovation in China: a new structural economics perspective. *Econ. Analysis Policy* 74, 365–381. doi:10.1016/j.eap.2022.03.007

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 14 October 2024
DOI 10.3389/fenvs.2024.1447728

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Adnan Abbas,
Nanjing University of Information Science and Technology, China
Kai Zhang,
Shandong University of Finance and Economics, China

*CORRESPONDENCE
Weichun Gao,
gaoweichun123@163.com

RECEIVED 12 June 2024
ACCEPTED 03 October 2024
PUBLISHED 14 October 2024

CITATION
Gao W, He W, Zhang J, Chen Y and Wei Z (2024) County-level carbon emissions in the guanzhong area of Shaanxi province: towards achieving China's dual carbon goals. *Front. Environ. Sci.* 12:1447728. doi: 10.3389/fenvs.2024.1447728

COPYRIGHT
© 2024 Gao, He, Zhang, Chen and Wei. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

County-level carbon emissions in the guanzhong area of Shaanxi province: towards achieving China's dual carbon goals

Weichun Gao[1,2]*, Wei He[1,2,3], Jun Zhang[1,2], Yifei Chen[1,2] and Zheng Wei[1,2]

[1]Shaanxi Dijian Guantian Investment and Construction Co., Ltd., Baoji, China, [2]Shaanxi Provincial Land Engineering Construction Group Co., Ltd., Xi'an, China, [3]School of Water Resources and Hydropower, Xi'an University of Technology, Xi'an, China

China's rapid urbanization has significantly impacted carbon emissions in rural areas, driving the need for region-specific carbon management strategies to achieve the country's dual carbon goals. However, previous research has primarily focused on large urban centers, leaving a gap in understanding the spatial and temporal patterns of carbon emissions at the county level in rural regions. This study focuses on the Guanzhong region of Shaanxi Province and develops a county-level carbon emission accounting system based on geographic, socio-economic, and land-use data. The carbon emissions are categorized into energy, industrial processes, agriculture, and waste management. Key findings indicate that industrial and residential sectors are the primary contributors to carbon emissions, with Xi'an being the largest emitter. Carbon emission intensity follows a ranking of Xi'an < Weinan < Baoji < Xianyang < Tongchuan. Spatial patterns show a "core-edge" distribution, with higher emissions in urban centers and lower emissions in rural areas. The study also highlights the carbon sink potential in the southern Qinling National Park. This research provides a valuable framework for rural low-carbon development and offers critical insights for policymakers aiming to balance carbon reduction and economic growth in rural China.

KEYWORDS

county scale, carbon emissions, carbon balance, influence factor, guanzhong urban agglomeration

1 Introduction

Greenhouse gases from agricultural, livestock and industrial sectors is the main reasons of climate change (Abbas et al., 2022b; Abbas et al., 2022a; Abbas et al., 2023; Ullah et al., 2022; Abam et al., 2023; Elahi et al., 2024a; Elahi et al., 2024b). Global climate change has always been one of the most pressing problems faced by the world (Sage, 2020). Controlling greenhouse gas emissions to slow down the pace of global warming has become a societal consensus. Climate change and sustainable development have become urgent and major issues requiring immediate attention (Ucal and Xydis, 2020; Zurek et al., 2022). As a result, governments and international organizations globally have proposed goals for carbon reduction and low-carbon development (Caetano et al., 2020; Wimbadi and Djalante, 2020; Li et al., 2022). China, the world's largest developing country, has committed to peaking carbon emissions by 2030 and striving to achieve carbon neutrality before 2060 (Sun et al.,

2022; Zhao, 2022). China's rapid urbanization process has led to a significant increase in carbon emissions in rural areas. Recent studies have shown that between 2000 and 2015, rural carbon emissions increased by 4.2% annually, primarily due to increased infrastructure development, modernization of agriculture, and the adoption of urban energy consumption patterns in rural communities (Zhu et al., 2021; Guo et al., 2023). The construction of rural residential buildings and the expansion of rural transportation networks further contributed to this rise in emissions (Zhang et al., 2020; Xu et al., 2024).

At present, extensive research has been conducted on low-carbon ecological rural areas (Song et al., 2020; Wang C. et al., 2020; Wang et al., 2021), primarily focusing on carbon emission accounting (Harris et al., 2020), carbon emission spatialization (Sun et al., 2024), carbon emission spatiotemporal patterns (Lin et al., 2021), and low-carbon ecological rural evaluation models (Yu et al., 2023). This is because through the systematic accounting and evaluation of carbon emissions in rural areas, the current status and trends can be precisely determined. Such data provides a basis for formulating scientific emission reduction measures and policies. Meanwhile, rural carbon emission accounting helps to identify key sources of carbon emissions and potential areas for emission reduction, optimize resource allocation, and improve energy efficiency (Zhang et al., 2014). In addition, establishing and improving a rural carbon emission accounting system can enable rural areas to participate in national and regional carbon trading markets, realize economic benefits through carbon trading, and promote the green and low-carbon transformation of rural areas.

Comprehensive research on regional carbon emissions, both domestically and internationally, mainly utilizes the emission factor method for calculation (Shan et al., 2017). Based on the scale differences of the research areas, it is observed that carbon emission accounting research mainly focuses on macro scales such as national and provincial regions, cities, or micro scales such as individual buildings. However, research on carbon emission accounting at the village scale is scarce (Lai et al., 2022). There are significant differences and interactions among regions regarding carbon emission intensity. In optimizing resource allocation, adjusting industrial structure, and promoting the application of clean energy, agriculture is an important area for carbon emission reduction, and regions must consider regional characteristics when formulating carbon emission reduction policies (Chen et al., 2020). In addition, the spatiotemporal pattern of carbon emissions helps identify hotspots of carbon emissions. It also provides a scientific basis for evaluating the effectiveness of carbon reduction policies and formulating more effective carbon reduction strategies (Wang Y. et al., 2020). The low-carbon ecological rural evaluation model can not only effectively reduce greenhouse gas emissions, but also promote sustainable development of the rural economy and improve the quality of life of rural residents (Zhang et al., 2021). Although numerous studies have achieved certain results, there are still problems in rural research, such as the synchronous growth of carbon emissions caused by infrastructure construction, the significant driving effect of rural industrial development on carbon emissions, and the serious lack of low-carbon management and research capabilities in rural areas, resulting in relatively weak green and low-carbon awareness (Zhou et al., 2020). Therefore, promoting agricultural and rural emission reduction and carbon sequestration during the implementation of the rural revitalization strategy is a practical requirement and top priority for achieving the "dual carbon" goal.

However, existing research on quantitatively calculating greenhouse gas emissions in spatial regions mainly focuses on the national, provincial, and large city levels (Guo et al., 2023), or the individual building level. Research at the village level is scarce, which is not conducive to low-carbon rural development and planning. In addition, the Guanzhong region has actively responded to the national low-carbon development strategy in recent years (Guo, 2023), committing to rural low-carbon development and ecological civilization construction. Preliminary results have been achieved through measures such as promoting agricultural greening, optimizing the rural energy structure, and utilizing agricultural waste resources. There is relatively little research on the Guanzhong region. The Guanzhong region still faces challenges such as a single industrial structure, limited application of green and low-carbon technologies, and outdated rural energy facilities (Yu et al., 2022). In the context of accelerating urbanization, addressing the major challenge of achieving sustainable economic and social development while protecting the ecological environment is a prerequisite for promoting the low-carbon ecological rural evaluation system and planning strategies.

In order to address these issues, the Guanzhong region of Shaanxi Province is examined in this paper, and based on the analysis of its geography, natural conditions, land use status, and socio-economic conditions, a county-level carbon emission accounting system and carbon balance zoning evolution are meticulously constructed. This study offers theoretical and practical guidance for rural development in this region and similar areas under the dual carbon background, and also has important theoretical and practical value for promoting low-carbon development and ecological civilization construction in China and globally.

2 Materials and methods

2.1 Overview of the study area

The object selected for this paper is located in the Guanzhong area of Shaanxi Province, positioned in the central part of Shaanxi Province and named after its location west of Hangu Pass. The geographical coordinates are approximately from 107° 40′E to 110° 10′E, and 33° 42′N to 35° 29′N. The Guanzhong Plain constitutes a part of the Loess Plateau in China. Due to the historical alluvial effect of the Yellow River, it has become a fertile plain area and is known as the "800 mile Qinchuan". The Guanzhong region is bordered by the Liupan Mountains to the north, the Qinling Mountains to the south, the Longdong Mountains to the west, and the Wei River to the east, making it a transportation hub connecting the three major geographical regions of east, west, and north. The geographical location of the Guanzhong region endows it with unique strategic and economic value. It has been a battleground for military strategists and a political center in Chinese history since ancient times. It is also a focus of economic and cultural development, having a profound impact on the development of ancient Chinese

civilization. Now, with the promotion of the national "Belt and Road" initiative (Zhu et al., 2024), the Guanzhong region has once again demonstrated its important strategic position, becoming an important transportation and economic corridor connecting China's eastern coast and western inland, and even connecting Asia and Europe. Therefore, examining the Guanzhong region as the research object is both representative and highly significant.

2.2 Data sources

The data used in this paper include DEM, basic geographic information, land use status, and socio-economic data. Among them, DEM data come from the geospatial data cloud platform; basic geographic information data mainly include water systems, residential areas, roads, *etc.*, sourced from the National Geographic Information Resource Catalog Service System. The data on the current state of land use are sourced from the land use change survey data of Huayi District for 2010, 2015, and 2020; socio-economic data include population density data, POI data, GDP data, and energy consumption data, which are sourced from data platforms such as WorldPop, the Resource and Environmental Science and Data Center, as well as statistical yearbooks.

2.3 Research methods

2.3.1 Carbon emission accounting checklist

The IPCC has published a series of technical guidelines for carbon emission accounting methodology based on relevant standards and guidelines (Amon et al., 2021). Based on two major categories of natural emission sources and socio-economic emission sources, carbon emission sources are subdivided into six sectors: energy, industrial processes, solvent and other product use, land use change and forest land, agriculture, and waste. Further detailed emission projects are provided for each sector. Subsequently, a new inventory guide was published, which merges carbon sources into four sectors: energy activities, industrial processes and product use, agriculture, forestry and other land use, and waste.

Energy: The main source of carbon emissions from human activities is energy activities, which account for 80% of the total greenhouse gas emissions from human activities (Zhong et al., 2021). According to the guidelines, energy activities are divided into four parts: fixed source combustion, mobile source combustion, fugitive emissions, and carbon dioxide transportation, injection, and geological storage. Energy activities specifically involve the energy industry, manufacturing, transportation, coal mining, oil and gas extraction and processing, and other aspects (Mehedi et al., 2022).

Industrial processes and product use: They mainly include carbon emissions from production processes in industries such as mining, chemical, metal, non-energy products, electronics, and other product manufacturing and use (Chen et al., 2024). The greenhouse gas emissions in product use mainly involve the use of ozone-depleting substances and fluoride substitutes.

Agriculture, forestry, and other land use: Land use change and management can affect ecosystem processes, biological processes, and physical processes, leading to carbon and nitrogen conversion, which in turn affects greenhouse gas flows (Noda et al., 2024). Agriculture, forestry, and other land use mainly involves forest land, cultivated land, grassland, wetland, residential land, other land use, livestock and poultry manure management, and the application of lime and urea. Subsequently, estimation methods for greenhouse gas emissions and absorption in wetland drainage, wetland return, coastal wetlands, and constructed wetlands for sewage treatment were included.

Waste: Waste mainly includes urban solid waste, sludge, industrial waste, and other waste (Khan et al., 2022). During the waste disposal process, methane, carbon dioxide, non-methane volatile organic compounds, and relatively small amounts of nitrous oxide, nitrogen oxides, and carbon monoxide are produced.

The carbon emission accounting boundary of this study is limited to the administrative divisions within the study area, and the carbon exchange occurring within and outside the study area due to atmospheric activities falls outside the scope of this study's accounting. Based on the energy activities of the Guanzhong Plain urban agglomeration and the availability of data, the carbon emission accounting system of this study is depicted in Figure 1.

2.3.2 Carbon emission accounting methods

This paper calculates carbon emissions using a carbon emission accounting checklist, incorporating the four aforementioned sectors. Energy: The calculation of carbon emissions from fossil fuels is shown in Equation 1 (Meng and Niu, 2011):

$$E_e = AC \times CF \times CC \times COF \tag{1}$$

where E_e is the carbon emissions from energy use, AC is the apparent consumption, CF is the conversion factor for converting fuel to energy units (TJ) based on net calorific value, CC is the carbon content, and COF is the carbon oxidation factor. $EF = CF \times CC \times COF$, and Equation 1 can be simplified to Equation 2 (Liu et al., 2024):

$$E_e = AC \times EF \tag{2}$$

where EF is the carbon emission factor.

Table 1 provides the default values for commonly used fossil fuel-related parameters. Industrial processes and product use: Carbon emissions accounting for industrial processes and product usage mainly focuses on industries such as cement, steel, raw aluminum, and flat glass. Among these, the carbon emissions from the production process of cement clinker represent the most significant part of the carbon emissions from industrial processes and product usage (Na et al., 2024). Table 2 presents carbon emission products and emission factors for industrial processes.

Agricultural carbon emissions: Using the carbon emission coefficient method released by the IPCC and combining existing research results to calculate agricultural carbon emissions, the calculation is shown in Equation 3 (Meng et al., 2024).

$$C = \sum C_i = \sum T_i \times \delta_i \tag{3}$$

where C is the total agricultural carbon emissions, Ci is the carbon emissions of each source category, Ti is the activity level of each source category, δ_i is the carbon emission coefficient for each source category.

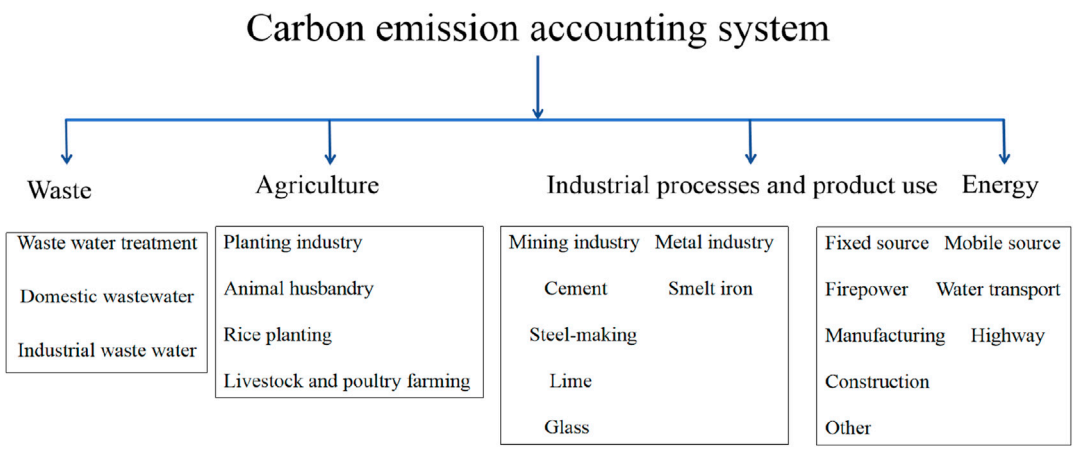


FIGURE 1
Carbon emission accounting inventory system.

Table 3 presents the carbon emissions from the planting and livestock industries, while Table 4 presents the agricultural carbon emission factors. Waste: Due to the availability of waste data, this paper only covers carbon emissions during the treatment process of industrial and domestic sewage treatment plants (Lv et al., 2022). The production of methane depends on the amount of degradable organic matter in wastewater. The commonly used parameters for determining the organic components of wastewater are Biochemical Oxygen Demand (BOD) and Chemical Oxygen Demand (COD). The reporting frequency of BOD in domestic wastewater is higher, while COD is mainly used for industrial wastewater. This paper calculates the carbon emissions related to sewage based on data from sewage treatment plants. The reduction of BOD (or COD) can be obtained by the concentration of BOD (or COD) in the inlet and outlet of the sewage treatment plant. The calculation of carbon emissions during sewage treatment and carbon emissions into the environment is shown in Equation 4 (Liu et al., 2023).

$$CE_W = TOW \times B_0 \times MCT \quad (4)$$

where CE_w is the carbon emissions from sewage treatment, TOW is the total amount of organic matter in the wastewater in the inventory year, B_0 is the maximum CH_4 production, MCF is the methane correction factor. The default values are shown in Table 5.

3 Result and analysis

3.1 Carbon emission accounting and characteristics

The total carbon emissions of each city are shown in Table 6. Table 6 shows that the industrial and living sectors in each city exhibit high carbon emissions, while the agricultural sector demonstrates low carbon emissions. Xi'an has the highest total carbon emissions and is at a relatively high level in all sectors. The total carbon emissions are as follows: Xi'an (29.8978 million tons) > Baoji (9.837 million tons) > Weinan (7.2974 million tons) > Tongchuan (3.4849 million tons) > Xianyang (3.3163 million tons). Xi'an records the highest carbon emissions, especially in its domestic and industrial sectors, which are 7.301 million tons and 13.4619 million tons, respectively. This is attributed to its population size and industrial activity intensity. The total carbon emissions of Xianyang and Baoji are relatively high, while the total carbon emissions of Tongchuan and Weinan are relatively low due to their smaller populations (Meng et al., 2023). The carbon emissions statistics for each city are shown in Figure 2.

As shown in the carbon emission structure in Figure 2, the agricultural carbon emissions of all cities are relatively low. Specifically, Tongchuan City has the lowest agricultural carbon emissions (259,000 tons), while Xianyang City has the highest agricultural carbon emissions (346,600 tons). The carbon emissions from daily life vary greatly among cities, with Xi'an having the highest carbon emissions (730.1 million tons), far higher than other cities. There are significant differences in industrial carbon emissions among cities, with Xi'an having the highest industrial carbon emissions (13.4619 million tons), followed by Xianyang (7.8736 million tons). The carbon emissions from waste in various cities are relatively low, with Xi'an having the highest (4.9785 million tons). In terms of carbon emissions from transportation, Xi'an has the highest (3.8923 million tons), followed by Xianyang (1.6865 million tons), and Tongchuan has the lowest (3.005 million tons). Further analysis of carbon emission intensity is presented in Table 7.

From the perspective of carbon emission intensity, the average carbon emission intensity of the Shaanxi section of the Guanzhong Plain urban agglomeration is 0.506 tons per 10,000 yuan. There are significant differences in carbon emission intensity among different cities, and the order of carbon emission intensity from low to high is: Xi'an < Weinan < Baoji < Xianyang < Tongchuan. The carbon emission intensity in Xi'an is the lowest, at 0.260 tons per 10,000 yuan, indicating that the amount of carbon dioxide emitted per unit of GDP in Xi'an is relatively low. The economic development is more focused on low-carbon industries and has higher energy utilization efficiency (Meng et al., 2023). Next is Weinan City, with a carbon emission intensity of 0.332 tons per 10,000 yuan. It has a relatively high carbon emission efficiency in economic development. Baoji City ranks third, with a carbon emission intensity of 0.359 tons per 10,000 yuan, slightly higher

TABLE 1 Default values for fossil fuels.

Type	Unit	Low calorific value CF(GJ/t)	Carbon content per unit calorific value CC (tC/GJ)	Carbon oxidation rate COF(%)
Anthracite	ton	20.304	27.49×10^{-3}	94
Bituminous coal	ton	19.570	26.18	93
Lignite	ton	14.080	28.00	96
Washed clean coal	ton	26.344	25.40	90
Other coal washing	ton	8.363	25.40	90
Briquette	ton	17.460	33.60	90
Other coal products	ton	17.460	33.60	90
Coke	ton	28.447	29.50	93
Crude oil	ton	41.816	20.10	98
Fuel oil	ton	41.816	21.10	98
Gasoline	ton	43.070	18.90	98
Diesel oil	ton	42.652	20.20	98
General kerosene	ton	44.750	19.60	98
Petroleum coke	ton	31.998	27.50	98
Other petroleum products	ton	41.031	20.00	98
Tar	ton	33.453	22.00	98
Crude benzene	ton	41.816	22.70	98
Liquefied natural gas	ton	41.868	17.20	98
Liquefied petroleum gas	ton	50.179	17.20	98
Coke oven gas	10,000 cubic meters	173.540	12.10	99
Blast furnace gas	10,000 cubic meters	33.000	70.80	99
Converter gas	10,000 cubic meters	84.000	49.60	99
Other gas	10,000 cubic meters	52.270	12.20	99
Natural gas	10,000 cubic meters	389.31	15.30	99
Refinery Gas	10,000 cubic meters	45.998	18.20	99
Closed calcium carbide furnace gas	10,000 cubic meters	111.190	39.51	99

TABLE 2 Carbon emission products and emission factors in industrial processes.

Product	Unit	EF (tC/t)
Cement clinker	ton	0.1417
Flat glass	10,000 weight box	29.4996
Lime	ton	0.2050
Pig iron	ton	0.0469
Crude steel	ton	0.0404

than Weinan City, but still at a relatively low level. Xianyang City ranks fourth, with a carbon emission intensity of 0.473 tons per 10,000 yuan. Although the carbon emission intensity of Xianyang City is lower than the average level of the Guanzhong Plain urban agglomeration, there is still room for improvement, and further optimization of the industrial structure is needed to improve energy efficiency. The carbon emission intensity in Tongchuan City is the highest, at 0.689 tons per 10,000 yuan. Tongchuan City emits the highest amount of carbon dioxide per unit of GDP, indicating that its industrial structure is biased, the energy structure is not clean enough, or its technological level needs to be improved.

TABLE 3 Agricultural carbon emission calculation indicators.

Index		Direct carbon emission coefficient	Indirect carbon emission coefficient	
Primary indicators	Secondary indicators	CO_2	CH_4	N_2O
Carbon emissions from agricultural materials (kg/kg^{-1})	chemical fertilizer	0.896	-	-
	pesticide	4.934	-	-
	Agricultural film	5.18	-	-
	diesel oil	0.5927	-	-
Carbon emissions from farmland soil (kg/hm^{-1})	wheat	2.5	-	-
	corn	2.532	-	-
	Oilseeds	0.95	-	-
	vegetable	4.21	-	-
	Melons and fruits	4.21	-	-
Carbon emissions from straw combustion (kg/kg^{-1})	wheat	13.557,852	-	-
	corn	32.7888	-	-
	rape	25.59384	-	-
Carbon emissions from livestock and poultry farming (kg/kg^{-1})	Large livestock	-	48.8	1.39
	Live pigs	-	4.5	0.53
	sheep	-	5.16	0.33
	rabbit	-	0.334	0.02
	poultry	-	0.02	0.02

TABLE 4 Agricultural carbon emission factor.

Straw burning	Combustion ratio	Grain grass ratio	Combustion efficiency	Carbon emission factor (CO_2 kg/kg)
Wheat	13.4	1.1	0.63	1.46
Corn	22	1.2	0.92	1.35
Rape	14.4	1.5	0.82	1.445

TABLE 5 Default values for waste related emission factors.

B_0		MCT	
(kg CH_4/kg BOD)	(kg CH_4/kg COD)	River and lake emissions	Concentrated oxygen consumption treatment plant
0.6	0.25	0.1	0.165

3.2 Overall carbon emission spatial pattern

The overall carbon emission distribution of the Guanzhong Plain urban agglomeration is shown in Figure 3.

Figure 3 shows that the spatial pattern of carbon emissions in the Shaanxi section of the Guanzhong Plain urban agglomeration exhibits “core-edge” and “layered agglomeration” characteristics, with significant differences in carbon emissions between urban and rural areas. Carbon emission cores are formed in the central areas of cities such as Xi’an and Baoji. Weinan and Xianyang also exhibit higher carbon emissions, while the surrounding Guanzhong Plain is a region with lower carbon emissions. The southern Qinling National Park and the northern Loess Plateau are mainly rural areas, exhibiting the lowest total carbon emissions. This is because in the core areas, Xi’an and Baoji, as the core cities of the Guanzhong Plain urban agglomeration, have become the core areas of carbon emissions due to their dense population, concentrated industry, and frequent economic activities. The energy consumption,

TABLE 6 Total carbon emissions of each city.

City	Agriculture (10,000 tons)	Living (10,000 tons)	Industry (10,000 tons)	Waste (10,000 tons)	Traffic (10,000 tons)	Total
Tongchuan	25.90	62.32	167.14	63.08	30.05	348.49
Xianyang	28.45	216.16	787.36	131.01	168.65	1331.63
Weinan	31.72	75.58	359.35	172.83	90.26	729.74
Baoji	34.66	139.77	604.28	62.32	142.66	983.70
Xi'an	26.42	730.10	1346.19	497.85	389.23	2989.78

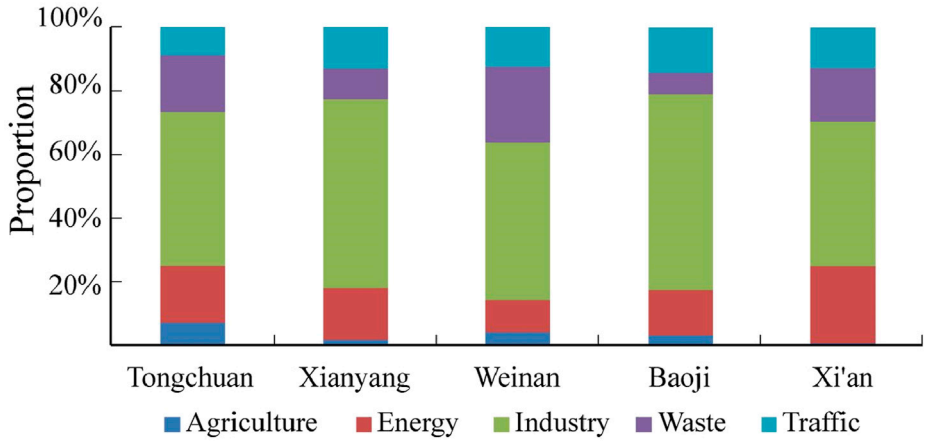


FIGURE 2
Carbon emission structure of each city.

TABLE 7 Carbon emission intensity of each city.

City	Total carbon emissions (10,000 tons)	GDP (100 million yuan)	Carbon emission intensity (ton·10,000 yuan^{-1})
Tongchuan	348.49	505.55	0.689
Xianyang	1331.63	2817.55	0.473
Weinan	729.74	2201.13	0.332
Baoji	983.70	2743.1	0.359
Xi'an	2989.78	11,486.51	0.260

transportation, industrial production, and residential activities in these urban centers are the main sources of carbon emissions. In high-value areas, Weinan City and Xianyang City, as secondary cities, although their scale and economic activity intensity are not as high as Xi'an and Baoji, they still have high levels of carbon emissions. These cities play an important role in regional development, and their industrialization and urbanization processes have resulted in relatively high carbon emissions. In the lower value areas, the peripheral areas of the Guanzhong Plain have relatively low carbon emissions due to low population density and relatively fewer industrial activities. These regions may be predominantly agricultural, with relatively low energy consumption and carbon emission intensity. In the lowest value areas, the Qinling National Park in the south and the Loess Plateau in the north have limited human activities due to the importance of natural protection and ecological restoration. These areas are mainly rural, resulting in the lowest total carbon emissions. However, when formulating regional carbon reduction strategies, it is important to consider this layered and clustered carbon emission spatial pattern, along with the development characteristics and carbon emission characteristics of different regions. To further analyze the carbon emission patterns of each sector, refer to Figure 4.

As shown in Figures 4, 4A shows a clustering distribution feature of high in the east and low in the west, with high agricultural carbon emissions in the Guanzhong Plain region. The spatial pattern of agricultural carbon emissions exhibits certain regional

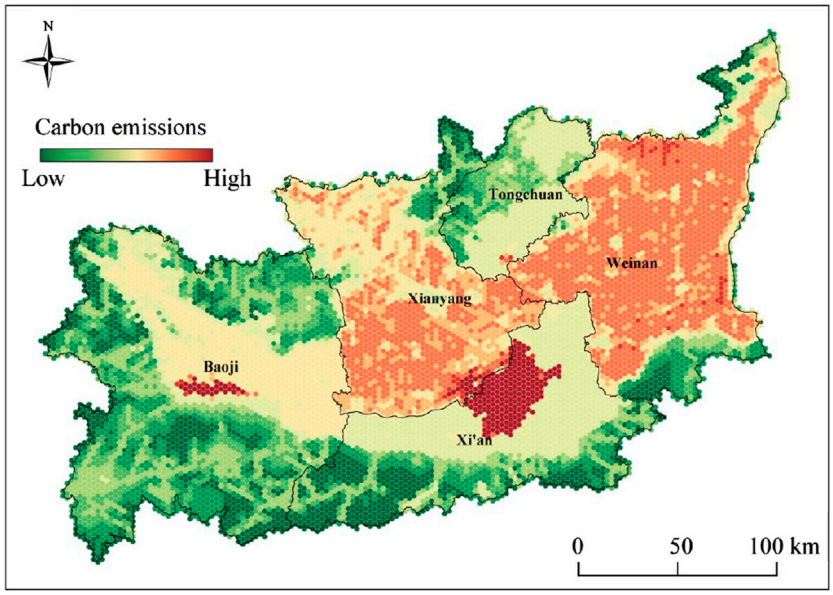


FIGURE 3
Overall carbon emission spatial pattern.

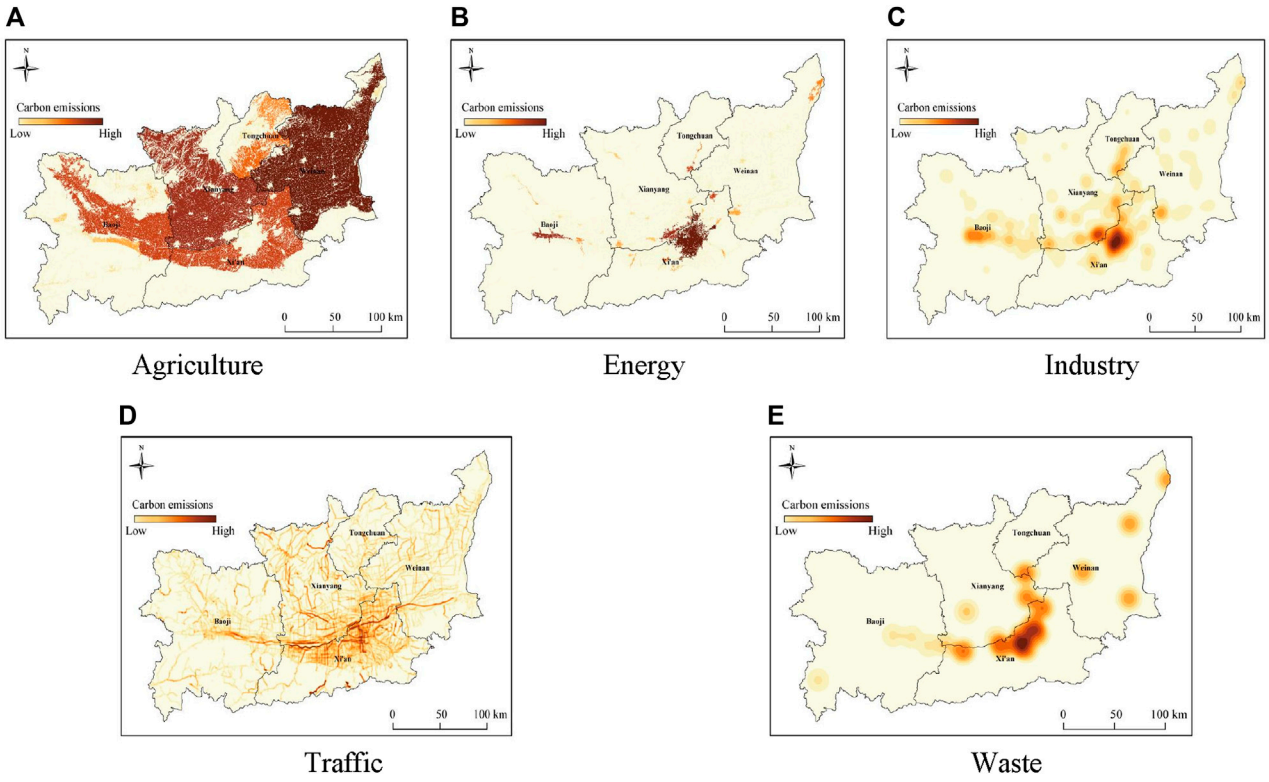


FIGURE 4
Carbon emission patterns of agriculture **(A)**, energy **(B)**, industry **(C)**, traffic **(D)**, waste **(E)** departments.

characteristics, which are influenced by various factors, including land use types, agricultural production methods, topography, *etc.* In the Guanzhong Plain region, due to its geographical location and natural conditions (Yan et al., 2023), agricultural activities are relatively concentrated and arable land resources are abundant, resulting in relatively high agricultural carbon emissions. The Qinling National Park in the southern part of the Guanzhong Plain and the Loess Plateau area on the northern side have

limited arable land and relatively fewer agricultural activities due to terrain, topography, and soil conditions, resulting in lower agricultural carbon emissions. At the urban scale, the total agricultural carbon emissions in Weinan and Xianyang regions are relatively high, which may be related to their agricultural industry structure, agricultural technology level, and agricultural production scale. The relatively low agricultural carbon emissions in cities such as Tongchuan, Baoji, and Xi'an may be related to their higher proportion of non-agricultural industries, higher level of agricultural modernization, and possible carbon reduction measures.

Figure 4B shows that the spatial pattern of energy carbon emissions presents a "core periphery" feature. In the Guanzhong Plain region, the central urban areas of Xi'an and Baoji have formed the core areas of energy and carbon emissions due to their large urban scale and population density. The production activities and energy consumption of residents in the central areas of these cities are relatively concentrated, resulting in higher levels of energy and carbon emissions (Hu and Fan, 2020). At the same time, the central areas of peripheral districts and counties have formed a sub-core area of carbon emissions due to their relatively small scale and population. Although their energy carbon emissions are lower than those of the core areas, they are still higher than those of rural areas. Rural areas have relatively low energy consumption and carbon emissions due to sparse population distribution and relatively dispersed living and production activities. The formation of this spatial difference is closely related to the changes in land use patterns during the urbanization process. The construction land area in urban areas is relatively large, and with the concentration of population and intensive economic activities, energy demand and consumption have increased, especially in residential, commercial, and industrial construction land. On the other hand, rural areas are mainly occupied by agriculture and natural land, with relatively low energy consumption and correspondingly reduced carbon emissions.

Figure 4C shows that the spatial pattern of industrial carbon emissions presents a core-edge feature of "two centers and one belt," forming a core area of industrial carbon emissions in the central urban areas of Xi'an and Baoji. The Guanzhong transportation corridor connecting Xi'an and Baoji forms a high-value industrial carbon emission belt, with secondary high industrial carbon emission centers in the central areas of peripheral districts and counties. Rural areas have almost no industrial carbon emissions. Xi'an and Baoji, as important cities in the region, have formed core areas for industrial carbon emissions due to their high level of industrialization and concentration of industrial enterprises. These cities have a relatively high proportion of manufacturing and heavy industry in terms of energy consumption and carbon emissions. The Guanzhong transportation corridor connecting Xi'an and Baoji serves as an important channel for regional transportation and logistics, with numerous industrial parks and bases distributed along the route. As a result, it forms a high-value zone for industrial carbon emissions (Chen et al., 2021). The frequent industrial activities and dense logistics transportation in this area have led to high energy consumption and carbon emissions. The central areas of peripheral districts and counties have formed secondary centers of industrial carbon emissions due to their relatively small industrial scale. Although the industrial carbon emissions in these regions are lower than those in the core areas, they are still an undeniable source of carbon emissions within the region. In contrast, rural areas have almost no industrial carbon emissions due to their lower level of industrialization. Rural areas are mainly dominated by agricultural production with fewer industrial activities, resulting in relatively low carbon emissions.

Figure 4D shows obvious networked characteristics in the Guanzhong Plain region. The formation of this pattern is closely related to factors such as transportation infrastructure construction, urban development level, and population distribution within the region. Xi'an and Xianyang, as important cities in the Guanzhong Plain region, have dense road networks and highly developed transportation systems. These cities are not only transportation hubs within the region, but also centers of economic activity and population gathering, resulting in relatively high carbon emissions from transportation. The dense road network and frequent vehicle traffic have led to high energy consumption and carbon emissions, especially in the central urban areas and surrounding major transportation arteries. The Guanzhong transportation corridor connecting Baoji, Xianyang, Xi'an, and Weinan has formed a high-value zone of transportation carbon emissions due to the distribution of many high-grade roads, such as highways and national highways. These transportation arteries serve as the main channels for internal and external connections within the region, carrying a large amount of logistics and human flow, resulting in higher carbon emissions from transportation in the areas along them. In contrast, rural areas have lower traffic carbon emissions due to lower road network density, fewer roads, and relatively lower frequency and density of transportation. The main modes of transportation in rural areas may be non-motorized and low-speed motor vehicles, which have relatively low carbon emission intensity. In addition, the population distribution in rural areas is relatively scattered, and the demand for transportation is relatively small, which also leads to a reduction in transportation carbon emissions.

Figure 4E exhibits a "one core, multiple points" feature, with Xi'an as the regional center city, forming the core area of waste carbon emissions. The formation of this pattern is closely related to factors such as the population size, economic development level, industrial structure, and distribution of environmental protection facilities in cities. As the largest city in the Guanzhong Plain region, Xi'an has a large population, frequent economic activities, and a large amount of waste generated in daily life and industrial production. These wastes generate a certain amount of carbon emissions during the treatment process, especially in the sewage treatment process (Wang et al., 2023). Due to the fact that urban sewage treatment plants typically consume energy and may produce greenhouse gases such as methane during the treatment of sewage and industrial wastewater, these factors collectively contribute to Xi'an's core position in waste carbon emissions. Baoji, Xianyang, Tongchuan, Weinan, and other cities, as secondary cities in the region, have also formed their own waste carbon emission centers. Although the economic development level, industrial structure, and population size of these cities are not as high as Xi'an, they still have a certain amount of waste generation and carbon emissions, with a multi-point distribution feature in their spatial pattern. In addition, due to the fact that sewage treatment plants are often laid out along major rivers to facilitate the use of water resources and reduce transportation costs, this has led to the phenomenon of waste carbon emission centers being distributed in a strip pattern along major rivers. The distribution pattern along the river is conducive to the

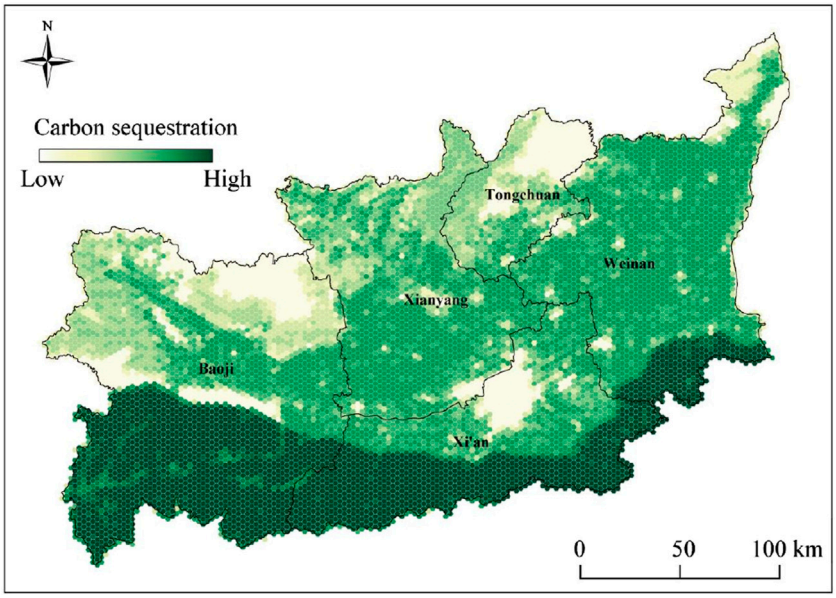


FIGURE 5
Carbon sink space.

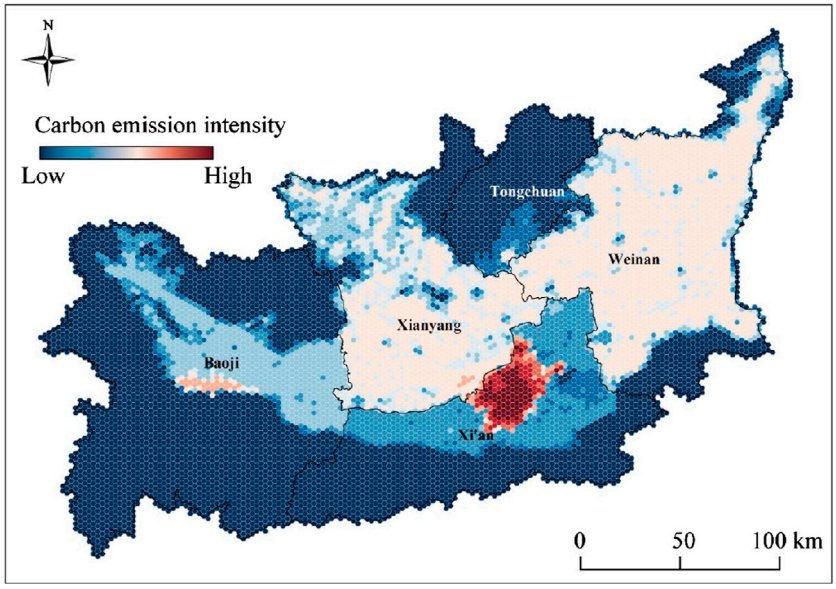


FIGURE 6
Carbon emission intensity.

construction and operation of sewage treatment stations, and also facilitates the discharge or reuse of wastewater.

3.3 Carbon sink distribution and carbon intensity distribution

The distribution of carbon sinks in the Guanzhong Plain region is shown in Figure 5, and the distribution of carbon intensity is shown in Figure 6. Figure 5 shows that the distribution characteristics of carbon sinks in the Guanzhong Plain region exhibit a spatial pattern of "high in the south and low in the north," which is closely related to factors such as natural geographical conditions, vegetation types, and land use patterns. The southern Qinling Mountains, as the geographical boundary between North and South China, have rich biodiversity and high vegetation coverage. This area is mainly dominated by tree forests, and the carbon sequestration capacity of forest ecosystems is strong,

resulting in high carbon sequestration. The central Guanzhong Plain region is mainly dominated by modern agriculture. Crops such as wheat and rapeseed have a good protective effect on the soil and absorb carbon dioxide through vegetation growth, contributing to a high carbon sink (Liu et al., 2016). In addition, agricultural measures such as organic matter management and straw returning in farmland can also help improve soil carbon storage capacity. Due to natural limitations, the vegetation coverage in the northern Loess Plateau region is relatively low, mainly consisting of shrubs and grasslands. The carbon sequestration capacity of vegetation types in these regions is relatively weak, resulting in lower carbon sinks. Moreover, soil erosion and land degradation issues may also affect the carbon sequestration capacity of the region. In addition, urban areas have the lowest carbon sequestration due to their large amount of construction land and dense population, resulting in less natural vegetation coverage. The carbon sink in urban areas mainly comes from parks, green spaces, roadside trees, and rooftop greenery. Compared to natural ecosystems, the carbon sink capacity of cities is relatively weak.

As shown in Figure 6, the carbon emission intensity exhibits a layered agglomeration feature. As the core of the Guanzhong Plain urban agglomeration, the central urban area of Xi'an has a dense population and frequent economic activities, including industrial production, transportation, construction industry, and residential life. These activities have led to significant energy consumption, especially the use of fossil fuels, resulting in higher carbon emission intensity. In addition, the expansion of construction land and infrastructure construction in the process of urbanization is also an important source of carbon emissions. As an important industrial city in the region, Baoji City has numerous industrial enterprises, especially in heavy industry and manufacturing. The production and operation activities of these industrial enterprises require a large amount of energy input, often accompanied by high carbon emissions. Therefore, the carbon emission intensity in the central urban area of Baoji is relatively high, second only to the central urban area of Xi'an. Weinan City and Xianyang City have a relatively large population and a considerable number of enterprises, including industrial and service industries. The economic and population activities in these cities are relatively concentrated, resulting in higher carbon emission intensity. Meanwhile, Weinan and Xianyang are also important agricultural areas, and agricultural production activities also contribute to carbon emission intensity. The carbon emission intensity in rural areas of the Guanzhong Plain is relatively low, mainly due to agriculture and sparse population distribution. Although agricultural production activities generate certain carbon emissions, such as fertilizer use and agricultural machinery operations, their carbon emission intensity is lower compared to urban and industrial activities. Qinling National Park and the northern Loess Plateau have sparse populations and relatively low human activities, mainly relying on natural ecosystems and agricultural production. The carbon emission intensity in these areas is relatively low.

3.4 Carbon balance zoning

The carbon sink zoning in the Guanzhong Plain region is shown in Figure 7. Figure 7 shows that the carbon sequestration functional areas of the Guanzhong Plain urban agglomeration are mainly distributed in the southern Qinling National Park and northern Tongchuan City. These regions have a relatively large proportion of ecological land and good carbon sequestration capacity. As an important nature reserve, Qinling National Park has high vegetation coverage and strong carbon sequestration capacity of forest ecosystems, making it an important carbon sink area in the region (Gogoi et al., 2022). Due to its specific natural conditions and ecological protection measures, Tongchuan City also exhibits strong carbon sequestration potential. These regions are dominated by agriculture, and overall carbon sinks exceed carbon emissions. The carbon balance zone is mainly located in rural areas of the Guanzhong Plain. These areas have relatively dense villages, mainly focused on agriculture, with strong carbon sequestration capabilities. Due to agricultural production activities generating certain carbon emissions, such as fertilizer use and agricultural machinery operations, overall carbon emissions and carbon sinks are essentially balanced (Huang et al., 2024). The low-carbon optimization zone is mainly located in rural areas of Xianyang City and Weinan City. Agricultural carbon emissions in these regions are relatively high, and measures such as promoting low-carbon agricultural technology and optimizing land use structure are needed to further reduce carbon emissions. The carbon intensity control zone is mainly distributed in the central urban areas of cities such as Xi'an and Baoji. These regions have a high population density and a large number of industrial enterprises, resulting in much higher energy consumption and carbon emissions than carbon sinks. The human activity intensity in the central urban area of Xi'an is high, with the highest carbon emission intensity, while there are many industrial enterprises in Baoji City, resulting in high carbon emission intensity. These urban centers need to take measures such as promoting green and low-carbon development, optimizing energy structure, and improving energy efficiency to reduce carbon emissions and enhance carbon sequestration capacity.

4 Conclusion

This study presents a comprehensive analysis of county-level carbon emissions in the Guanzhong area of Shaanxi Province, using a detailed carbon emission accounting system that reflects the unique geographic, socio-economic, and land-use characteristics of the region. The innovative aspect of this research lies in its focus on rural county-level emissions, which are often underrepresented in existing literature that primarily focuses on urban areas or national-level studies. By adopting a granular, county-level approach, this study fills a critical gap in understanding rural emissions and offers a replicable model for similar regions across China.

In terms of carbon neutrality, the study reveals that industrial and residential sectors are the largest contributors to carbon emissions, while agricultural emissions remain relatively low. The findings indicate that achieving carbon neutrality at the county level will require a targeted approach, focusing on optimizing industrial energy use, promoting renewable energy, and enhancing energy efficiency in residential areas. The study also underscores the importance of integrating low-carbon agricultural practices and land-use management to further balance carbon emissions.

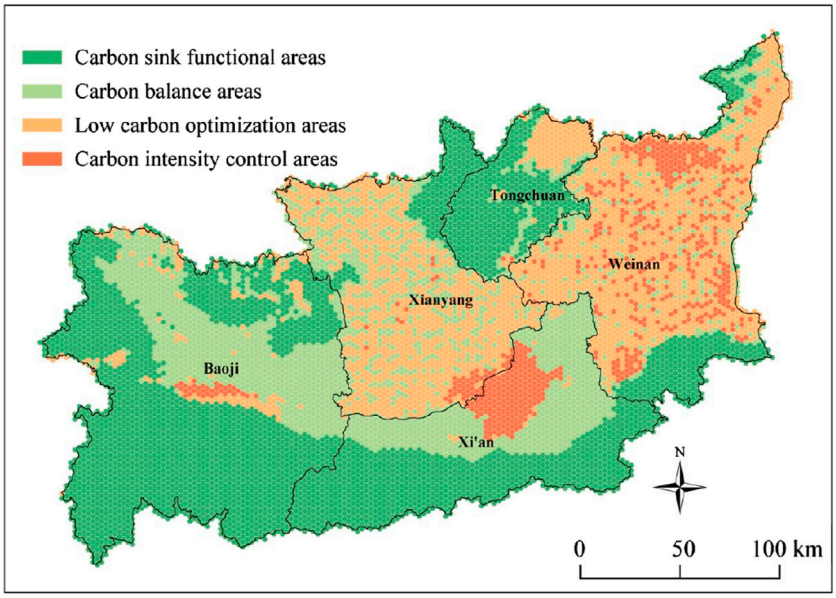


FIGURE 7
Results of carbon sink spaceCarbon balance zoning.

The unique contribution of this research is its practical framework for understanding and managing carbon emissions in rural regions, providing policymakers with critical insights on how to balance economic development and environmental sustainability. By focusing on county-level emissions, the study provides a crucial foundation for China's broader efforts to achieve its dual carbon goals, demonstrating that effective carbon management strategies must extend beyond urban areas to include the rural sectors that are essential to the country's overall carbon neutrality objectives.

5 Policy suggestion

Firstly, focus on optimizing industrial and energy structures. The study reveals that the industrial and energy sectors contribute significantly to carbon emissions in the Guanzhong region. To address this, policymakers should prioritize the optimization of industrial structures by promoting low-carbon industries and technologies. This includes supporting the development of renewable energy sources, such as solar and wind power, and incentivizing the adoption of clean energy in industrial processes. Additionally, the implementation of energy efficiency standards and regulations can help reduce energy consumption and carbon emissions across various sectors.

Secondly, enhance agricultural carbon management and land use practices. While agricultural carbon emissions are relatively low compared to industrial and energy sectors, there is still potential for improvement. Policymakers should encourage farmers to adopt low-carbon agricultural practices, such as precision agriculture, organic farming, and straw returning. These practices can help reduce chemical fertilizer and pesticide usage, decrease greenhouse gas emissions, and improve soil carbon sequestration. Furthermore, optimizing land use patterns, such as restoring degraded land and promoting afforestation, can significantly enhance the carbon sink capacity of the region.

Third, establish a comprehensive carbon management and trading system. To effectively reduce carbon emissions and promote low-carbon development, it is crucial to establish a comprehensive carbon management system. This includes developing clear carbon emission reduction targets and implementing effective monitoring and reporting mechanisms. Additionally, policymakers should explore the feasibility of establishing a regional carbon trading market, which can incentivize emitters to reduce their carbon footprint and reward those who sequester carbon. This approach can not only help achieve carbon reduction goals but also stimulate economic growth and innovation in low-carbon technologies.

Finally, the policy recommendations derived from this study are not only pertinent to the Guanzhong region but also offer valuable insights for other rural areas across China. For instance, agricultural carbon management practices in northeastern China could inform efforts in other western and central regions, while the optimization of rural energy structures in eastern coastal regions provides valuable lessons for inland areas like the Guanzhong Plain. As such, it is recommended that the national government support the dissemination and implementation of county-level carbon emission accounting systems across the country. Tailored carbon emission reduction strategies, based on local characteristics, will be crucial to achieving China's broader rural carbon neutrality goals.

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

WG: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. WH: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. JZ: Conceptualization, Data curation, Formal Analysis, Methodology, Writing–original draft, Writing–review and editing. YC: Software, Supervision, Validation, Visualization, Writing–original draft, Writing–review and editing. ZW: Data curation, Funding acquisition, Investigation, Validation, Writing–original draft, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This paper was granted by Technology Innovation Center for Land Engineering and Human Settlements, Shaanxi Land Engineering Construction Group Co., Ltd and Xi'an Jiaotong University (Grant No. 2024WHZ0234), 2023 Annual Shaanxi Province State Capital Operation Budget Science and Technology Innovation Special Fund Project "Guanzhong Area Green Farmland Construction Key Technology Research and Demonstration Promotion Project".

Conflict of interest

Authors WG, WH, JZ, YC, and ZW were employed by Shaanxi Dijian Guantian Investment and Construction Co., Ltd.

Authors WG, WH, JZ, YC, and ZW were employed by Shaanxi Provincial Land Engineering Construction Group Co., Ltd.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Abam, F. I., Inah, O. I., Ekwe, E. B., Igbong, D. I., Effiom, S. O., Ovat, F. A., et al. (2023). CO2 emissions decoupling from added value growth in the chemical and pharmaceutical (CHPH) industry in Nigeria. *Green Low-Carbon Econ.* 1, 52–59. doi:10.47852/bonviewGLCE3202622

Abbas, A., Mushtaq, Z., Ikram, A., Yousaf, K., and Zhao, C. (2023). Assessing the factors of economic and environmental inefficiency of sunflower production in Pakistan: an epsilon-based measure model. *Front. Environ. Sci.* 11. doi:10.3389/fenvs.2023.1186328

Abbas, A., Waseem, M., Ahmad, R., khan, K. A., Zhao, C., and Zhu, J. (2022a). Sensitivity analysis of greenhouse gas emissions at farm level: case study of grain and cash crops. *Environ. Sci. Pollut. Res.* 29, 82559–82573. doi:10.1007/s11356-022-21560-9

Abbas, A., Zhao, C., Waseem, M., Ahmed khan, K., and Ahmad, R. (2022b). Analysis of energy input–output of farms and assessment of greenhouse gas emissions: a case study of cotton growers. *Front. Environ. Sci.* 9. doi:10.3389/fenvs.2021.826838

Amon, B., Çinar, G., Anderl, M., Dragoni, F., Kleinberger-Pierer, M., and Hörtenhuber, S. (2021). Inventory reporting of livestock emissions: the impact of the IPCC 1996 and 2006 Guidelines. *Environ. Res. Lett.* 16, 075001. doi:10.1088/1748-9326/ac0848

Caetano, T., Winkler, H., and Depledge, J. (2020). Towards zero carbon and zero poverty: integrating national climate change mitigation and sustainable development goals. *Clim. Policy* 20, 773–778. doi:10.1080/14693062.2020.1791404

Chen, L., Xu, L., Cai, Y., and Yang, Z. (2021). Spatiotemporal patterns of industrial carbon emissions at the city level. *Resour. conservation Recycl.* 169, 105499. doi:10.1016/j.resconrec.2021.105499

Chen, S., Shi, A., and Wang, X. (2020). Carbon emission curbing effects and influencing mechanisms of China's Emission Trading Scheme: the mediating roles of technique effect, composition effect and allocation effect. *J. Clean. Prod.* 264, 121700. doi:10.1016/j.jclepro.2020.121700

Chen, Y., Billings, B. W., and Powell, K. M. (2024). Industrial processes and the smart grid: overcoming the variability of renewables by using built-in process storage and intelligent control strategies. *Int. J. Prod. Res.* 62, 1686–1698. doi:10.1080/00207543.2023.2199436

Elahi, E., Li, G., Han, X., Zhu, W., Liu, Y., Cheng, A., et al. (2024a). Decoupling livestock and poultry pollution emissions from industrial development: a step towards reducing environmental emissions. *J. Environ. Manag.* 350, 119654. doi:10.1016/j.jenvman.2023.119654

Elahi, E., Zhu, M., Khalid, Z., and Wei, K. (2024b). An empirical analysis of carbon emission efficiency in food production across the Yangtze River basin: towards sustainable agricultural development and carbon neutrality. *Agric. Syst.* 218, 103994. doi:10.1016/j.agsy.2024.103994

Gogoi, A., Ahirwal, J., and Sahoo, U. K. (2022). Evaluation of ecosystem carbon storage in major forest types of Eastern Himalaya: implications for carbon sink management. *J. Environ. Manag.* 302, 113972. doi:10.1016/j.jenvman.2021.113972

Guo, D., Li, B., Yu, W., Han, J.-C., Zhou, Y., Ye, Z., et al. (2023). Revisiting China's domestic greenhouse gas emission from wastewater treatment: a quantitative process life-cycle assessment. *Sci. Total Environ.* 876, 162597. doi:10.1016/j.scitotenv.2023.162597

Guo, S. (2023). Exploring low-carbon pilot city policy implementation: evidence from China. *Clim. Policy* 23, 1045–1057. doi:10.1080/14693062.2022.2140096

Harris, S., Weinzettel, J., Bigano, A., and Källmén, A. (2020). Low carbon cities in 2050? GHG emissions of European cities using production-based and consumption-based emission accounting methods. *J. Clean. Prod.* 248, 119206. doi:10.1016/j.jclepro.2019.119206

Hu, W., and Fan, Y. (2020). City size and energy conservation: do large cities in China consume more energy? *Energy Econ.* 92, 104943. doi:10.1016/j.eneco.2020.104943

Huang, H., Jia, J., Chen, D., and Liu, S. (2024). Evolution of spatial network structure for land-use carbon emissions and carbon balance zoning in Jiangxi Province: a social network analysis perspective. *Ecol. Indic.* 158, 111508. doi:10.1016/j.ecolind.2023.111508

Khan, S., Anjum, R., Raza, S. T., Bazai, N. A., and Ihtisham, M. (2022). Technologies for municipal solid waste management: current status, challenges, and future perspectives. *Chemosphere* 288, 132403. doi:10.1016/j.chemosphere.2021.132403

Lai, S., Lu, J., Luo, X., and Ge, J. (2022). Carbon emission evaluation model and carbon reduction strategies for newly urbanized areas. *Sustain. Prod. Consum.* 31, 13–25. doi:10.1016/j.spc.2022.01.026

Li, W., Bao, L., Li, Y., Si, H., and Li, Y. (2022). Assessing the transition to low-carbon urban transport: a global comparison. *Resour. Conservation Recycl.* 180, 106179. doi:10.1016/j.resconrec.2022.106179

Lin, Q., Zhang, L., Qiu, B., Zhao, Y., and Wei, C. (2021). Spatiotemporal analysis of land use patterns on carbon emissions in China. *Land* 10, 141. doi:10.3390/land10020141

Liu, C., Cutforth, H., Chai, Q., and Gan, Y. (2016). Farming tactics to reduce the carbon footprint of crop cultivation in semiarid areas. A review. *Agron. Sustain. Dev.* 36, 69. doi:10.1007/s13593-016-0404-8

Liu, T., Wu, Z., Chen, C., Chen, H., and Zhou, H. (2024). Carbon emission accounting during the construction of typical 500 kV power transmissions and substations using the carbon emission factor approach. *Buildings* 14, 145. doi:10.3390/buildings14010145

Liu, Z., Xu, Z., Zhu, X., Yin, L., Yin, Z., Li, X., et al. (2023). Calculation of carbon emissions in wastewater treatment and its neutralization measures: a review. *Sci. Total Environ.* 912, 169356. doi:10.1016/j.scitotenv.2023.169356

Lv, Z., Shan, X., Xiao, X., Cai, R., Zhang, Y., and Jiao, N. (2022). Excessive greenhouse gas emissions from wastewater treatment plants by using the chemical oxygen demand standard. *Sci. China Earth Sci.* 65, 87–95. doi:10.1007/s11430-021-9837-5

Mehedi, T. H., Gemechu, E., and Kumar, A. (2022). Life cycle greenhouse gas emissions and energy footprints of utility-scale solar energy systems. *Appl. Energy* 314, 118918. doi:10.1016/j.apenergy.2022.118918

Meng, B., Zhang, J., and Zhang, X. (2023). Detecting the spatial network structure of the Guanzhong Plain urban agglomeration, China: a multi-dimensional element flow perspective. *Land* 12, 563. doi:10.3390/land12030563

Meng, F., Chen, H., Tan, Y., and Xiong, W. (2024). Changes in crop mix and the effects on agricultural carbon emissions in China. *Int. J. Agric. Sustain.* 22, 2335141. doi:10.1080/14735903.2024.2335141

Meng, M., and Niu, D. (2011). Modeling CO2 emissions from fossil fuel combustion using the logistic equation. *Energy* 36, 3355–3359. doi:10.1016/j.energy.2011.03.032

Na, H., Yuan, Y., Du, T., Zhang, T., Zhao, X., Sun, J., et al. (2024). Multi-process production occurs in the iron and steel industry, supporting 'dual carbon'target: an in-depth study of CO2 emissions from different processes. *J. Environ. Sci.* 140, 46–58. doi:10.1016/j.jes.2023.03.031

Noda, I., Asada, M., and Nagao, H. (2024). Elucidation of the mechanism of greenhouse gas generation by abiotic transformation of nutrient ions flowing into closed water areas with little phytoplankton. *ACS ES&T Water* 4, 436–443. doi:10.1021/acsestwater.3c00455

Sage, R. F. (2020). Global change biology: a primer. *Glob. Change Biol.* 26, 3–30. doi:10.1111/gcb.14893

Shan, Y., Guan, D., Liu, J., Mi, Z., Liu, Z., Liu, J., et al. (2017). Methodology and applications of city level CO2 emission accounts in China. *J. Clean. Prod.* 161, 1215–1225. doi:10.1016/j.jclepro.2017.06.075

Song, M., Zhao, X., and Shang, Y. (2020). The impact of low-carbon city construction on ecological efficiency: empirical evidence from quasi-natural experiments. *Resour. Conservation Recycl.* 157, 104777. doi:10.1016/j.resconrec.2020.104777

Sun, J., Qi, Y., Guo, J., Zheng, J., Zhang, L., and Yang, X. (2024). Impact of nighttime light data saturation correction on the application of carbon emissions spatialization: a comparative study of the correction effect and application effect based on five methods in China. *J. Clean. Prod.* 438, 140815. doi:10.1016/j.jclepro.2024.140815

Sun, L.-L., Cui, H.-J., and Ge, Q.-S. (2022). Will China achieve its 2060 carbon neutral commitment from the provincial perspective? *Adv. Clim. Change Res.* 13, 169–178. doi:10.1016/j.accre.2022.02.002

Ucal, M., and Xydis, G. (2020). Multidirectional relationship between energy resources, climate changes and sustainable development: technoeconomic analysis. *Sustain. Cities Soc.* 60, 102210. doi:10.1016/j.scs.2020.102210

Ullah, S., You, Q., Wang, G., Ullah, W., Sachindra, D. A., Yan, Y., et al. (2022). Characteristics of human thermal stress in South Asia during 1981–2019. *Environ. Res. Lett.* 17, 104018. doi:10.1088/1748-9326/ac8fa6

Wang, C., Zhan, J., and Xin, Z. (2020a). Comparative analysis of urban ecological management models incorporating low-carbon transformation. *Technol. Forecast. Soc. Change* 159, 120190. doi:10.1016/j.techfore.2020.120190

Wang, Q., Li, X., Liu, W., Zhai, S., Xu, Q., Nie, S., et al. (2023). Carbon source recovery from waste sludge reduces greenhouse gas emissions in a pilot-scale industrial wastewater treatment plant. *Environ. Sci. Ecotechnology* 14, 100235. doi:10.1016/j.ese.2022.100235

Wang, Y., Fang, X., Yin, S., and Chen, W. (2021). Low-carbon development quality of cities in China: evaluation and obstacle analysis. *Sustain. Cities Soc.* 64, 102553. doi:10.1016/j.scs.2020.102553

Wang, Y., Yang, H., and Sun, R. (2020b). Effectiveness of China's provincial industrial carbon emission reduction and optimization of carbon emission reduction paths in "lagging regions": efficiency-cost analysis. *J. Environ. Manag.* 275, 111221. doi:10.1016/j.jenvman.2020.111221

Wimbadi, R. W., and Djalante, R. (2020). From decarbonization to low carbon development and transition: a systematic literature review of the conceptualization of moving toward net-zero carbon dioxide emission (1995–2019). *J. Clean. Prod.* 256, 120307. doi:10.1016/j.jclepro.2020.120307

Xu, Y., Li, H., Zhang, R., Wang, T., Sui, P., Sheng, J., et al. (2024). Balancing the development and carbon emissions in rural areas of China. *J. Clean. Prod.* 454, 142338. doi:10.1016/j.jclepro.2024.142338

Yan, Z., Li, Z., Li, P., Zhao, C., Xu, Y., Cui, Z., et al. (2023). Spatial and temporal variation of NDVI and its driving factors based on geographical detector: a case study of Guanzhong plain urban agglomeration. *Remote Sens. Appl. Soc. Environ.* 32, 101030. doi:10.1016/j.rsase.2023.101030

Yu, Y., Yin, S., and Zhang, A. (2022). Clean energy-based rural low carbon transformation considering the supply and demand of new energy under government participation: a three-participators game model. *Energy Rep.* 8, 12011–12025. doi:10.1016/j.egyr.2022.09.037

Yu, Z., Wang, Y., Zhao, B., Li, Z., and Hao, Q. (2023). Research on carbon emission structure and model in low-carbon rural areas: bibliometric analysis. *Sustainability* 15, 12353. doi:10.3390/su151612353

Zhang, L. X., Wang, C. B., and Bahaj, A. S. (2014). Carbon emissions by rural energy in China. *Renew. Energy* 66, 641–649. doi:10.1016/j.renene.2014.01.005

Zhang, W., Zhang, M., Wu, S., and Liu, F. (2021). A complex path model for low-carbon sustainable development of enterprise based on system dynamics. *J. Clean. Prod.* 321, 128934. doi:10.1016/j.jclepro.2021.128934

Zhang, Y., Wang, W., Liang, L., Wang, D., Cui, X., and Wei, W. (2020). Spatial-temporal pattern evolution and driving factors of China's energy efficiency under low-carbon economy. *Sci. Total Environ.* 739, 140197. doi:10.1016/j.scitotenv.2020.140197

Zhao, W. (2022). China's goal of achieving carbon neutrality before 2060: experts explain how. *Natl. Sci. Rev.* 9, nwac115. doi:10.1093/nsr/nwac115

Zhong, X., Hu, M., Deetman, S., Steubing, B., Lin, H. X., Hernandez, G. A., et al. (2021). Global greenhouse gas emissions from residential and commercial building materials and mitigation strategies to 2060. *Nat. Commun.* 12, 6126. doi:10.1038/s41467-021-26212-z

Zhou, Z., Nie, L., Ji, H., Zeng, H., and Chen, X. (2020). Does a firm's low-carbon awareness promote low-carbon behaviors? Empirical evidence from China. *J. Clean. Prod.* 244, 118903. doi:10.1016/j.jclepro.2019.118903

Zhu, H., Chen, S., Irfan, M., Hu, M., and Hu, J. (2024). Exploring the role of the belt and road initiative in promoting sustainable and inclusive development. *Sustain. Dev.* 32, 712–723. doi:10.1002/sd.2705

Zhu, X., Zou, X., Lu, E., Deng, Y., Luo, Y., Chen, H., et al. (2021). Litterfall biomass and nutrient cycling in karst and nearby non-karst forests in tropical China: a 10-year comparison. *Sci. Total Environ.* 758, 143619. doi:10.1016/j.scitotenv.2020.143619

Zurek, M., Hebinck, A., and Selomane, O. (2022). Climate change and the urgency to transform food systems. *Science* 376, 1416–1421. doi:10.1126/science.abo2364

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 12 November 2024
DOI 10.3389/fenvs.2024.1454256

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Amar Razzaq,
Huanggang Normal University, China
Bingnan Guo,
Jiangsu University of Science and Technology, China

*CORRESPONDENCE
Ubair Nisar,
ubair.nisar@gmail.com
Khyati Kathuria,
khyati.economics@satyawatie.du.ac.in
Zhiyuan Qiao,
qiaozy0328@gmail.com

RECEIVED 24 June 2024
ACCEPTED 28 October 2024
PUBLISHED 12 November 2024

CITATION
Sun P, Nisar U, Qiao Z, Ahmad S, Kathuria K, Al Bahir A and Ahmad M (2024) Digital economy, technology, and urban carbon emissions nexus: an investigation using the threshold effects and mediation effects tests. *Front. Environ. Sci.* 12:1454256. doi: 10.3389/fenvs.2024.1454256

COPYRIGHT
© 2024 Sun, Nisar, Qiao, Ahmad, Kathuria, Al Bahir and Ahmad. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Digital economy, technology, and urban carbon emissions nexus: an investigation using the threshold effects and mediation effects tests

Pengsheng Sun[1], Ubair Nisar[2]*, Zhiyuan Qiao[3]*, Shadab Ahmad[4,5], Khyati Kathuria[6]*, Areej Al Bahir[7] and Mahmood Ahmad[8,9]

[1]School of Economics, Shandong University of Technolog, Zibo, China, [2]Institute of Business and Policy Research, SKUAST-K, Jammu and Kashmir, India, [3]Business School, Shandong University of Technology, Shandong, China, [4]School of Mechanical Engineering, Shandong University of Technology, Zibo, China, [5]Centre for Research Impact and Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India, [6]Department of Economics, Satyawati College (E), University of Delhi, Delhi, India, [7]Chemistry Department, Sirat Obaida Applied College, King Khalid University, Abha, Saudi Arabia, [8]School of Economics and Business, Western Caspian University, Baku, Azerbaijan, [9]Department of Green Economics, Tashkent State University of Economics, Tashkent, Uzbekistan

Introduction: This study aims to explore the mechanisms by which the digital economy influences urban carbon emissions in China, with a particular focus on potential threshold effects and the mediating role of technology. As the digital economy grows, it impacts various environmental metrics, including carbon emissions, necessitating a deeper understanding of its nonlinear dynamics and implications for sustainable urban development.

Methods: Using panel data from 286 prefecture-level cities in China spanning from 2012 to 2021, we apply threshold effect models and mediation effect tests. The threshold effect model is employed to investigate non-linear characteristics of the digital economy's impact on carbon emissions, while the mediation effect model assesses the role of technology as an intermediary in this relationship.

Results: The threshold effect model reveals a single threshold in the impact of the digital economy on urban carbon emissions, indicating a nonlinear relationship. Initially, the influence of the digital economy on emissions is weak, but as the digital economy develops, its effect becomes more pronounced. The mediation effect model demonstrates that technological advancement can offset the increase in emissions associated with digital economic growth, thus showcasing technology's potential to mitigate environmental impacts.

Discussion: The findings suggest that while the digital economy generally promotes urban carbon emissions, its impact is non-linear and mitigatable through technological innovation. To curb emissions in urban areas, fostering technological innovation and supporting green technology research and development are critical. Moreover, enhancing management and supervision within the digital economy sector can contribute to balancing economic growth with environmental goals. These insights are valuable for policymakers striving to harmonize digital economic expansion with sustainable environmental practices.

KEYWORDS

digital economy, carbon emissions, threshold effects, mediation effect, China

1 Introduction

As global climate change worsens, "carbon reduction" has become both a shared obligation and a challenge for nations worldwide. In recent years, with the continuous advancement of new-type urbanization and industrialization, most countries, including China, have witnessed a continuous increase in energy demand, leading to a rising trend in carbon dioxide emissions. Consequently, the Chinese government has proposed strategic goals to achieve carbon peaking by 2030 and carbon neutrality by 2060. Cities, being the "main battleground" for promoting China's green and low-carbon transformation and high-quality economic development (Zhao et al., 2023; Wang et al., 2019), have become a significant topic of concern regarding how to effectively curb urban carbon emissions (Shang and Luo, 2021).

In urban carbon emissions, academia has conducted extensive theoretical and empirical research on influencing factors. Prior studies have identified several effective means of reducing carbon emissions, including economic development level, industrial structure, population size, and energy structure. Furthermore, scholars have evaluated the carbon reduction effects of policy-related factors such as low-carbon pilot policies (Zhang and Feng, 2021), energy-consuming rights trading policies (Wang M. et al., 2024), and eco-province construction.

Recent research has expanded our understanding of various factors influencing carbon emissions. For instance, Elahi et al. (2024a) examined the decoupling of livestock and poultry pollution emissions from industrial development, while Elahi et al. (2024b) analyzed carbon emission efficiency in food production across the Yangtze River basin. Huang et al. (2024) investigated the impact of aging rural populations on agricultural carbon emissions in China, highlighting the importance of demographic shifts in land use policy. These studies underscore the complexity of carbon emission sources and the need for targeted policies across different sectors.

Concurrently, China has been experiencing rapid development in its digital economy. The digital economy, as an emerging industry, has the potential to play a crucial role in supporting carbon reduction and sustainable urban development (Yan and Zhang, 2023). However, the relationship between the digital economy and carbon emissions is complex and multifaceted, warranting further investigation. Existing literature on the relationship between the digital economy and carbon emissions presents two primary perspectives.

Firstly, the digital economy contributes to carbon emission reduction. Studies have shown that the digital economy affects carbon emissions through "digital industrialization" and "industrial digitization," with "digital industrialization" contributing more significantly to emission reduction. Research by Xie (2022) and Tian and Meng (2023) found that the digital economy can dramatically reduce carbon emission intensity across different regions by improving energy structure and technological advancement. Ge et al. (2022) noted that the digital economy promotes industrial structural transformation, thereby improving urban energy efficiency to achieve carbon reduction goals. Zha et al. (2022) highlighted how the expansion of the digital economy improves the attraction of cities to rural labor and businesses, offering advantageous economies of scale for energy conservation and emission reduction. Furthermore, Xu et al. (2022) and Xu et al. (2024a) observed that the rise of the digital economy not only supports the fall of carbon emissions locally but also helps reduce carbon emissions in surrounding cities, albeit with boundary effects in its spatial spillover effects. Recent studies have provided additional insights into this perspective. Jiang et al. (2024) explored how the digital economy encourages sustainable consumption and reduces carbon emissions. Guo et al. (2024b) examined the effect of digital infrastructure development on enterprise green transformation, while Zhao et al. (2024b) investigated enterprise pollution reduction through digital transformation in Chinese manufacturing enterprises. These studies collectively suggest that digitalization can be a powerful tool for environmental sustainability.

Secondly, the digital economy does not result in considerable environmental gains. Contrasting studies suggest that the digital economy has not led to significant environmental improvements in terms of carbon emissions. Tian and Meng (2023) found that in terms of digital products and new infrastructure, the digital economy lacks environmentally favorable characteristics such as green buildings and low carbon emissions. Qu et al. (2022) reported that the digital economy ranks 17th among 27 manufacturing industries in terms of carbon emissions intensity, surpassing conventional labor-intensive industries. Li et al. (2021) used the Environmental Kuznets Curve (EKC) as a theoretical framework to affirm the presence of an EKC curve within the realm of the digital economy. Lujun et al. (2022) pointed out that while the digital economy has a simple carbon reduction effect, it also has a "green blind spot." Wang and Zhu (2021) highlighted that while digital infrastructure development directly increases overall energy consumption, the digital economy also has the ability to conserve energy and reduce emissions at the micro level, leaving the overall influence on energy usage unclear. More recent research has added nuance to this perspective. Li et al. (2023) examined the carbon emissions of 5G mobile networks in China, highlighting the environmental challenges posed by new digital technologies. Similarly, Li and Li (2023) explored the potential of artificial intelligence in reducing carbon emissions from 5G networks, suggesting that technological advancements within the digital economy could mitigate its environmental impact.

Recent research has expanded into various aspects that indirectly influence the digital economy-carbon emissions relationship. Zhang et al. (2023) proposed a new structural economic growth model considering labor income share, which could impact carbon emissions through economic dynamics. In the realm of organizational behavior, Zhu et al. (2023) and Jabeen et al. (2024) (Jabeen et al., 2024) explored the roles of leadership and human resource management in environmental performance, highlighting the importance of human factors in sustainability efforts. Yin et al. (2019) demonstrated the application of advanced analytical methods in performance evaluation, which could be extended to assess the environmental impact of digital technologies. Feng et al. (2024) conducted a life cycle cost analysis of power generation with carbon capture and storage, providing insights into the economic feasibility of emission reduction technologies. Huang et al. (2021) and Jiang et al. (2024) focused on ecological security patterns and the digital economy's role in encouraging sustainable consumption, respectively. Li and Yue

(2024) analyzed energy demand and emissions in the urban transport sector, while Wang (2023) examined the broader implications of digitalization for climate change adaptation in China. These diverse studies underscore the complexity of the digital economy-carbon emissions nexus and the need for interdisciplinary approaches in addressing environmental challenges.

The literature also reveals emerging areas of research that bridge the gap between these two perspectives. For instance, Fan et al. (2024) analyzed how digitalization drives the green transformation of supply chains, proposing a two-stage evolutionary game analysis. Xu H. et al. (2024) investigated the influence of fintech, digitalization, and green technologies on sustainable environments in CIVETS nations. These studies suggest that the relationship between digital economy and carbon emissions is not binary but rather complex and context-dependent.

Furthermore, previous literature focused into related areas that indirectly impact the digital economy-carbon emissions nexus. For example, Zhao et al. (2024a) examined the role of CEOs' information technology backgrounds in driving digital technology innovation. Zheng and Chen (2023) revisited the linkage between financial inclusion and energy productivity, considering technology implications for climate change. These studies highlight the importance of human factors and financial systems in shaping the environmental impact of the digital economy.

Despite this rich body of research, several gaps remain. First, there is a lack of comprehensive studies that examine the threshold effects of digital economy development on carbon emissions, particularly in the context of rapidly developing economies like China. Second, while many studies have explored direct relationships, few have investigated the potential mediating role of technology in the digital economy-carbon emissions relationship. Lastly, there is a need for more research that synthesizes insights from various sectors and approaches to provide a holistic understanding of how digital transformation can be leveraged for environmental sustainability.

Given these research gaps, this paper aims to contribute to the ongoing debate by focusing on the following aspects:

- It explores the mechanism of how the digital economy affects urban carbon emissions, as well as the characteristics of the impact of different levels of digital economy development on urban carbon emissions. This provides a more complex and comprehensive perspective for understanding the relationship between the two.
- It investigates the transmission mechanism of the digital economy's impact on urban carbon emissions, selecting technology as an intermediary variable to test whether technology can offset the increase in carbon emissions caused by digital economic growth. This approach offers new ideas and methods for addressing carbon emission issues.
- By examining the impact of digital economic development on urban carbon emissions in the context of China, this paper contributes to extending China's experience to other countries and provides a reference for scientific decision-making by government departments.

While focusing on China, this study has broader international implications. As countries worldwide navigate digital transformation and climate change mitigation, understanding the relationship between digital economic growth and carbon emissions is crucial. This research provides a methodological framework and empirical insights applicable to diverse global contexts. By examining nonlinear effects and technology's mediating role, it contributes to the global discourse on leveraging digital economies for sustainable development. The findings and policy recommendations offer valuable reference points for policymakers and urban planners internationally, aiding in balancing digital innovation with environmental stewardship.

The article consists of five main sections. In the introduction, the study's background, and objectives are discussed. Following that, the theoretical analysis and hypothesis development section outlines the theoretical framework and proposes the key hypotheses that guide the research. The materials and methods section provides a detailed description of the data sources, analytical tools, and methodologies employed to conduct the study. Next, the results and discussion section presents the findings of the research and offers an in-depth analysis, comparing them with existing literature. Lastly, the conclusion and recommendations section summarize the key insights from the study, provides practical recommendations, and suggests areas for future research.

2 Theoretical analysis and hypothesis development

The relationship between the digital economy and urban carbon emissions is complex and multifaceted, as evidenced by recent literature. This complexity stems from the dual nature of digital technologies' impact on carbon emissions.

On one hand, the rapidly growing digital economy leads to widespread adoption of massive data centers, cloud computing facilities, and electronic devices. These facilities have substantial electricity requirements, primarily sourced from fossil fuels, which amplifies urban energy consumption and carbon emission levels. Li et al. (2023) quantified the carbon emissions of 5G mobile networks in China, highlighting the significant environmental impact of digital infrastructure. Additionally, the flourishing digital economy encourages the growth of carbon-intensive sectors such as transportation and industry, further raising urban carbon emissions levels (Xu et al., 2024b).

On the other hand, the growth of the digital economy also creates new opportunities to reduce carbon emissions from urban areas. Smart energy management systems, enabled by digital technologies, continuously monitor and optimize energy consumption, effectively reducing energy waste and carbon emissions (Zhao et al., 2024b). The development of the digital economy also promotes the construction of digital infrastructure, facilitating the green transformation of enterprises, thereby potentially reducing urban carbon emissions (Guo et al., 2024b). Furthermore, the digital economy fosters the creation and application of environmental protection technologies and renewable energy sources. For instance, it promotes the development of energy storage technologies and enhances the utilization of renewable energy sources such as solar and wind

power, which can ultimately mitigate urban carbon emissions (Xu et al., 2024b).

Thus, the effects of the digital economy on urban carbon emissions could be both favorable and unfavorable, depending on factors such as policy reinforcement and industrial composition. This dual nature is supported by recent studies such as Jiang et al. (2024), who found that the digital economy can encourage sustainable consumption and reduce carbon emissions. Conversely, Ma et al. (2023) argued that the digital economy lacks environmentally favorable characteristics in terms of digital products and new infrastructure. Based on these contrasting findings, we propose the following competing hypotheses:

H1a: The digital economy has a positive impact on urban carbon emissions.
H1b: The digital economy has a negative impact on urban carbon emissions.

Additionally, China's stark regional development imbalance results in distinct "staircase" features at different levels of technical development across regions. This could lead to notable variations in industrial structure, degrees of digitalization, and decarbonization capabilities across different regions (Guo et al., 2024a). Such regional disparities suggest that the relationship between the digital economy and carbon emissions may not be linear. This notion is supported by studies like Li et al. (2021), who found evidence of an Environmental Kuznets Curve within the realm of the digital economy. Therefore, we posit the following hypothesis:

H2: There is a nonlinear threshold feature between the digital economy and urban carbon emissions.

The advancement of the digital economy spurs technological innovation and investment in research and development by both businesses and governments. During digital transformation, enterprises continuously explore new business models and technological applications, enhancing the quality, efficiency, and experience of their products and services through environmental information disclosure (Guo et al., 2024a). This innovation not only enhances the competitiveness of enterprises but also provides impetus for technological progress (Dong, 2023). Simultaneously, governmental intervention plays a pivotal role in fostering the digital economy's development through the formulation of pertinent policies and investment strategies (Su et al., 2021).

Digital technology facilitates collaborative research, fosters interdisciplinary cross-border innovation, and accelerates the dissemination of innovative outcomes. This open innovation model creates a more expansive platform for the advancement of scientific and technological standards. By enabling the transmission and sharing of knowledge and information, the widespread use of digital technology accelerates the diffusion and application of scientific and technical breakthroughs (Ma et al., 2024).

The development of the digital economy is largely dependent on increased investment in science and technology, innovation, and technological application across diverse domains by both governments and enterprises. This investment promotes comprehensive research, speeds up the transformation and application of scientific discoveries, and facilitates breakthroughs in key technologies within the digital economy. The resulting innovation not only creates a strong basis for the sustainable expansion of the digital economy but also enhances its industrial chain's competitiveness.

Recent studies have highlighted the role of technology as a potential mediator between the digital economy and environmental outcomes. For instance, Li and Li (2023) explored how artificial intelligence could be used to reduce the carbon emissions of 5G networks, suggesting that technological advancements within the digital economy could mitigate its environmental impact. Similarly, Fan et al. (2024) demonstrated how digitalization drives the green transformation of supply chains through technological innovation.

Considering these findings and the potential for technology to act as a bridge between digital economic growth and environmental sustainability, we propose the following hypothesis:

H3: There is a mediating effect of technology between the digital economy and urban carbon emissions.

This theoretical framework, supported by recent literature, provides a comprehensive basis for examining the complex relationship between the digital economy, technology, and urban carbon emissions in China.

3 Materials and methods

3.1 Data

The study employs panel data encompassing 286 prefecture-level cities in China spanning from 2012 to 2021. The Digital Inclusive Finance Index is sourced from the Digital Finance Research Center, Peking University. Additional pertinent data originates from the "China Urban Statistical Yearbook" (2013–2022) and statistical yearbooks of prefecture-level cities (2013–2022). Missing data are supplemented via interpolation.

3.2 Analytical framework

To investigate the direct relationship between urban carbon emissions and digital economy, this study builds the following baseline regression model (Equation 1):

$$Carbon_{it} = \alpha_0 + \alpha_1 DIGI_{it} + \alpha_2 CL_{it} + \alpha_3 EDU_{it} + \alpha_4 FGB_{it} + \alpha_5 SI_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

where, i represents the city, t shows the year, and $Carbon_{it}$ indicates urban carbon emissions. Similarly, DIGI, CL, EDU, FGB, SI, and TECH denote the digital economy, consumption level, education, financial general budget, social insurance, and technology respectively. Moreover, μ_i represents city fixed effects, ν_t represents time-fixed effects, and ε_{it} denotes the random error term, assumed to be normally distributed at zero mean value and constant variance.

TABLE 1 Evaluation index system of the digital economy.

Index	Descriptions	Expected signs
Internet Penetration Rate	Number of internet users per hundred population	+
Number of Internet-related Employees	Proportion of employees in computer services and software	+
Output Related to Internet	Per capita total volume of telecommunications services	+
Number of Mobile Internet Users	Number of mobile phone users per hundred population	+
Development of Inclusive Digital Finance	Digital Inclusive Finance Index	+

To explore the possibility of a nonlinear threshold feature regarding the technological level between the digital economy and carbon emissions, this study establishes a threshold model based on Hansen's panel threshold model (Hansen, 1999). The single threshold model can be written as (Equation 2):

$$\begin{aligned} Carbon_{it} = {} & \theta_0 + \theta_1 CL_{it} + \theta_2 EDU_{it} + \theta_3 FGB_{it} + \theta_4 SI_{it} \\ & + \varphi_1 DIGI_{it} \times I(DIGI_{it} \le \pi_1) \\ & + \varphi_2 DIGI_{it} \times I(DIGI_{it} > \pi_1) + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \quad (2)$$

where θ *and* φ are the parameters to be estimated, π is the threshold value to be estimated, and I is the indicator function (I equals 1 if the expression enclosed in the parentheses is true; otherwise 0).

To further confirm the indirect impact of the digital economy on carbon emissions through technology, the study contruct a mediation effect model based on the baseline regression model:

$$\begin{aligned} TECH_{it} = {} & \beta_0 + \beta_1 DIGI_{it} + \beta_2 CL_{it} + \beta_3 EDU_{it} + \beta_4 FGB_{it} \\ & + \beta_5 SI_{it} + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \quad (3)$$

$$\begin{aligned} Carbon_{it} = {} & \gamma_0 + \gamma_1 DIGI_{it} + \gamma_2 TECH_{it} + \gamma_3 CL_{it} + \gamma_4 EDU_{it} \\ & + \gamma_5 FGB_{it} + \gamma_6 SI_{it} + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \quad (4)$$

where *TECH* stands for the intermediary variable technology. β *and* γ are parameters to be estimated. Equation 3 establishes the relationship between the digital economy and the intermediary variable, technology, while Equation 4 examines the combined effect of both on urban carbon emissions.

3.3 Description of variables

3.3.1 Dependent variable

The concept of "carbon emissions" encompasses both direct and indirect emissions, as defined by Kennedy et al. (2010) and Cong et al. (2014). Direct emissions occur within the accounting boundary, while indirect emissions result from inputs originating outside the boundary but are nonetheless contained within it.

For comprehensive carbon emissions accounting, the greenhouse gas accounting system delineates three distinct categories. Category 1 includes all direct carbon emissions stemming from energy-related activities within the boundary, such as construction, industrial processes, transportation, agriculture, and waste disposal. Category 2 covers energy-related indirect carbon emissions occurring outside the boundary, primarily comprising emissions from purchased electricity, heating, and cooling systems. Category 3 encompasses additional indirect carbon emissions from sources beyond the boundary not included in Category 2. These emissions typically arise from the production, transportation, use, and disposal of goods procured from external sources (Liu X. et al., 2024; Liu Z. et al., 2024).

In alignment with existing research methodologies, the present study adopts a comprehensive approach to urban carbon emissions, incorporating all three categories in its analysis. This holistic perspective allows for a more accurate assessment of the total carbon footprint associated with urban activities and provides a robust foundation for examining the relationship between the digital economy and urban carbon emissions.

3.3.2 Independent variables

To compute the Comprehensive Development Index of the digital economy, the study uses the index system proposed by Tao et al. (2022). The evaluation index system used in the study is given in Table 1.

3.3.3 Control variables

Four indicators namely, consumption, education, government fiscal expenditure, and social security are used as control variables as they may have a significant influence on urban carbon emissions. Consumption level is closely correlated with the lifestyle and resource usage of urban dwellers; the higher the level of consumption, the more will be energy consumption and carbon emission levels. Education level is a good indicator of the technological and environmental knowledge of the urban residents. Better education can encourage the use of environmental protection technology and raise environmental awareness which will lower carbon emissions. The amount of money the government spends on environmental preservation and carbon reduction is reflected in its fiscal expenditures; more fiscal expenditures may indicate the implementation of more environmental projects and carbon reduction initiatives. Social security may have complicated effects on carbon emissions due to its influence on people's lifestyle and productivity. A more accurate assessment of the impact of digital economy on urban carbon emissions can be obtained by controlling these variables, providing scientific support for policy formulation.

3.3.4 Mediating variables

Technology is used as a mediating variable in the study as it can help explain the mechanism through which the development of the digital economy affects urban carbon emissions. The development of a digital economy may indirectly affect urban carbon emissions by influencing technological innovation and progress (Hu et al., 2024;

TABLE 2 Descriptive statistics.

Variables	Mean	Standard deviation	Minimum	Maximum
Carbon	3,926.2845	5,086.8889	663.9600	62,600.0000
Digital economy (DIGI)	0.2363	0.0959	0.0143	0.7140
Consumption level (CL)	1,128.2893	1,617.3743	0.0238	18,080.0000
Education (EDU)	7,848.1926	10,082.3489	0.0037	114,782.9300
Financial general budget (FGB)	462.6522	688.7615	19.6245	8,430.8562
Social insurance (SI)	61.7637	126.2304	0.4000	1,359.0157
Technology (TECH)	13.0022	40.5220	0.0753	554.9817

TABLE 3 Parametric results using regression analysis.

Variables	Fixed effects	Threshold effects
Digital economy	0.5156*** (0.0430)	
Consumption level	0.0836*** (0.00919)	0.0845*** (0.00917)
Education	−0.0315** (0.0125)	−0.0298** (0.0125)
Financial general budget	0.2688*** (0.0128)	0.2649*** (0.0128)
Social insurance	−0.0965*** (0.0137)	−0.0997*** (0.0137)
C (Digital economy ≤ 0.3604)		0.4618*** (0.0453)
C (Digital economy>0.3604)		0.5661*** (0.0450)
Constant	−0.1218*** (0.0103)	−0.1114*** (0.0106)

The given values in parentheses are the standard errors. ***, and ** show significance at $p < 0.01$, and $p < 0.05$, respectively.

Xu H. et al., 2024; Dong et al., 2022; Hu et al., 2023). By offering a more thorough analysis for comprehending the mechanics behind carbon emissions, technology as a mediating variable can help uncover the pathways by which the digital economy affects urban carbon emissions.

4 Results and discussion

4.1 Summary of basic statistics

The given results in Table 2 offer an overview of various variables, focusing on their average values. Carbon emissions have an average of 3,926 units, suggesting a considerable level of emissions across the regions or sectors in question. The digital economy (DIGI) shows an average of 0.236, indicating a modest level of digitalization in the sample. For the consumption level (CL), the mean is 1,128, reflecting average consumption patterns. Education (EDU), on the other hand, stands out with a high average value of 7,848, indicating substantial investments in or access to education in some areas.

The financial general budget (FGB) averages 462, suggesting moderate financial resources across the sample, while social insurance (SI) shows a lower average of about 61, reflecting relatively limited coverage or access. Lastly, technology (TECH) averages around 13, highlighting the level of technological development within the regions being studied. This table provides a concise picture of how these variables perform on average, giving a sense of the general landscape without delving into variability or extreme values.

4.2 Baseline regression

The findings of the regression analysis presented in Table 3 indicate a considerable positive correlation between urban carbon emissions and the digital economy. Urban carbon emissions are also substantially positively associated with the level of consumption and government spending. Urban carbon emissions, on the other hand, are inversely correlated with social security and the level of education. Combining existing research, the rapid development of the digital economy often accompanies industrial expansion and increased energy consumption, especially in the production and service processes of digital technologies, which may lead to significant carbon emissions. Additionally, the rapid development of the digital economy may drive population growth and accelerate urbanization, thereby increasing urban carbon emissions.

Higher consumption levels are often associated with increased production and activities such as transportation and tourism, which can lead to greater energy use and higher carbon emissions (Tang et al., 2017). Additionally, increased fiscal expenditure tends to promote investment in urban infrastructure and the provision of public services, further driving energy consumption and contributing to carbon emissions (Elheddad et al., 2020).

TABLE 4 Results of the threshold effect test.

Variable	Type	F-value	Threshold
DIGI	Single	14.36 (0.073)*	0.3604
	Double	6.37 (0.423)	1.2839

The values in parentheses represent *p*-values. Moreover, * shows a significant level of parameter at $p < 0.10$.

Education is frequently linked to an individual's capacity for technological innovation and environmental awareness. People with higher levels of education are more likely to adopt cleaner energy sources, lead low-carbon lifestyles, and use environmentally friendly technologies (Sovacool et al., 2022). Moreover, a strong social security system can help reduce social instability, improve living standards, and lower excessive carbon consumption, ultimately contributing to a reduction in carbon emissions (Zhang et al., 2022).

4.3 Threshold effect

Based on the empirical analysis, it is evident that the growth of the digital economy contributes to increasing carbon emissions in cities. However, this conclusion assumes a linear relationship between the digital economy and urban carbon emissions, overlooking potential differences at various stages of economic growth. The impact on urban carbon emissions during the early and mature stages of digital economy growth may vary. To account for this, the study considers the digital economy as a threshold variable, allowing for an examination of its threshold effect on urban carbon emissions.

The results of the threshold effect test, shown in Table 4, indicate that after controlling for relevant variables, the digital economy is significant in a single threshold test. With a threshold value estimated at 0.3604, the digital economy can be categorized into a primary stage when it is below this value and into intermediate or advanced stages when it exceeds this threshold.

Threshold regression, conducted for both the primary and advanced stages of the digital economy (as seen in Table 3), reveals that the digital economy promotes urban carbon emissions in both stages. This demonstrates a nonlinear relationship between the digital economy and urban carbon emissions, supporting hypothesis H2. In the initial stages, the digital economy drives the modernization and transformation of traditional industries, leading to increased energy and resource demands, which result in higher carbon emissions. As the digital economy develops further, the adoption of clean energy and green technologies improves energy efficiency and optimizes industrial structures, gradually reducing carbon emissions. However, as the digital economy expands further, the scale of the digital industry itself may introduce new sources of energy consumption and carbon emissions, thereby amplifying its impact on urban carbon emissions once again.

4.4 A test of mediation effect

The digital economy can have both a direct and an indirect impact on urban carbon emissions, with technology serving as an intermediary (Li and Zhou, 2024). However, when using the stepwise regression method, the indirect effects of variables like technology may be underestimated, leading to bias in their estimation. To address this issue and assess the robustness of the indirect effect of technology, the Sobel-Goodman mediation effect model has been employed. The results of this mediation model, shown in Table 5, indicate that the coefficients from the Sobel, Aroian, and Goodman tests are all 0.004, confirming that the indirect effect of technology is robust and consistent with the findings from the stepwise regression method.

The analysis reveals a total effect value of −0.135, signifying a shift in the overall impact of the digital economy on urban carbon emissions when technology is considered as a mediating factor. This shift occurs because the digital economy influences technology, and the positive impact of technological advancements can offset the negative effects of the digital economy on carbon emissions (Ma et al., 2022). In other words, the overall influence of the digital economy becomes negative when accounting for technology. Technological progress can enhance urban productivity, helping to mitigate carbon emissions and counterbalance any potential increases in emissions caused by the growth of the digital economy (Wang L. et al., 2024).

With a mediation effect of approximately 2.96%, technology plays a crucial role as a mediator between the digital economy and urban carbon emissions. This underscores the importance of considering both the digital economy and technological advancements when developing policies aimed at reducing carbon emissions in urban areas. Implementing targeted policy measures that promote technological innovation is essential for addressing the environmental impacts of the digital economy and achieving sustainable urban development.

4.5 Robustness test

Robustness tests were conducted by altering econometric methods, performing trimming, and substituting core explanatory variables to more thoroughly examine the nonlinear influence of the digital economy on urban carbon emissions. Specifically, the original digital economy index was replaced with one derived through principal component analysis, and the ordinary least squares method was used for analysis instead of the fixed effects model. The robustness test results, presented in Table 6, show that the signs and significance levels of the estimated coefficients for each variable are largely consistent with the original regression results, reinforcing the reliability of the previous findings.

TABLE 5 Results of mediation effects test.

Mediation effect test	Estimate	Standard error	Z-value	*P*-value
Sobel	0.004	0.002	1.770	0.077
Aroian	0.004	0.002	1.765	0.078
Goodman	0.004	0.002	1.775	0.076
Digital Economy→Technology	0.003	0.002	1.786	0.074
Technology→Carbon	1.267	0.097	13.038	0.000
Indirect Effect	0.004	0.002	1.770	0.077
Direct Effect	−0.139	0.009	−15.989	0.000
Total Effect	−0.135	0.009	−15.121	0.000
Proportion of Mediation Effect to Total Effect			2.96%	

TABLE 6 Results of the robustness test.

Variables	Replacement of the core explanatory variables	Change measurement method	Trim treatment
Digital economy	0.0558*** (0.0041)	1.2148*** (0.1619)	0.7630*** (0.0427)
Consumption level	0.0828*** (0.0091)	−0.4916*** (0.0853)	0.1036*** (0.0091)
Education	−0.0325*** (0.0124)	0.124 (0.1812)	0.018 (0.0117)
Financial general budget	0.261*** (0.0127)	1.3971*** (0.1562)	−0.0147 (0.0151)
Social insurance	−0.0946*** (0.0135)	−0.2996*** (0.1139)	0.1093*** (0.0116)
Constant	0.0000 (0.0015)	−0.2870*** (0.0401)	−0.1966*** (0.0103)
R^2	0.5749	0.7819	0.4936

The given values in parentheses are the standard errors. Moreover, *** shows a significant level of parameters at $p < 0.01$.

5 Conclusion and recommendations

This study aimed to investigate the complex relationship between the digital economy and urban carbon emissions in China, focusing on potential threshold effects and the mediating role of technology. Using panel data from 286 prefecture-level cities in China from 2012 to 2021, we employed threshold models and mediation effect tests to analyze this relationship.

The empirical findings reveal several key insights. First, the growth of the digital economy is associated with an increase in urban carbon emissions. However, this relationship is not linear. The threshold effect model indicates a nonlinear threshold characteristic between the digital economy and urban carbon emissions, exhibiting a pattern that is initially weak and then strengthens. This suggests that the impact of digital economic development on carbon emissions varies at different stages of digital maturity.

Furthermore, the analysis demonstrates that technology plays a significant mediating role between the digital economy and urban carbon emissions. This finding suggests that technological advancements have the potential to offset the increase in carbon emissions caused by the growth of the digital economy. This highlights the crucial role of innovation and technological progress in mitigating the environmental impact of digital economic development. These results have important implications for policymakers and urban planners in China and potentially other rapidly digitalizing economies. To counteract the nonlinear influence of the digital economy on urban carbon emissions, we propose several focused intervention measures:

Governments should vigorously promote the development of the digital economy while simultaneously optimizing the performance of digital infrastructure and specialized equipment. This should be coupled with increased investment in green technology research and development, encouraging firms to adopt clean production technologies and environmentally friendly equipment. Policymakers should formulate and implement policies that encourage the use of renewable energy sources such as solar and wind power. Financial incentives and favorable policies should be offered to lower the cost of renewable energy adoption.

A reasonable system of carbon emission trading and quotas should be established, along with an integrated energy management and control platform to strengthen the supervision of corporate carbon emissions behaviors. This platform should leverage digital technologies for monitoring, measurement, prediction, and efficiency enhancement of carbon emissions. Urban planning should be optimized to carry out green transformations in key carbon emission sectors such as transportation and industrial manufacturing. Public awareness of environmental protection

should be enhanced through the promotion of green and low-carbon travel and products.

To address the mediating impact of scientific and technological factors, governments and enterprises should increase investments in scientific and technological innovation and green technologies. This involves fostering a symbiotic relationship between the digital economy and scientific advancements to achieve carbon emission reduction. A comprehensive system for the precise transformation of traditional industries with high energy consumption should be established. This includes regulating the direction of technological innovation, establishing a technology assessment mechanism, and evaluating the environmental impact of digital economy projects.

This study's insights extend beyond China, offering global relevance. The findings and recommendations can inform international policies balancing digital economic growth with environmental sustainability, especially in rapidly developing economies facing similar challenges.

While the study provides valuable insights, it is not without limitations. Firstly, due to data availability, our analysis is based solely on data from China. The applicability of our findings to other countries with different economic and environmental conditions remains to be tested. Secondly, while we focused on the mediating effect of technology, there may be other potential influencing factors that were not considered in this study.

For future research, we recommend several directions. The scope of the study should be expanded to include data from other countries, allowing for comparative analysis and assessment of the validity and universality of our conclusions across different economic and environmental contexts. Other potential mediating or moderating factors in the relationship between the digital economy and urban carbon emissions, such as institutional quality, industrial structure, or urban density, should be investigated.

In-depth case studies of cities that have successfully balanced digital economic growth with carbon emission reduction could be conducted to identify best practices and transferable strategies. The long-term dynamics of the relationship between digital economy development and carbon emissions should be explored, potentially using longer time series data and more advanced econometric techniques. Lastly, future research could investigate the specific mechanisms through which different aspects of the digital economy (e.g., e-commerce, smart city initiatives, Industry 4.0) impact carbon emissions.

By addressing these research directions, future studies can build upon our findings and provide a more comprehensive understanding of how to leverage digital economic development for sustainable urban growth and effective carbon emission reduction. This knowledge will be crucial as countries worldwide strive to balance economic development with environmental sustainability in an increasingly digital age.

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

PS: Writing–original draft, Writing–review and editing. UN: Writing–original draft, Writing–review and editing. ZQ: Writing–original draft, Writing–review and editing. SA: Writing–original draft, Writing–review and editing. KK: Writing–original draft, Writing–review and editing. AAB: Funding acquisition, Writing–original draft, Writing–review and editing. MA: Conceptualization, Formal analysis, Writing–original draft, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. The current work was assisted financially to the Dean of Science and Research at King Khalid University via the Large Group Project under grant number RGP. 2/591/45.

Acknowledgments

The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through large Groups Project under grant number RGP.2/ 591/45.

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Cong, J., Liu, X., and Zhao, X. (2014). Demarcation problems and the corresponding measurement methods of the urban carbon accounting. *China Popul. Resour. Environ.* 24, 19–26.

Dong, B. (2023). How transformational leadership affects firm innovation performance-A perspective based on environmental dynamism and business model innovation. *J. Chin. Hum. Resour. Manag.* 14, 38–50. doi:10.47297/wspchrmwsp2040-800503.20231402

Dong, F., Hu, M., Gao, Y., Liu, Y., Zhu, J., and Pan, Y. (2022). How does digital economy affect carbon emissions? Evidence from global 60 countries. *Sci. Total Environ.* 852, 158401. doi:10.1016/j.scitotenv.2022.158401

Elahi, E., Li, G., Han, X., Zhu, W., Liu, Y., Cheng, A., et al. (2024a). Decoupling livestock and poultry pollution emissions from industrial development: a step towards reducing environmental emissions. *J. Environ. Manag.* 350, 119654. doi:10.1016/j.jenvman.2023.119654

Elahi, E., Zhu, M., Khalid, Z., and Wei, K. (2024b). An empirical analysis of carbon emission efficiency in food production across the Yangtze River basin: towards sustainable agricultural development and carbon neutrality. *Agric. Syst.* 218, 103994. doi:10.1016/j.agsy.2024.103994

Elheddad, M., Djellouli, N., Tiwari, A. K., and Hammoudeh, S. (2020). The relationship between energy consumption and fiscal decentralization and the importance of urbanization: evidence from Chinese provinces. *J. Environ. Manag.* 264, 110474. doi:10.1016/j.jenvman.2020.110474

Fan, W., Wu, X., and He, Q. (2024). Digitalization drives green transformation of supply chains: a two-stage evolutionary game analysis. *Ann. Operations Res.*, 1–20. doi:10.1007/s10479-024-06050-0

Feng, Y., Chen, J., and Luo, J. (2024). Life cycle cost analysis of power generation from underground coal gasification with carbon capture and storage (CCS) to measure the economic feasibility. *Resour. Policy* 92, 104996. doi:10.1016/j.resourpol.2024.104996

Ge, L., Mo, L., and Huang, N. (2022). Development of digital economy, upgrading of industrial structure and urban carbon emission. *Mod. Financ. Econ. J. Tianjin Univ. Financ. Econ.* 42, 20–37.

Guo, B., Feng, Y., and Wang, X. (2024a). The effect of environmental information disclosure on carbon emission. *Pol. J. Environ. Stud.* 33. doi:10.15244/pjoes/173106

Guo, B., Hu, P., and Lin, J. (2024b). The effect of digital infrastructure development on enterprise green transformation. *Int. Rev. Financial Analysis* 92, 103085. doi:10.1016/j.irfa.2024.103085

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: estimation, testing, and inference. *J. Econ.* 93, 345–368. doi:10.1016/s0304-4076(99)00025-1

Hu, F., Zhang, S., Gao, J., Tang, Z., Chen, X., Qiu, L., et al. (2024). Digitalization empowerment for green economic growth: the impact of green complexity. *Environ. Eng. and Manag. J. (EEMJ)* 23, 519–536. doi:10.30638/eemj.2024.040

Hu, Y., Zheng, H., Cai, J., and Ding, H. (2023). The impact of digital economy development on carbon emission intensity reduction: evidence from China. *Singap. Econ. Rev.*, 1–21. doi:10.1142/s0217590823470021

Huang, Q., Peng, B., Elahi, E., and Wan, A. (2021). Evolution and driving mechanism of ecological security pattern: a case study of Yangtze River urban agglomeration. *Integr. Environ. Assess. Manag.* 17, 573–583. doi:10.1002/ieam.4358

Huang, Y., Elahi, E., You, J., Sheng, Y., Li, J., and Meng, A. (2024). Land use policy implications of demographic shifts: analyzing the impact of aging rural populations on agricultural carbon emissions in China. *Land Use Policy* 147, 107340. doi:10.1016/j.landusepol.2024.107340

Jabeen, R., Mehmood, S., Ahmed, M., Ghani, T., Javaid, Z. K., and Popp, J. (2024). The role of green HRM on environmental performance: mediating role of green ambidexterity and green behavior and moderating role of responsible leadership. *J. Chin. Hum. Resour. Manag.* 15, 70–90. doi:10.47297/wspchrmWSP2040-800504.20241502

Jiang, H., Elahi, E., Gao, M., Huang, Y., and Liu, X. (2024). Digital economy to encourage sustainable consumption and reduce carbon emissions. *J. Clean. Prod.* 443, 140867. doi:10.1016/j.jclepro.2024.140867

Kennedy, C., Steinberger, J., Gasson, B., Hansen, Y., Hillman, T., Havránek, M., et al. (2010). Methodology for inventorying greenhouse gas emissions from global cities. *Energy policy* 38, 4828–4837. doi:10.1016/j.enpol.2009.08.050

Li, C., and Zhou, W. (2024). Can digital economy development contribute to urban carbon emission reduction? Empirical evidence from China. *J. Environ. Manag.* 357, 120680. doi:10.1016/j.jenvman.2024.120680

Li, S., and Yue, Q. (2024). Analysis on the energy demand, CO2 and pollutant emissions, and health benefits from urban road transport sector: a case study of Shenyang. *Green Low-Carbon Econ.* 2, 143–150. doi:10.47852/bonviewglce3202682

Li, T., and Li, Y. (2023). Artificial intelligence for reducing the carbon emissions of 5G networks in China. *Nat. Portf. Heidelb. PLATZ* 3. BERLIN, 14197, GERMANY.

Li, T., Yu, L., Ma, Y., Duan, T., Huang, W., Zhou, Y., et al. (2023). Carbon emissions of 5G mobile networks in China. *Nat. Sustain.* 6, 1620–1631. doi:10.1038/s41893-023-01206-5

Li, X., Liu, J., and Ni, P. (2021). The impact of the digital economy on CO2 emissions: a theoretical and empirical analysis. *Sustainability* 13 (13), 7267. doi:10.3390/su13137267

Liu, X., Zhu, C., Kong, M., Yin, L., and Zheng, W. (2024a). The value of political connections of developers in residential land leasing: case of chengdu, China. *Sage Open* 14, 21582440241245226. doi:10.1177/21582440241245226

Liu, Z., Zhao, Y., Wang, Q., Xing, H., and Sun, J. (2024b). Modeling and assessment of carbon emissions in additive-subtractive integrated hybrid manufacturing based on energy and material analysis. *Int. J. Precis. Eng. Manufacturing-Green Technol.* 11, 799–813. doi:10.1007/s40684-023-00588-3

Lujun, M., Jing, C., Tianzheng, F., and Yanqin, L. (2022). The impact of digital economy development on carbon emission: a panel data analysis of 278 prefecture-level cities [J]. *South China Finance* 2, 45–57.

Ma, Q., Tariq, M., Mahmood, H., and Khan, Z. (2022). The nexus between digital economy and carbon dioxide emissions in China: the moderating role of investments in research and development. *Technol. Soc.* 68, 101910. doi:10.1016/j.techsoc.2022.101910

Ma, Q., Zhang, Y., Hu, F., and Zhou, H. (2024). Can the energy conservation and emission reduction demonstration city policy enhance urban domestic waste control? Evidence from 283 cities in China. *Cities* 154, 105323. doi:10.1016/j.cities.2024.105323

Ma, Y., Wang, S., and Zhou, C. (2023). Can the development of the digital economy reduce urban carbon emissions? Case study of Guangdong Province. *Land* 12, 787. doi:10.3390/land12040787

Qu, S., Shi, D., and Yang, D. (2022). Carbon emissions of China's digital economy: calculations and trend outlook. *China Popul. Resour. Environ.* 32, 11–21.

Shang, M., and Luo, J. (2021). The tapio decoupling principle and key strategies for changing factors of Chinese urban carbon footprint based on cloud computing. *Int. J. Environ. Res. Public Health* 18, 2101. doi:10.3390/ijerph18042101

Sovacool, B. K., Newell, P., Carley, S., and Fanzo, J. (2022). Equity, technological innovation and sustainable behaviour in a low-carbon future. *Nat. Hum. Behav.* 6, 326–337. doi:10.1038/s41562-021-01257-8

Su, J., Su, K., and Wang, S. (2021). Does the digital economy promote industrial structural upgrading? a test of mediating effects based on heterogeneous technological innovation. *Sustainability* 13, 10105. doi:10.3390/su131810105

Tang, C., Zhong, L., and Ng, P. (2017). Factors that influence the tourism industry's carbon emissions: a tourism area life cycle model perspective. *Energy Policy* 109, 704–718. doi:10.1016/j.enpol.2017.07.050

Tao, Z., Zhang, Z., and Shangkun, L. (2022). Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban China. *Front. Econ. China* 17, 393. doi:10.3868/s060-015-022-0015-6

Tian, J., and Meng, Z. (2023). Study on the effect of digital economy development on carbon emissions: evidence from 30 provinces in China. *Environ. Sci. Pollut. Res.* 30, 126088–126103. doi:10.1007/s11356-023-31019-0

Wang, D. (2023). Digitalization and climate change adaptation in China. *Green Low-Carbon Econ.* doi:10.47852/bonviewglce32021306

Wang, L., Cao, Y., Hu, J., and Skibniewski, M. J. (2024b). Does digital economy development benefit low-carbon transition: evidence based on urban carbon lock-in. *J. Environ. Plan. Manag.*, 1–30. doi:10.1080/09640568.2024.2390573

Wang, L., and Zhu, T. (2021). Does the digital economy increase energy consumption? based on the analysis of ICT application research literature. *Urban Environ. Stud.* 3, 93–108.

Wang, M., Wang, Y., Yang, Z., and Guo, B. (2024a). Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? A quasi-natural experiment from China. *Front. Environ. Sci.* 12, 1430031. doi:10.3389/fenvs.2024.1430031

Wang, S., Huang, Y., and Zhou, Y. (2019). Spatial spillover effect and driving forces of carbon emission intensity at the city level in China. *J. Geogr. Sci.* 29, 231–252. doi:10.1007/s11442-019-1594-1

Xie, Y. (2022). The effect and mechanism of digital economy on regional carbon emission intensity. *Contemp. Econ. Manag.* 44, 68–78.

Xu, A., Jin, L., and Yang, J. (2024a). Balancing tourism growth, Fintech, natural resources, and environmental sustainability: findings from top tourist destinations using MMQR approach. *Resour. Policy* 89, 104670. doi:10.1016/j.resourpol.2024.104670

Xu, A., Song, M., Wu, Y., Luo, Y., Zhu, Y., and Qiu, K. (2024b). Effects of new urbanization on China's carbon emissions: a quasi-natural experiment based on the improved PSM-DID model. *Technol. Forecast. Soc. Change* 200, 123164. doi:10.1016/j.techfore.2023.123164

Xu, H., Yang, C., Li, X., Liu, R., and Zhang, Y. (2024c). How do fintech, digitalization, green technologies influence sustainable environment in CIVETS nations? An evidence from CUP FM and CUP BC approaches. *Resour. Policy* 92, 104994. doi:10.1016/j.resourpol.2024.104994

Xu, W., Zhou, J., and Liu, C. (2022). The impact of digital economy on urban carbon emissions: based on the analysis of spatial effects. *Geogr. Res.* 41, 111–129.

Yan, X., and Zhang, Y. (2023). Empirical study on the impact of digital economy on carbon emission intensity--based on the mediating role of technological innovation. *Front. Energy Res.* 11, 1300158. doi:10.3389/fenrg.2023.1300158

Yin, L., Pan, W.-T., Kuang, J., and Zhuang, M. (2019). Application of bootstrap-DEA with fuzzy computing in performance evaluation of forklift leasing supplier. *IEEE Access* 8, 66095–66104. doi:10.1109/access.2019.2959598

Zha, Q., Huang, C., and Kumari, S. (2022). The impact of digital economy development on carbon emissions--based on the Yangtze River Delta urban agglomeration. *Front. Environ. Sci.* 10, 1028750. doi:10.3389/fenvs.2022.1028750

Zhang, H., and Feng, C. (2021). Innovative low-carbon city: carbon emission performance evaluation of innovative city construction. *South China J. Econ.* 3, 36–53.

Zhang, H., Sun, X., Bi, C., Ahmad, M., and Wang, J. (2022). Can sustainable development policy reduce carbon emissions? Empirical evidence from resource-based cities in China. *Sci. Total Environ.* 838, 156341. doi:10.1016/j.scitotenv.2022.156341

Zhang, S., Zhang, C., Su, Z., Zhu, M., and Ren, H. (2023). New structural economic growth model and labor income share. *J. Bus. Res.* 160, 113644. doi:10.1016/j.jbusres.2023.113644

Zhao, S., Guan, Y., Zhou, H., and Hu, F. (2024a). Making digital technology innovation happen: the role of the CEO's information technology backgrounds. *Econ. Model.* 140, 106866. doi:10.1016/j.econmod.2024.106866

Zhao, S., Zhang, L., An, H., Peng, L., Zhou, H., and Hu, F. (2023). Has China's low-carbon strategy pushed forward the digital transformation of manufacturing enterprises? Evidence from the low-carbon city pilot policy. *Environ. impact Assess. Rev.* 102, 107184. doi:10.1016/j.eiar.2023.107184

Zhao, S., Zhang, L., Peng, L., Zhou, H., and Hu, F. (2024b). Enterprise pollution reduction through digital transformation? Evidence from Chinese manufacturing enterprises. *Technol. Soc.* 77, 102520. doi:10.1016/j.techsoc.2024.102520

Zheng, C., and Chen, H. (2023). Revisiting the linkage between financial inclusion and energy productivity: technology implications for climate change. *Sustain. Energy Technol. Assessments* 57, 103275. doi:10.1016/j.seta.2023.103275

Zhu, D., Bahadur, W., and Ali, M. (2023). The effect of spiritual leadership on proactive customer service performance: the roles of psychological empowerment and power distance. *Humanit. Soc. Sci. Commun.* 10, 792–812. doi:10.1057/s41599-023-02273-x

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 13 December 2024
DOI 10.3389/fenvs.2024.1518120

Check for updates

OPEN ACCESS

EDITED BY
Ji Zheng,
The University of Hong Kong, Hong Kong SAR, China

REVIEWED BY
Chen Li,
Shanghai University of Engineering Sciences, China
Sheng Cheng,
China University of Geosciences Wuhan, China

*CORRESPONDENCE
Yang Yang,
yangy@bjut.edu.cn
Yuanying Chi,
goodcyy@bjut.edu.cn

RECEIVED 28 October 2024
ACCEPTED 29 November 2024
PUBLISHED 13 December 2024

CITATION
Yang Y, Yang M, Luo J, Wang Z, Chi Y and Chen Y (2024) The evolution, characteristics, and driving forces of the rural-urban HCEs in China: based on the EIO-SDA model. *Front. Environ. Sci.* 12:1518120. doi: 10.3389/fenvs.2024.1518120

COPYRIGHT
© 2024 Yang, Yang, Luo, Wang, Chi and Chen. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The evolution, characteristics, and driving forces of the rural-urban HCEs in China: based on the EIO-SDA model

Yang Yang[1]*, Meijian Yang[2], Jia Luo[1], Zhengzao Wang[1], Yuanying Chi[1]* and Yahui Chen[1]

[1]College of Economics and Management, Beijing University of Technology, Beijing, China, [2]College of Economics and Management, Anhui Polytechnic University, Wuhu, China

Households' carbon emissions (HCEs) plays an important role in the overall carbon emission (CE) reduction. This study conducts a comparative analysis of the trends and characteristics of the rural and urban HCEs in China in 1997–2020, by applying the environmental input-output (EIO) model. Then, a three-stage SDA model is applied to decompose the driving forces of the rural and urban HCEs evolution into population effect, *per capita* HCEs effect, expenditure effect, CE intensity effect, energy structure effect, and energy consumption intensity effect. It is obtained that the rural HCEs increases before 2015 and then decreases, but its *per capita* HCEs has always shown an upward trend. The urban HCEs has been increasing, but its *per capita* HCEs starts to decrease after 2015. Indirect HCEs accounts for over 80% of both the rural and urban HCEs, and Residence, Food and Tobacco, Transportation and Communication are the three biggest contributing sectors. To reveal the driving forces of the rural and urban HCEs evolution, this study conducts phase decomposition analysis with 2015 as a turning point. For rural HCEs, in 1997–2015, rural HCEs increased due to the dominant expenditure effect; from 2015 to 2020, the driving force reversed, leading to a decline in rural HCEs. For urban HCEs, the positive population and expenditure effects have always been larger than the negative energy structure and energy consumption intensity effects, resulting growth in urban HCEs. For urban *per capita* HCEs, in 1997–2015, the positive expenditure effect is greater than the negative CE intensity effect, leading to an increase in urban *per capita* HCEs, and a positive urban *per capita* HCEs effect. In 2015–2020, the driving force reversed, leading to a decline in urban *per capita* HCEs. Based on above results, countermeasures to promote rural and urban HCEs reduction are discussed.

KEYWORDS

households' carbon emissions (HCEs), evolutionary trend, characteristics, driving forces, EIO-SDA model

1 Introduction

Greenhouse gas emissions, represented by CO_2, are the primary cause of global climate change. The Paris Agreement (2015) states that to avoid a climate catastrophe, it is necessary to hold the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to

1.5°C above pre-industrial levels, and requires that countries achieve carbon neutrality by the second half of this century. As the world's largest emitter of CO_2, in 2020, General Secretary Xi Jinping committed at the general debate of the 75th Session of the United Nations General Assembly that China would strive to peak carbon emissions (CEs) before 2030 and achieve carbon neutrality before 2060 (the dual carbon goals), and has integrated these goals into the overall planning of social-economic development and ecological civilization construction, making them an intrinsic requirement and driving force for high-quality development in China. For a time, the whole society sparked a research craze on the implementation path and action plans for China's dual carbon goals. Experts and scholars explored coping strategies from multiple dimensions such as energy transition, industrial upgrading, and technological innovation (Zhang et al., 2022; Lin, 2022; Hu, 2021; He et al., 2020; Wang and Zhang, 2020). However, achieving the dual carbon goals not only requires a persistent push for innovation and reform in the supply side, but also calls for attention to the significant role of HCEs. The "Emissions Gap Report (2020)" published by UNEP indicates that household greenhouse gas emissions account for about two-thirds of the total global emissions. "Climate Change (2022): Mitigation of Climate Change" of IPCC also suggests that implementing correct policies, infrastructure, and technologies, and changing lifestyles and behaviors, would reduce greenhouse gas emissions by 40%–70% by 2050. Thus, the role of HCEs reduction in the overall CE reduction is evident. Therefore, with the urgent constraints of global climate change and China's dual carbon goals, fully revealing the evolutionary trend and characteristics of China's HCEs, clarifying its key driving factors, and proposing countermeasures to promote HCEs reduction, are vital to reduce China's HCEs and promoting the achievement of the dual carbon goals.

Currently, research on HCEs in China mainly focuses on two aspects: 1) Accounting and trend analysis of HCEs. For instance, Peng et al. (2023) analyzed the trend of HCEs in China in 2010–2017, and concluded that the amount of HCEs in China is gradually increasing, accounting for approximately one-third of China's total CEs. Mi et al. (2020) analyzed the HCEs of different income groups in China in 2007–2012 and concluded that the HCEs from the top 5% high-income groups accounted for 19% of the total HCEs, while HCEs from the bottom 50% income groups only accounted for 25% of the total HCEs. This finding is consistent with the study conducted by Wiedenhofer et al. (2017). Additionally, Xie et al. (2020) calculated the direct HCEs in Guangdong province in 1995–2017. Wang and Yang (2016) analyzed the trend of HCEs in Beijing in 2000–2010. 2) Examining the driving factors of HCEs in China. One approach involves using econometric regression models to analyze the main factors influencing HCEs and the extent of their impact. Zhao et al. (2023) employed a panel data regression model to analyze the impact of housing wealth and financial wealth on HCEs in China in 2012–2016, and concluded that housing wealth has an evidently larger impact on HCEs, almost twice as large as that of financial wealth. Shi et al. (2020) analyzed the driving forces of indirect HCEs in China in 2012–2016, and obtained that income, urban or rural residency, and fuel type are the three most important influencing factors. Li et al. (2015) analyzed the impact of urbanization on China's HCEs and concluded that the direct HCEs and indirect HCEs increased by 2.9% and 1.1%, respectively, for every 1% increase in the urbanization rate. The other approach is to decompose the evolution of HCEs by applying factor decomposition methods. Peng et al. (2021) used the SDA model to decompose the evolution of indirect HCEs in China in 2002–2017 into the effect caused by change of direct CE intensity, production technology, consumption structure, propensity to consume, income scale, and population. They concluded that income scale has always been the main driving factor promoting CE growth, while direct CE intensity is the main inhibiting factor. Liu et al. (2019) used the LMDI method to decompose the evolution of HCEs in China in 2002–2012, they obtained that *per capita* consumption is the main factor driving the HCEs growth, and that the decrease in CE intensity is the main inhibiting factor. In addition, Fan et al. (2021), Zhao et al. (2021), Yuan et al. (2019) also analyzed the main driving forces of HCEs in China.

Existing research plays a significant role in analyzing the trend of HCEs in China and its main driving factors. However, it is not hard to identify following limitations: 1) There is a lack of accounting for China's HCEs in long-term and in latest years, which makes it difficult to uncover the long-term trend and characteristics of its evolution and the current patterns; 2) In terms of driving factor decomposition, few studies have conducted phase decomposition, especially when there has been a significant turning point in the total or *per capita* HCEs. Consequently, it doesn't truly reflect the driving effects of the influencing factors at different stages. 3) Moreover, China's urban-rural dual structure is pronounced, with significant differences in the total and *per capita* HCEs, as well as the effects of driving factors. However, few studies have conducted comparative analysis of the evolution and driving factors of the rural and urban HCEs in China, leading to a lack of targetability and effectivity of countermeasures in urban and rural HCEs reduction.

Aiming at above deficiencies, this study, based on the latest long-term input-output tables of China in 1997–2020, sectoral energy consumption data, etc., conducts a comparative analysis of the evolutionary trends, characteristics, and driving forces of the rural and urban HCEs in China, by applying the EIO and SDA (EIO-SDA) model. Consequently, it proposes countermeasures to promote rural and urban HCEs reduction, which can help the implementation of China's dual carbon goals.

2 Methods and data sources

2.1 Methods

To reveal the evolutionary trends of the rural and urban HCEs in China, the sectoral accounting method provided by IPCC was applied to account the direct HCEs, and the EIO model was applied to account the indirect HCEs. Then, the SDA model was applied to quantify the effects of the driving forces in evolution of the rural and urban HCEs.

2.1.1 Accounting of HCEs in China

2.1.1.1 Accounting of direct HCEs in China

The direct HCEs is obtained from "China CO_2 inventory in 1997–2021 (by IPCC Sectoral Emission)" provided by CEADs (2024). CEADs calculated CEs of 47 sectors, including both rural

and urban direct HCEs, based on the sectoral accounting method provided by IPCC, as shown in Equation 1. $HCEs_d$ for direct HCEs, i for energy fuels, E_i for energy consumption of energy fuels, μ_i for CO_2 coefficient of energy fuels.

$$HCEs_d = \sum_i \mu_i \times E_i \quad (1)$$

2.1.1.2 Accounting of indirect HCEs in China by EIO model

EIO model has been widely used in accounting of indirect HCEs (Meng et al., 2023; Yang et al., 2022; Jakob and Marchiniski, 2013; Peters and Hertwich, 2008). It is based on the IO table and take into account the inter-relationships between economic activities and the environment. The accounting method is as shown as Equation 2. $HCEs_{ind}$ for indirect HCEs, $(I-A)^{-1}$ for Leontief inverse matrix, F_u/ F_r represent the consumption value matrices for urban or rural households, respectively, CE_m denotes the CEs of industry m, which is also obtained from "China CO_2 inventory in 1997–2021 (by IPCC Sectoral Emission)." Due to the inconsistency in the number of sectors in "China CO_2 inventory in 1997–2021 (by IPCC Sectoral Emission)" with the number of sectors in China's input-output tables, integration of some sectors is required in the accounting process. To retain as much sectoral information as possible, the sectors are integrated into 28 categories, as shown in Table A1.

$$HCEs_{ind} = \sum_m CE_m \times (I-A)^{-1} \times \left(F_u / F_r\right) \quad (2)$$

2.1.1.3 Accounting of total HCEs

The total HCEs equals the sum of direct HCEs and indirect HCEs, as shown in Equation 3.

$$HCEs = HCEs_d + HCEs_{ind} \quad (3)$$

2.1.2 SDA decomposition of evolution of HCEs in China

SDA model is a classic model for quantifying the effect of evolution of driving factors. It is based on IO table and decomposes the dependent variable into the product of several driving factors, and reflects the change of the dependent variable as the product of the changes of its driving factors. The SDA model has been widely used in decomposing the evolution of CEs (Yang et al., 2024; Yang et al., 2024; Cheng et al., 2018; Su et al., 2010).

To analyze the driving factors of HCEs, this study employs a three-stage SDA model, in which, we analyze the driving forces through a three-stage decomposition. Firstly, the evolution of HCEs is decomposed into the product of population (P) change and *per capita* HCEs ($HCEs_{pc}$) change, as shown in Equation 4. 0 and 1 represent the starting and ending years, respectively. $1/2 \times \triangle P \times (HCEs_{pc1} + HCEs_{pc0})$ reflects the change of HCEs driven by population change, which is referred to as the population effect. $1/2 \times \triangle HCEs_{pc} \times (P_1 + P_0)$ reflects the change of HCEs driven by change of *per capita* HCEs, which is referred to as the *per capita* HCEs effect.

Secondly, the change of *per capita* HCEs is decomposed into the product of change of CE intensity (CO_2 emissions per households' consumption expenditure, CI_{ex}) and the change of households' consumption expenditure (Ex). $1/2 \times \triangle CI_{ex} \times (Ex_1 + Ex_0)$ reflects the change of *per capita* HCEs driven by CE intensity change, its effect on HCEs is referred to as the CE intensity effect. $1/2 \times \triangle Ex \times (CI_{ex1} + CI_{ex0})$ reflects the change of *per capita* HCEs driven by households' consumption expenditure change, its effect on HCEs is referred to as the expenditure effect. As shown in Equation 5.

Thirdly, the change of CE intensity is furtherly decomposed into product of CE coefficient (CC_{ex}) change and change of energy consumption intensity of households' consumption expenditure (EI_{ex}). $1/2 \times \triangle CC_{ex} \times (EI_{ex1} + EI_{ex0})$ reflects the change of CE intensity driven by change of CE coefficient. Since the CC_{ex} is mainly determined by the energy structure, it effect on HCEs is referred to as the energy structure effect. $1/2 \times \triangle EI_{ex} \times (CC_{ex0} + CC_{ex1})$ reflects the change of CE intensity driven by change of energy consumption intensity, its effect on HCEs is referred to as the energy consumption intensity effect. As shown in Equation 6.

Based on the three-stage SDA model, we can quantify the driving effects of changes of population, *per capita* HCEs, CE intensity, households' consumption expenditure, energy structure, and energy consumption intensity on changes of the rural and urban HCEs.

The first-stage decomposition:

$$\begin{aligned} \triangle HCEs &= \triangle P \times \triangle HCEs_{pc} \\ &= 1/2 \times \triangle P \times \left(HCEs_{pc1} + HCEs_{pc0}\right) \\ &\quad + 1/2 \times \triangle HCEs_{pc} \times (P_1 + P_0) \end{aligned} \quad (4)$$

The second-stage decomposition:

$$\begin{aligned} \triangle HCEs_{pc} &= \triangle CI_{ex} \times \triangle Ex \\ &= 1/2 \times \triangle CI_{ex} \times (Ex_1 + Ex_0) \\ &\quad + 1/2 \times \triangle Ex \times (CI_{ex1} + CI_{ex0}) \end{aligned} \quad (5)$$

The third-stage decomposition:

$$\begin{aligned} \triangle CI_{ex} &= \triangle CC_{ex} \times \triangle EI_{ex} \\ &= 1/2 \times \triangle CC_{ex} \times (EI_{ex1} + EI_{ex0}) \\ &\quad + 1/2 \times \triangle EI_{ex} \times (CC_{ex1} + CC_{ex0}) \end{aligned} \quad (6)$$

2.2 Data sources

The input-output tables of China are obtained from the "China Statistical Yearbook" and includes 10 years of data, 1997, 2000, 2002, 2005, 2007, 2012, 2015, 2017, 2018, and 2020. Since the year 2000 only includes 17 sectors, the coarse industry classification would lead to significant changes in the direct consumption coefficients in the input-output table, thereby reducing data accuracy. Therefore, to ensure the unity of the accounting process and the reliability and comparability of the results, the indirect HCEs in 2000 is not accounted. Data of the rural and urban population, *per capita* households' consumption expenditure, and sectoral energy consumption are all sourced from the official website of the National Bureau of Statistics (2024) of China.

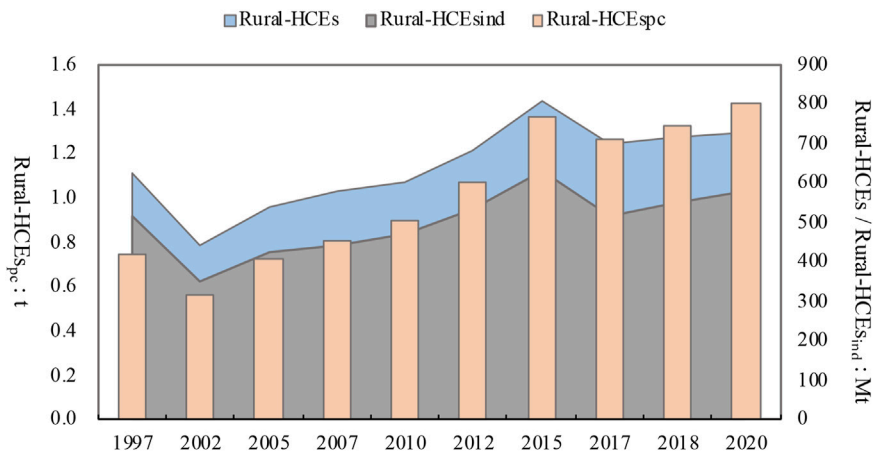


FIGURE 1
Rural-HCEs, Rural-HCEs$_{ind}$, and Rural-HCEs$_{pc}$ in China in 1997–2020.

3 Results

3.1 Overall trend comparison of HCEs in China

3.1.1 Trend of rural HCEs in China

In 1997–2020, the rural HCEs in China showed a trend of first increasing and then decreasing (Figure 1), rising from 625 Mt to 807 Mt in 2015 and then decreasing to 730 Mt in 2020. The *per capita* rural HCEs showed a wave-like upward trend, gradually increasing from 0.74 t in 1997 to 1.43 t 2020. Among rural HCEs, the proportion of indirect HCEs accounted for about 80%, which is the main component.

Combining the changes of the rural population (in 1997–2020, the total rural population in China decreased rapidly from 842 million to 510 million), rural HCEs, and rural *per capita* HCEs, it can be observed that, before 2015, the increase in rural HCEs was driven by the positive effect (+) of the increase in rural *per capita* HCEs, which outweighed the negative effect (−) of the decrease in the rural population. After 2015, the negative effect (−) of the population decrease exceeded the positive effect (+) of the increase in rural *per capita* HCEs, leading to a reduction in rural HCEs.

3.1.2 Trend of urban HCEs in China

The urban HCEs in China has shown an upward trend, increasing from 709 Mt in 1997–2,505 Mt in 2020, but the growth rate has gradually slowed down after year 2015 (Figure 2). The *per capita* urban HCEs first increased and then decreased, rising from 1.8 t in 1997 to 2.96 t in 2015, and then gradually decreasing to 2.78 t in 2020, but is still significantly higher than rural *per capita* HCEs (1.43 t). Among urban HCEs, indirect HCEs accounts for about 90%, which is higher than that of rural households.

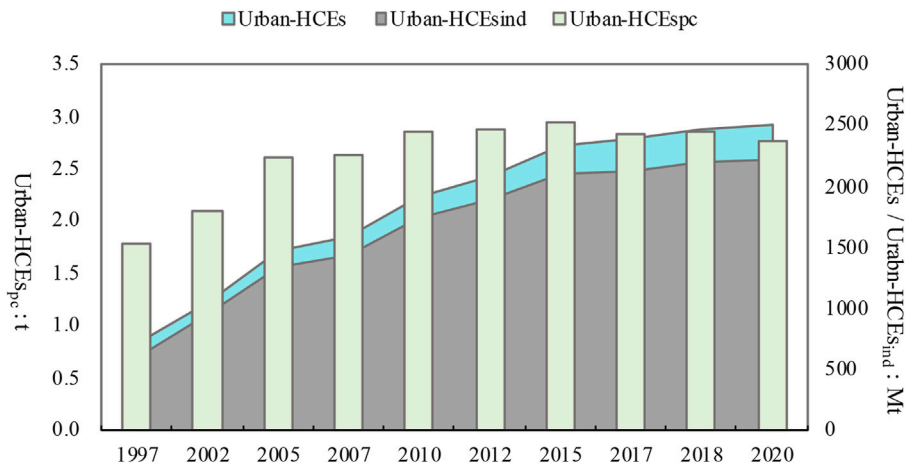


FIGURE 2
Urban-HCEs, Urban-HCEs$_{ind}$, and Urban-HCEs$_{pc}$ in China in 1997–2020.

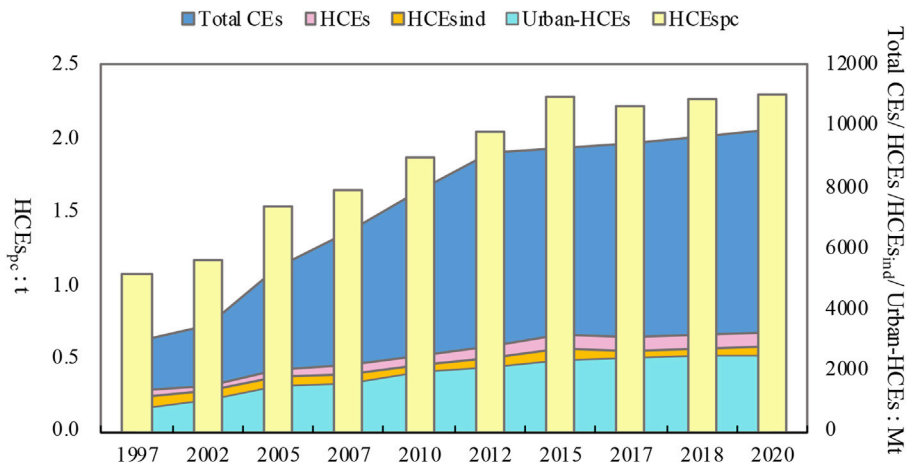


FIGURE 3
Total CEs, HCEs, $HCEs_{ind}$, Urban-HCEs, and $HCEs_{pc}$ in China in 1997–2020.

China is in the midst of rapid urbanization, with the urbanization rate increasing from 31.9% in 1997 to 63.9% in 2020, and the urban population growing from 395 million to 902 million during the same period. Combined with the evolutionary trend of the urban HCEs, it can be observed that from 1997 to 2015, the increase in urban HCEs was driven by two positive effects: the increase in urban population and the increase in *per capita* urban HCEs. After 2015, although the decrease in *per capita* urban HCEs had a negative effect on urban HCEs, it was smaller than the positive effect by the increase in urban population, thus the urban HCEs still shows an upward trend, but at a slower rate of increase.

3.1.3 Trend of the total HCEs in China

Integrating the rural and urban HCEs, the total HCEs in China showed an upward trend. It firstly increased fast from 1,333 Mt to 3,152 Mt in1997–2015 (Figure 3), with an annual growth rate of 4.9%, which was due to the rapid rise in both urban and rural HCEs. After 2015, the growth rate of total HCEs slowed down, only reaching 3,235 Mt in 2020, with an annual growth rate of 0.5%, mainly because the rural HCEs began to decline and the growth rate of urban HCEs slowed down. The total HCEs in China accounts for about one-third of its total CEs, which is consistent with the research results of Peng et al. (2023), Li et al. (2015), Liu et al. (2011), and Guan et al. (2018).

The *per capita* HCEs in China showed a significant upward trend before 2015, increasing from 1.08 t in 1997 to 2.28 t in 2015. After 2015, the variations were relatively small, with a value of 2.29 t in 2020.

In terms of urban-rural structure, the urban HCEs is the main source of HCEs in China, accounting for nearly 80%. Although *per capita* urban HCEs is on a downward trend, it is still far higher than the *per capita* level in rural areas.

In terms of emission sources, the proportion of indirect HCEs (both rural and urban included) in the total HCEs exceeds 80%. This indicates that promoting HCEs reduction not only requires attention to reduce direct energy consumption from households' electricity and energy use, but also to reduce indirect energy consumption from residence, clothing, transportation, entertainment, education, etc.

3.2 Comparison of major contributing sectors in rural and urban indirect HCEs

To reveal the main contributors of the rural and urban indirect HCEs, we interact the 28 sectors in accounting indirect HCEs with the eight consumption types (the relation between the 28 sectors and the consumption types is in Table A2). It can be obtained that Residence, Food and Tobacco, Transportation and Communication are the main contributors of both rural and urban indirect HCEs. They account for 66.65%, 9.78%, 4.54% of the rural indirect HCEs (Figure 4), and 66.68%, 9.36%, 3.23% of the urban indirect HCEs (Figure 5), respectively in 2020.

3.3 Phase analysis and driving force decomposition

3.3.1 Phase analysis

Summarizing the above analysis results, the evolution of rural and urban HCEs in China, as well as that of rural and urban *per capita* HCEs, show different trends. The rural HCEs increased before 2015 and then decreased, but its *per capita* HCEs has always shown an upward trend. The urban HCEs has been increasing, but its *per capita* HCEs started to decrease after 2015. Therefore, in order to deeply analyze the driving forces of rural and urban HCEs in China, this study conducts SDA on the evolution of rural and urban HCEs, separately. Moreover, because 2015 is a turning point for the rural HCEs and the urban *per capita* HCEs, this study conduces a phase SDA analysis of the rural and urban HCEs in 1997–2015 and 2015–2020.

3.3.2 Driving force decomposition of rural HCEs in China

From 1997 to 2015, the rural HCEs increased from 625 Mt to 807 Mt, with the population effect was −265 Mt, and the rural *per capita* HCEs effect was 448 Mt. The decrease in the rural population, which decreased from 842 million to 590 million, led to a reduction in rural HCEs by 265 Mt (Figure 6). The increase in *per capita* rural

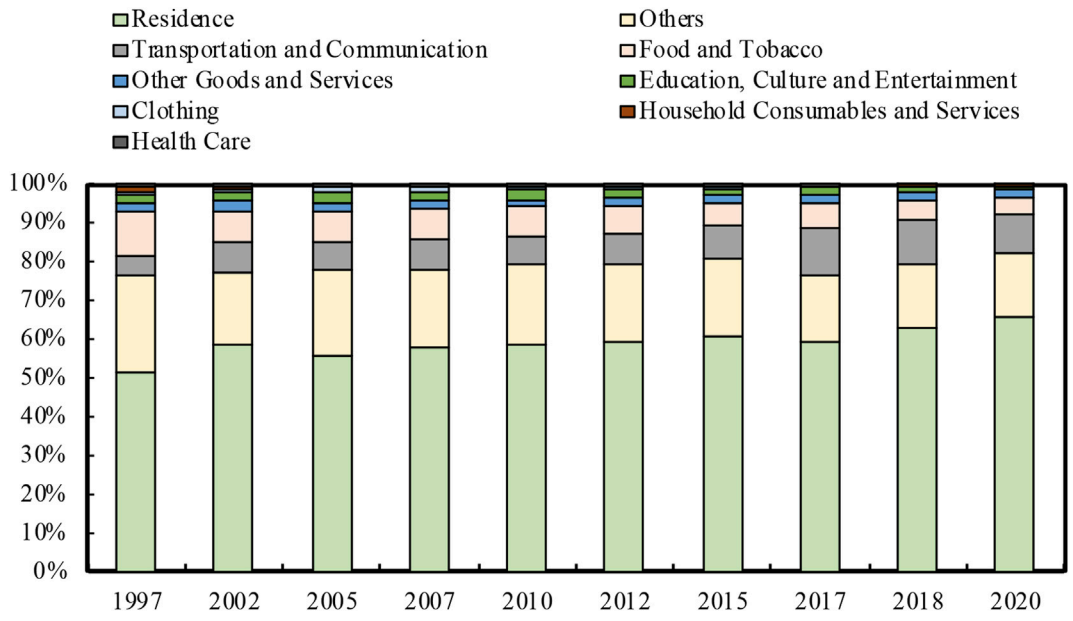


FIGURE 4
Structure of the rural indirect HCEs by consumption types in 1997–2020.

HCEs, which increased from 0.74 t to 1.37 t, contributed to an increase in rural HCEs by 448 Mt. Therefore, the rural HCEs increased. In the decomposition of *per capita* HCEs, the rise in rural households' consumption expenditure (increased from 1,617 to 9223 yuan) was the driving factor for the increase in rural *per capita* HCEs, which promotes the rural *per capita* HCEs increase by 2.31t, while the decline in CE intensity (decreased from 4.59 t/10^4 yuan to 1.67 t/10^4 yuan) was the inhibiting factor, leading to a decrease of 1.68 t for urban *per capita* HCEs. The positive driving forces of households' consumption expenditure is greater than the inhibiting forces of CE intensity, leading to a growth in rural *per capita* HCEs, and a positive expenditure effect of 1,654 Mt, and a negative CE intensity effect of −1,206 Mt, on the total rural HCEs. For change of CE intensity, the optimization of the energy structure (with the CE coefficient decreased from 1.96 to 1.67) and the reduction in energy consumption intensity (decreased from 2.34 t/10^4 to 0.89 t/10^4) in rural areas collectively push down the rural CE intensity, and correspondingly negative effects of −180 Mt and −1,026 Mt on rural HCEs, respectively.

From 2015 to 2020, The population effect remains negative, −112 Mt, the rural *per capita* HCEs effect remains positive, 35 Mt, hence rural HCEs shows a downward trend. In terms of the decomposition of change of rural *per capita* HCEs, the increase in rural households' consumption expenditure (increased from 9223 yuan to 13713 yuan) leading to an increase in rural *per capita* HCEs (0.57 t), is still higher than the decrease caused by the reduction in CE intensity (0.5 t), thus rural *per capita* HCEs continue to rise but with a declining speed, leading to a positive rural *per capita* HCEs effect of 35 Mt, a positive expenditure effect of 312 Mt, and a negative effect of −277 Mt on the rural HCEs. As a result, the negative population effect is greater than the positive *per capita* HCEs effect, and the rural HCEs starts to decrease. The effects of energy structure and energy consumption intensity continue to be negative, at −139 Mt and −138 Mt, respectively, jointly promoting the decrease in rural CE intensity.

In summary, the increase in rural households' consumption expenditure promotes an increase in rural HCEs, while the reduction in the rural population, the optimization of the energy structure, and the decrease in energy consumption intensity jointly drive its reduction. From 1997 to 2015, the negative population effect, energy structure effect, and energy consumption intensity effect is smaller than the positive expenditure effect, thus the rural HCEs increase. From 2015 to 2020, the driving forces reversed, the rural HCEs decreases.

3.3.3 Driving force decomposition of urban HCEs in China

From 1997 to 2015, the growth in urban population (increased from 395 million to 793 million, with the urbanization rate growing from 31.9% to 57.3%) and the increase in urban *per capita* HCEs (increased from 0.74 tons to 1.37 tons) jointly drove the growth in urban HCEs. The population effect and the urban *per capita* HCEs effect are 947 Mt and 689 Mt, respectively (Figure 7). For the urban *per capita* HCEs effect, the rise in urban households' consumption expenditure (increased from 4,186 yuan to 21,392 yuan) promotes the urban *per capita* HCEs increase by 4.88 t, and the decline in CE intensity (decreased from 4.59 t/10^4 yuan to 1.48t/10^4 yuan) leads to the urban *per capita* HCEs reduce by 3.72 t, causing a positive urban *per capita* HCEs effect of 689 Mt, a positive expenditure effect of 2,898 Mt, and a negative CE intensity of 2,209 Mt, respectively. Further decomposing the CE intensity effect, the optimization of the energy structure (with the CE coefficient decreasing from 1.99 to 1.85) and the decrease in energy consumption intensity (decreased from 2.16 t/10^4 yuan to 0.75 t/10^4 yuan) jointly pushed down CE intensity, thereby leading to a negative CE intensity effect. The energy structure effect and the energy consumption intensity effect were −154 Mt and −2,055 Mt, respectively.

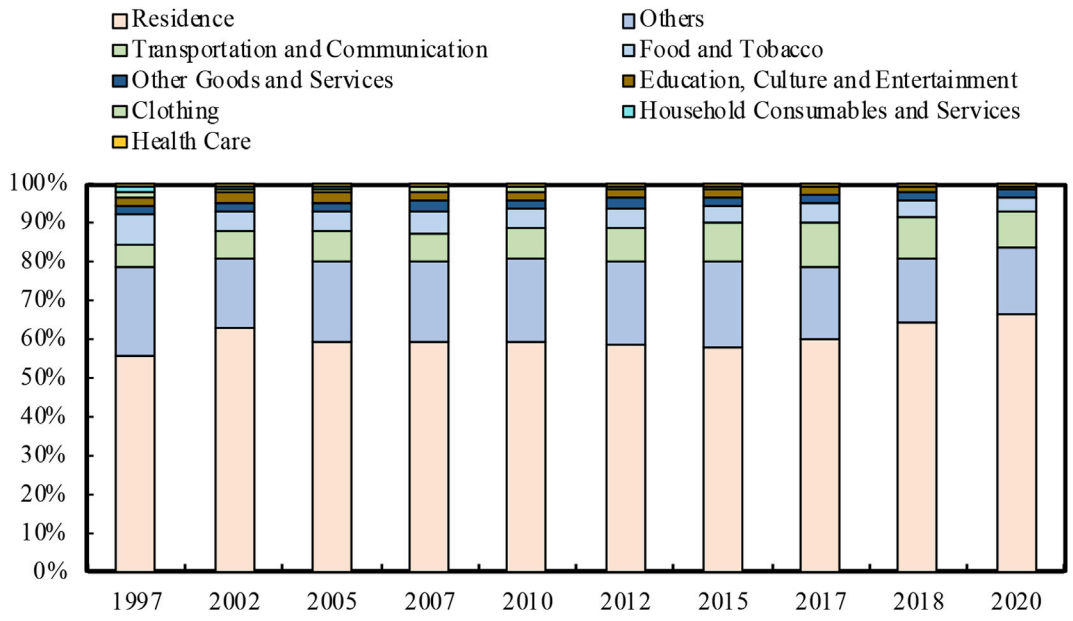


FIGURE 5
Structure of the urban indirect HCEs by consumption types in 1997–2020.

From 2015 to 2020, the continuous growth of the urban population (increased to 902.2 million, and the urbanization rate grew to 63.9%) further boosted the urban HCEs, with a population effect of 312.96 Mt. However, the urban *per capita* HCEs effect turned negative due to the decline in urban *per capita* HCEs, amounting to −153.20 Mt, which inhibits the increase in urban HCEs. Decomposing the urban *per capita* HCEs, it can be seen that the promotional effect of the rise in urban households' consumption expenditure on urban *per capita* urban HCEs (+0.68t) was smaller than the inhibitory effect of the decline in CE intensity (−0.86t), resulting in a decrease in urban *per capita* HCEs, presenting an positive expenditure effect of 573.55 Mt, while a negative CE intensity effect of −726.75 Mt. Furtherly decomposing the urban CE intensity effect, it can be obtained that the energy structure effect and the energy consumption intensity effect were −239 million tons and −487 million tons, respectively.

In summary, the increase in urban population and the rise in expenditure have promoted the growth of urban HCEs, while optimization of the energy structure and a decline in energy consumption intensity have inhibited its increase. However, the overall inhibiting effect is smaller than the promotional effect. From 1997 to 2015, the effect caused by the rise in urban households' consumption expenditure is greater than the decrease caused by the decline in CE intensity, leading to an increase in urban *per capita* HCEs, and a positive urban *per capita* HCEs effect. From 2015 to 2020, the magnitudes of the two effects were reversed, resulting in a decrease in urban *per capita* urban HCEs, a negative urban *per capita* urban HCEs effect.

4 Policy recommendations and implications

Based on above results, it can be obtained that the evolutionary trends and driving forces of rural and urban HCEs in China, as well as that of rural and urban *per capita* HCEs in China are obviously different. For urban HCEs, although the urban *per capita* HCEs have decreased, the continued rapid growth of the urban population has promoted the urban HCEs to continue rising. China is now in the process of rapid urbanization, according to the "National Population Development Plan (2016)", by 2030, the rate of permanent urbanization in China will reach 70%. The continued increase in urban population will further have a positive effect on the urban HCEs and promote its growth. For rural HCEs, although the rural HCEs shows a downward trend, this is mainly due to the decrease in the rural population. The rural *per capita* HCEs is still on the rise, and the gap between rural and urban *per capita* HCEs is still significant (the rural *per capita* HCEs is 1.43t, while the urban *per capita* HCEs is 2.78t, in 2020). In the future, as the expenditure level of rural households continues to rise, the rural *per capita* HCEs will continue to grow, leading to a positive effect on rural HCEs. Therefore, when analyzing China's HCEs and formulating policy recommendations for HCEs reduction, it is essential to fully consider the urban-rural characteristics, so as to ensure their relevance and effectiveness.

Meanwhile, China is the world's largest developing country, with a strong development momentum and tremendous potential. According to China's second centennial goal, by the mid-21st century, the *per capita* GDP should reach the level of middle-income countries, achieving a range of 40,000 to 50,000 US dollars (Wang, 2023). In the future, with China's economic growth and the improvement of people's income and expenditure levels, the expenditure effect will continue to be positive. The dual positive effects of increased urban population and increased expenditure in both urban and rural households will promote an increase in HCEs. In this case, to inhibit increase in HCEs or to promote its reduction, it is crucial to intensify efforts to optimize the energy structure and reduce energy consumption intensity. To achieve these goals, on one hand, it is necessary to develop clean

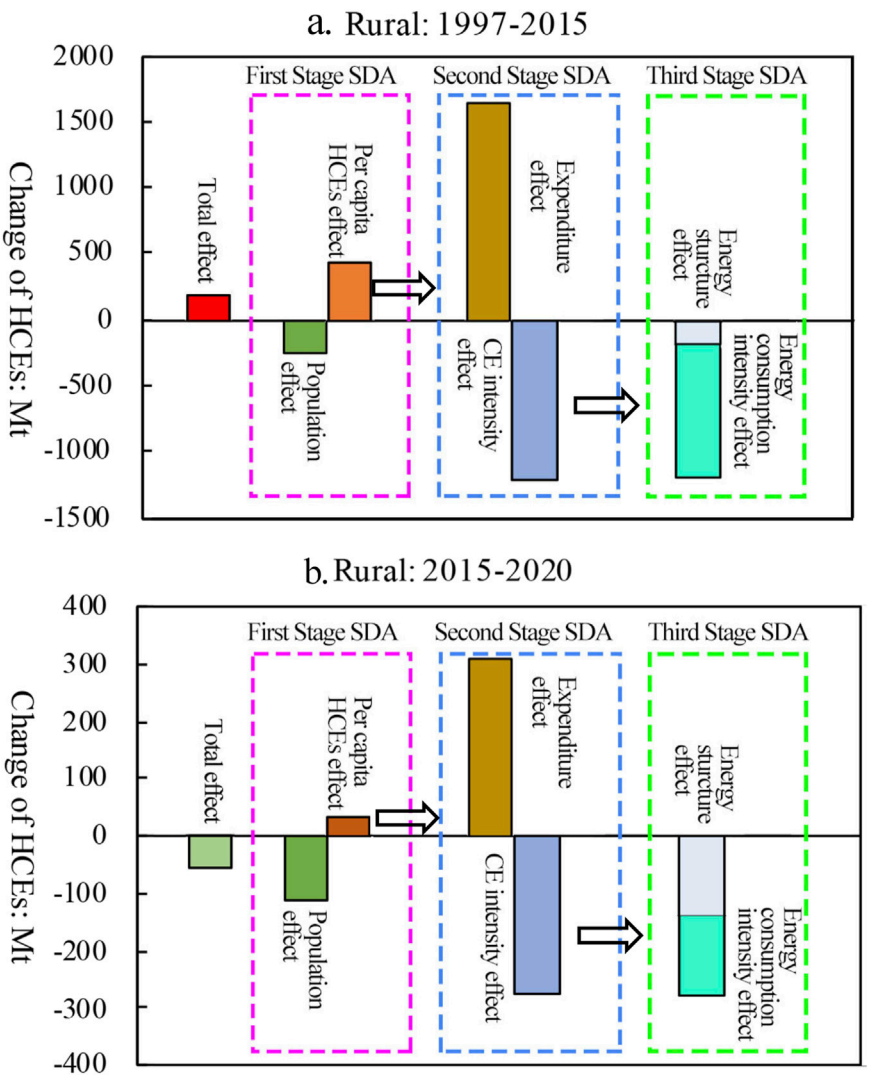


FIGURE 6
The SDA results of change of the rural HCEs in China. **(A)** Rural: 1997–2015. **(B)** Rural: 2015–2020.

and renewable energy sources, especially solar energy, to increase their proportion in the energy structure. In China, the cost of photovoltaic power generation is far lower than that of coal - fired power generation. China has a vast territory and is rich in solar energy resources. Thereby, promoting photovoltaic power generation is essential for energy conservation and CE reduction. In rural areas, utilize the advantages of rural residences to promote distributed photovoltaic power generation, and strengthen the construction of household energy - storage devices, to achieve self - sufficiency in energy use for rural households. In urban area, build distributed photovoltaic power generation systems on large - area surface areas such as the roofs and walls of industrial parks, large - scale commercial and public buildings in the city, construct solar power stations on vacant lands around the city, and integrate photovoltaic power generation into the urban power grid. In addition, use solar lights in urban street lighting, parks, squares and other lighting systems. Take multiple measures simultaneously to promote the development of renewable and clean energy in rural and urban areas. On the other, it is necessary to accelerate the construction of a circular economy system, promote the recycling of resources, and achieve energy conservation and emission reduction.

Additionally, China's HCEs accounts for one-third of the country's total CEs, with indirect HCEs accounting for over 80% (both rural and urban included). Therefore, promoting the reduction of HCEs not only requires reduction in direct energy consumption, but also in indirect energy consumption. Among the indirect HCEs, Residence, Food and Tobacco, and Transportation and Communication are the three main contributing sectors, both in rural and urban households. Thus, promoting the low-carbon transformation of households' consumption, especially low-carbon transformation of these three types, and encouraging households to adopt low-carbon consumption behaviors, such as frugal consumption, waste avoidance, recycling, and choosing low-carbon products, is of great significance. It will not only directly promote the HCEs reduction, but also indirectly incentivize the production side to save energy and reduce CEs, which is of great significance both for HCEs reduction and the overall production CEs reduction. To promote the low-carbon transformation of households'

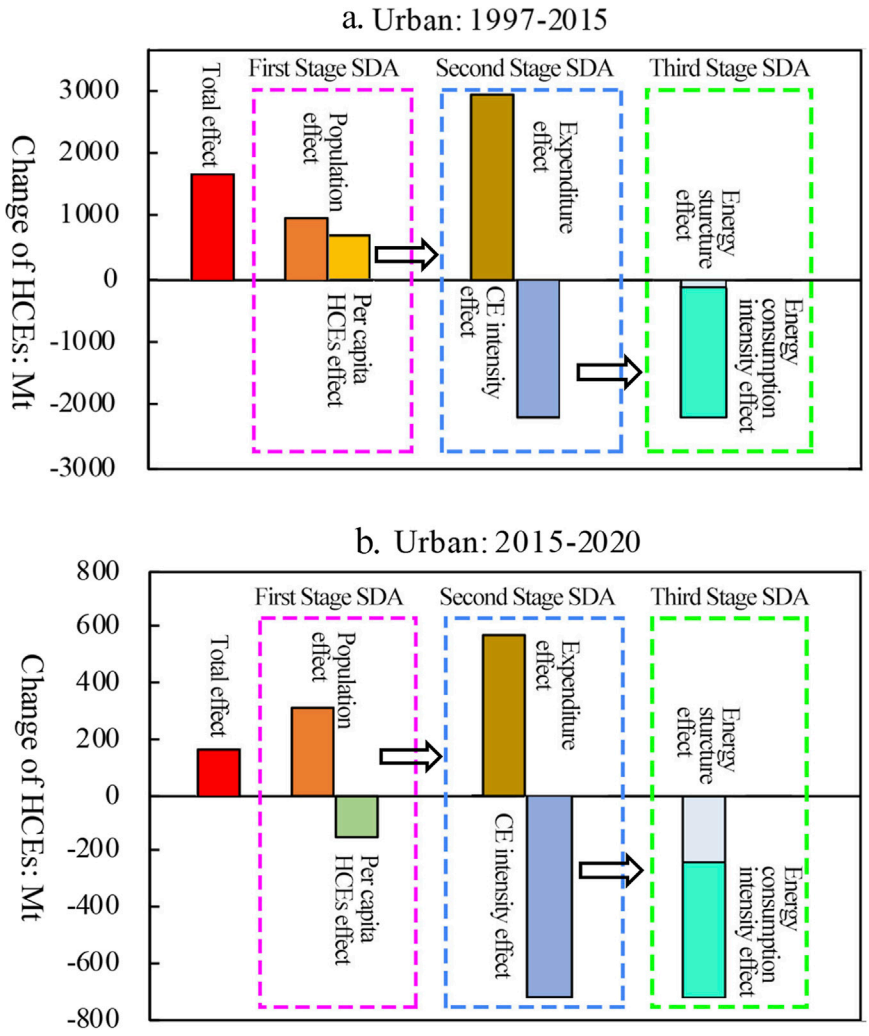


FIGURE 7
The SDA results of change of the urban HCEs in China. **(A)** Urban: 1997–2015. **(B)** Urban: 2015–2020.

consumption, following countermeasures could be implemented. ①Strengthen the publicity and promotion of low - carbon consumption, and gradually establish residents' awareness of low - carbon consumption. ② Establish a low - carbon consumption incentive mechanism. For example, subsidies can be obtained for purchasing products with lower carbon emissions among similar products. ③Moderately specify the legal obligations of residents in low-carbon consumption. For example, clearly specify in laws that residents bear the obligations of CE reduction and low - carbon consumption, etc. By integrating publicity and education, incentive mechanisms, and obligation, to promote the low - carbon transformation of households' consumption, thereby reducing the HCEs and forcing enterprises to improve energy efficiency and reduce CE intensity.

5 Conclusion

This study conducts a comparative analysis of the evolutionary trends, characteristics, and driving forces of the urban and rural HCEs in China by applying the EIO-SDA model, based on the latest long-term input-output tables of China from 1997 to 2020, sectoral energy consumption data, etc. It is acquired that the evolutionary trends and driving forces of rural and urban HCEs in China, as well as that of rural and urban *per capita* HCEs in China vary significantly. The rural HCEs increased before 2015 and then decreased, but the *per capita* HCEs has always shown an upward trend. The urban HCEs has been increasing, but its *per capita* HCEs started to decrease after 2015. The indirect HCEs accounting for over 80% of the total HCEs, and Residence, Food and Tobacco, Transportation and Communication are the three main contributing sectors, both for rural and urban households.

For driving forces, the rural HCEs: the increase in rural households' consumption expenditure promotes an increase in rural HCEs, while the reduction in the rural population, the optimization of the energy structure, and the decrease in energy consumption intensity jointly drive its reduction. From 1997 to 2015, the negative population effect, energy structure effect, and energy consumption intensity effect is smaller than the positive expenditure effect, thus the rural HCEs increase. From 2015 to 2020,

the magnitudes of these effects were reversed, the rural HCEs decreases. For rural *per capita* HCEs, its expenditure effect is always bigger than the CE intensity effect, thus the rural *per capita* HCEs keeps rising. For urban HCEs, the increase in urban population and the rise in expenditure have promoted the growth of urban HCEs, while optimization of the energy structure and a decline in energy consumption intensity have inhibited its increase. However, the overall inhibiting effect is smaller than the promotional effect. From 1997 to 2015, the effect caused by the rise in urban households' consumption expenditure was greater than the decrease caused by the decline in CE intensity, leading to an increase in urban *per capita* HCEs, and a positive urban *per capita* HCEs effect. From 2015 to 2020, the magnitude of the two effects was reversed, resulting in a decrease in urban *per capita* urban HCEs, a negative urban *per capita* urban HCEs effect.

Based on above results, some policy implications were proposed, including fully consider the urban-rural characteristics, so as to ensure policies' relevance and effectiveness, intensify efforts to optimize the energy structure and reduce energy consumption intensity, promotes the low-carbon transformation of households' consumption and encourage households to adopt low-carbon consumption behaviors. This study can promote urban and rural HCEs reduction, and help the implementation of China's dual carbon goals.

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

YY: Conceptualization, Formal Analysis, Funding acquisition, Methodology, Writing–original draft. MY: Data curation, Formal Analysis, Methodology, Writing–original draft. JL: Conceptualization, Methodology, Writing–original draft. ZW: Formal Analysis, Methodology, Writing–review and editing. YuC: Conceptualization, Formal Analysis, Supervision, Writing–review and editing. YaC: Data curation, Methodology, Writing–original draft.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This work is funded by the Science and Technology Basic Resources Investigation Program of China (2022FY101903), National Natural Science Foundation of China (72304026 and 72140001).

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 author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

CEADs (2024). China CO2 inventory in 1997-2021 (by IPCC sectoral emissions). *CEADs*. Available at: https://www.ceads.net.

Cheng, H., Dong, S. C., Li, F. J., Yang, Y., Li, S. T., and Li, Y. (2018). Multiregional input-output analysis of spatial-temporal evolution driving force for carbon emissions embodied in interprovincial trade and optimization policies: case study of northeast industrial district in China. *Environ. Sci. Technol.* 52, 346–358. doi:10.1021/acs.est.7b04608

Climate Change (2022). Mitigation of climate change. *IPCC*. Available at: https://www.ipcc.ch/report/ar6/wg3/.

Emissions Gap Report (2020). *Emissions gap Report*. Nairobi, Kenya: UNEP. Available at: https://www.unep.org/emissions-gap-report-2020.

Fan, J. S., Zhou, L., Zhang, Y., Shao, S., and Ma, M. (2021). How does population aging affect household carbon emissions? Evidence from Chinese urban and rural areas. *Energy Econ.* 100, 105356. doi:10.1016/j.eneco.2021.105356

Guan, D. B., Meng, J., David, R., Zhang, N., Shan, Y. L., Mi, Z. F., et al. (2018). Structural decline in China's CO_2 emissions through transitions in industry and energy systems. *Nat. Geosci.* 11, 551–555. doi:10.1038/s41561-018-0161-1

He, J. K., Li, Z., and Zhang, X. L. (2020). Comprehensive report on China's long-term low-carbon development strategy and transformation path. China Pop. Resour. *Environ.* 30 (11), 1–25. doi:10.12062/cpre.20201025

Hu, A. G. (2021). China's goal of achieving carbon peak by 2030 and its main approaches. *J. Beijing Univ. Technol.* 21 (03), 1–15. doi:10.12120/bjutskxb202103001

Jakob, M., and Marchiniski, R. (2013). Interpreting trade-related CO_2 emissions transfers. *Nat. Clim. Change* 3, 19–23. doi:10.1038/nclimate1630

Li, Y. M., Zhao, R., Liu, T. S., and Zhao, J. F. (2015). Does urbanization lead to more direct and indirect household carbon dioxide emissions? Evidence from China during 1996–2012. *J. Clean. Prod.* 102, 103–114. doi:10.1016/j.jclepro.2015.04.037

Lin, B. Q. (2022). China's high-quality economic growth in the process of carbon neutrality. *Econ. Res. J.* 57 (01), 56–71.

Liu, L. C., Gang, W., Jnw, A., and Ymwb, D. (2011). China's carbon emissions from urban and rural households during 1992–2007. *J. Clean. Prod.* 19, 1754–1762. doi:10.1016/j.jclepro.2011.06.011

Liu, X. Y., Wang, X. A., Song, J. N., Wang, H. N., and Wang, S. (2019). Indirect carbon emissions of urban households in China: patterns, determinants and inequality. *J. Clean. Prod.* 241, 118335. doi:10.1016/j.jclepro.2019.118335

Ma, X. W., Ye, Y., Du, J., and Li, H. Z. (2016). Calculation and analysis on indirect carbon emissions from household consumption between China and the United States based on input-output model. *J. Beijing Inst. Technol. Soc. Sci. ed.* 18 (1), 24–29. doi:10.15918/j.jbitss1009-3370.2016.0104

Meng, J., Huo, J. W., Zhang, Z. K., Liu, Y., Mi, Z. F., Guan, D. B., et al. (2023). The narrowing gap in developed and developing country emission intensities reduces global trade's carbon leakage. *Nat. Commun.* 14 (1), 3775. doi:10.1038/s41467-023-39449-7

Mi, Z. F., Zheng, J. L., Meng, J., Qu, J. M., Hubacek, K., Liu, Z., et al. (2020). Economic development and converging household carbon footprints in China. *Nat. Sustain.* 3 (7), 529–537. doi:10.1038/s41893-020-0504-y

National Bureau of Statistics (2024). Annual data. National Bureau of Statistics of China. Available at: https://www.stats.gov.cn.

National Population Development Plan (2016). State Council of China. Beijing, China, 12–30. Available at: https://www.gov.cn/gongbao/content/2017/content_5171324.htm.

Paris Agreement (2015). The UN. Available at: https://www.un.org/en/climatechange/paris-agreement.

Peng, L. L., Li, N., Zheng, Z. Y., Li, F., and Wang, Z. (2021). Spatial-temporal heterogeneity of carbon emissions and influencing factors on household consumption of China. *China Environ. Sci.* 41 (01), 463–472. doi:10.19674/j.cnki.issn1000-6923.2021.0052

Peng, S., Wang, X., Du, Q., Wu, K. R., Lv, T. T., Tang, Z., et al. (2023). Evolution of household carbon emissions and their drivers from both income and consumption perspectives in China during 2010-2017. *J. Environ. Manage.* 326, 116624. doi:10.1016/j.jenvman.2022.116624

Peters, G. P., and Hertwich, E. G. (2008). CO_2 embodied in international trade with implications for global climate policy. *Environ. Sci. Technol.* 42, 1401–1407. doi:10.1021/es072023k

Shi, X. P., Wang, K. Y., Cheong, T. S., and Zhang, H. W., 2020. Prioritizing driving factors of household carbon emissions: An application of the LASSO model with survey data. *Energy Econ.* 92, 104942. doi:10.1016/j.eneco.2020.104942

Su, B., Huang, H. C., Ang, B. W., and Zhou, P. (2010). Input-output analysis of CO_2 emissions embodied in trade: the effects of sector aggregation. *Energy Econ.* 32, 166–175. doi:10.1016/j.eneco.2009.07.010

Wang, C., and Zhang, Y. X. (2020). Implementation pathway and policy system of carbon neutrality vision. *Chin. J. Environ. Manage.* 12 (06), 58–64. doi:10.16868/j.cnki.1674-6252.2020.06.058

Wang, Y. M. (2023). Promote Chinese-style modernization with high-quality development. Available at: http://theory.people.com.cn/n1/2023/0407/c40531-32659090.html.

Wang, Z. H., and Yang, Y. T. (2016). Features and influencing factors of carbon emissions indicators in the perspective of residential consumption: evidence from Beijing, China. *Ecol. Indic.* 61 (2), 634–645. doi:10.1016/j.ecolind.2015.10.015

Wiedenhofer, D., Guan, D. B., Liu, Z., Meng, J., Zhang, N., and Wei, Y. M. (2017). Unequal household carbon footprints in China. *Nat. Clim. Change* 7 (1), 75–80. doi:10.1038/nclimate3165

Xie, Z. Q., Gao, X. N., Yuan, W. H., Fang, J. D., and Jiang, Z. B. (2020). Decomposition and prediction of direct residential carbon emission indicators in Guangdong Province of China. *Ecol. Indic.* 115, 106344. doi:10.1016/j.ecolind.2020.106344

Yang, Y., Dong, S. C., Li, F. J., Cheng, H., Chi, Y. Y., Li, Z. H., et al. (2022). Interregional polarized and trickling-down effect of carbon emission space and the optimization policies: case studies of the Jing-Jin-Ji region. *J. Clean. Prod.* 370, 133426. doi:10.1016/j.jclepro.2022.133426

Yang, Y., Zhou, Y. N., Shan, Y. L., and Klaus, H. (2024). The shift of embodied energy flows among the Global South and Global North in the post-globalisation era. *Energy Econ.* 107408. doi:10.1016/j.eneco.2024.107408

Yuan, R., Rodrigues, J., and Behrens, P. (2019). Driving forces of household carbon emissions in China: a spatial decomposition analysis. *J. Clean. Prod.* 233, 932–945. doi:10.1016/j.jclepro.2019.06.110

Zhang, X. L., Huang, X. D., Zhang, D., Geng, Y., Tian, L. X., Fan, Y., et al. (2022). Research on the pathway and policies for China's energy and economy transformation toward carbon neutrality. *Manage. World.* 38 (01), 35–66. doi:10.19744/j.cnki.11-1235/f.2022.0005

Zhao, L. T., Zhao, T., and Yuan, R. (2021). Drivers of household decarbonization: decoupling and decomposition analysis. *J. Clean. Prod.* 289, 125154. doi:10.1016/j.jclepro.2020.125154

Zhao, M. X., Yuan, Z. H., and Chan, H. S. (2023). Housing wealth and household carbon emissions: the role of homeownership in China. *Ecol. Econ.* 212, 107908. doi:10.1016/j.ecolecon.2023.107908

Zhao, Y. H., Li, W. L., and Wang, S., 2018. Calculation and driving forces of indirect carbon emissions from household consumption in Beijing. *J. Beijing Inst. Technol. Soc. Sci. ed.* 20(3), 33–44. doi:10.15918/j.jbitss1009-3370.2018.3265

Appendix

TABLE A1 The names of the 28 sectors.

Sector	Name	Sector	Name
S1	Agriculture	S15	Metal products
S2	Coal mining and processing	S16	Machinery and equipment
S3	Crude petroleum and natural gas products	S17	Transport equipment
S4	Metal ore mining	S18	Electric equipment and machinery
S5	Non-ferrous mineral mining	S19	Electronic and telecommunication equipment
S6	Manufacture of food products and tobacco processing	S20	Instruments, meters cultural and office machinery
S7	Textile goods	S21	Other manufacturing products
S8	Wearing apparel, leather, furs, down and related products	S22	Electricity steam and hot water production and supply
S9	Wood processing and furniture	S23	Gas production and supply
S10	Paper and products, printing and record medium reproduction	S24	Water production and supply
S11	Petroleum processing and coking	S25	Construction
S12	Chemicals	S26	Transport, storage and post
S13	Nonmetal mineral products	S27	Wholesale, retail trade and hotel, restaurants
S14	Metals smelting and pressing	S28	Others

TABLE A2 The interactive relation between the 28 sectors and the consumption types.

Code	Consumption types	Corresponding sectors
1	Food and Tobacco	Agriculture, Manufacture of food products and tobacco processing
2	Clothing	Textile goods, Wearing apparel, leather, furs, down and related products
3	Residence	Nonmetal mineral products, Metal products, Electricity steam and hot water, Gas production and supply, Water production and supply, Construction
4	Household Consumables and Services	Electric equipment and machinery, Other manufacturing products
5	Transportation and Communication	Transport equipment, Electronic and telecommunication equipment, Transport, storage and post
6	Education, Culture and Entertainment	Paper and products, printing and record medium reproduction, Instruments, meters cultural and office machinery, Wholesale, retail trade and hotel, restaurants
7	Health cCare	Machinery and equipment
8	Other Goods and Services	Other sectors
9	Others	Coal mining and processing, Crude petroleum and natural gas products, Metal ore mining, Non-ferrous mineral mining, Petroleum processing and coking, Chemicals, Metals smelting and pressing

Note: The relation between sectors and consumption types is established based on research of Peng et al. (2021), Zhao et al. (2018), and Ma et al. (2016).

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 23 January 2025
DOI 10.3389/fenvs.2025.1539223

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Guoxiang Li,
Nanjing Normal University, China
Bright Obuobi,
Nanjing Forestry University, China

*CORRESPONDENCE
Kaiyi Song,
497202408@qq.com

RECEIVED 04 December 2024
ACCEPTED 08 January 2025
PUBLISHED 23 January 2025

CITATION
Hu R and Song K (2025) Carbon reduction effects of government digital attention. *Front. Environ. Sci.* 13:1539223. doi: 10.3389/fenvs.2025.1539223

COPYRIGHT
© 2025 Hu and Song. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Carbon reduction effects of government digital attention

Rong Hu[1] and Kaiyi Song[2]*

[1]School of Air Transportation and Engineering, Nanjing University of Aeronautics and Astronautics Jincheng College, Nanjing, Jiangsu, China, [2]School of Business, Nanjing Xiaozhuang University, Nanjing, China

In the digital economy era, increasing government's adoption and attention to digital technology is not only conducive to accelerating the improvement of governance capacity, but also an important measure to achieve green economic development. This paper uses text analysis to measure the government digital attention at the city level, and then uses panel data econometric models to estimate the impact of government digital attention on carbon emissions reduction. The findings reveal that government digital attention can significantly reduce carbon dioxide emissions by improving the government's low-carbon governance, strengthening the public's low-carbon attention, and encouraging the enterprises' low-carbon transformation. Further, government digital attention mainly reduces carbon dioxide from direct energy consumption, transportation and electricity product. The carbon reduction effect of government digital attention is also affected by degree of marketization, and the high degree of marketization helps to reinforce the effect. Moreover, there is spatial heterogeneity in the effect, it is more significant in the eastern region. Our conclusions are then of important implications for promoting China's carbon dioxide reduction and achieving high-quality sustainable development.

KEYWORDS

government digital attention, carbon reduction, low-carbon governance, public concern, enterprise low-carbon transformation

1 Introduction

In the face of increasingly serious environmental and climate issues, the Chinese government has made achieving carbon reduction an important aspect of promoting high-quality economic development in recent years. In 2020, the Chinese government proposed at the 75th United Nations General Assembly: "China will increase its nationally determined contributions, adopt more effective policies and measures, strive to peak carbon dioxide emissions before 2030, and strive to achieve carbon neutrality before 2060".[1] This has also become an important goal constraint for China's low-carbon transformation at present.

Especially after entering the digital economy era, with the popularization of technologies such as the Internet of Things, cloud computing, and big data, the Chinese government attaches great importance to applying digital technology to social governance and high-quality economic development. The *14th Five Year Plan* clearly

1 Originating from the speech of Chinese President Xi Jinping at the 75th General Debate of the United Nations General Assembly on 20 September 2020.

pointed out that accelerating digital development, building a digital China, and promoting deep integration of digital technology and real economy.[2] The government is increasingly valuing the application of digital technology and placing greater emphasis on it in order to better rely on digital technology to enhance governance capabilities and help the economy and society achieve low-carbon transformation. For example, on 26 October 2021, China issued the *Action Plan for Peaking Carbon Emissions Before 2030*, which clearly stated the need to promote the integration of digital, intelligent, green and integrated development. More importantly, government digital attention can not only optimize its own carbon reduction policies, but also help improve the carbon footprint of micro subjects, including the public low-carbon concern and enterprise low-carbon transformation.

Specifically, the application of digital technology in governance helps to improve the government's access to more economic information (Li and Yue, 2025), strengthen its supervision of enterprise carbon emissions, and achieve low-carbon governance. Government digital attention has diversified social governance channels and opened up channels for expressing public environmental demands (Yuan et al., 2023), enhanced public attention to low-carbon initiatives. Besides, the allocation of enterprise attention is closely linked to government actions. Government digital attention will achieve proactive induction, guiding enterprises to pay attention to the government's carbon reduction policies, thereby incentivizing enterprises to achieve low-carbon transformation.

Exploring the influencing factors of carbon reduction has always been one of the important fields concerned by the academic. The explanation based on data enabling attributes in the new era has become a very important entry point. More and more scholars have discussed the factors affecting the carbon emissions from the economic development, energy structure, industrial structure, technological progress, population size, green finance, etc. (Rahman et al., 2022; Danish et al., 2019; Zhang et al., 2025). For China during the transition period, the government plays a direct or indirect role in promoting regional sustainable development and carbon emissions (Xian et al., 2025). However, previous studies have not paid attention to how the government's attention to digital technology affects regional carbon emissions reduction after entering the digital economy era. This paper is based on attention theory and examines the impact mechanism and effect of government digital attention on regional carbon reduction within the tripartite framework of government-public-enterprise.

This paper may have the following two marginal contributions. (1) This paper is based on the background of government governance in the digital economy era, and from the perspective of government digital attention, focuses on exploring the impact of government digital attention on carbon reduction. This may help to gain a more comprehensive understanding of low-carbon governance strategies in the digital economy era and provide more perspectives for studying the key factors affecting low-carbon development. (2) This paper focuses on the three main entities of government, public, and enterprises in low-carbon development, and examines the impact mechanism of government digital attention on carbon reduction from three aspects: government low-carbon governance, public low-carbon attention, and enterprise low-carbon transformation. It examines the promoting role of government attention to digital technology in fulfilling governance responsibilities, authorizing multi-party governance, and optimizing corporate attention allocation. This also helps to gain a more comprehensive understanding of the pathways through which government digital attention affects regional carbon emissions.

The following is arranged as follows: The second part is literature review; The third part is the mechanism analysis; The fourth part is empirical analysis, constructing the econometric model and introducing the data selection as well as variable construction. The fifth part is the analysis and discussion of estimation results. The sixth part is extended analysis; Finally, we summarize the above conclusions and draw policy implications.

2 Literature review

Government digital attention can be understood as government's concern about the application of digital technology and the development of digital economy. The academic research on concepts such as government digitization, digital government generally revolves around three aspects: enabling elements, process reengineering, and transformation goals. In terms of enabling elements, the scholars generally agreed that government digitalization takes digital technology as governance means, digital space as governance field, and data itself as governance (Chen and Liu, 2022; Luna-Reyes and Gil-Garcia, 2014; Luca et al., 2021; Hamish et al., 2021). In terms of process reengineering, it can be simply defined as the use of digital technology by government organizations to implement their governance processes. Lee et al. (2016) proposed that digital government should not be limited to breakthroughs at the technical level. More importantly, it should achieve overall governance by integrating institutional functions and reengineering work processes. In terms of transformation goals, digital government should realize digitalization, intelligence and precision of government services (Guo and Lin, 2022), effectively coordinate the relationship between government, market, and society (Mergel et al., 2019), and provide government services to stakeholders of a country.

Existing studies have basically held a positive attitude towards the role of digital government in improving the social governance. Digital government can promote information disclosure (Sohail et al., 2020), citizens' participation in government affairs and the development of accountability system, which will help transform government functions (Yang et al., 2024), and build a service-oriented government (Han and Zhang, 2024). Government digitalization can ensure a stable, orderly and vibrant society by enabling multiple entities to participate in social governance, thus improving the quality of governance (Xing and Yao, 2022). In addition, many scholars' research has focused on the impact of digital government, including the technological innovation (Li et al., 2023), manufacturing productivity (Yu et al., 2025), enterprises'

2 *Outline of the 14th Five Year Plan for National Economic and Social Development of the People's Republic of China and the Long-Range Objectives by 2035*. www.gov.cn.

intelligent transformation (Zhang and Zhang, 2025) and digital transformation (Li and Yue, 2025). Currently, there is little research on the impact of government digitization on the natural environment and sustainable development. Castro and Lopes (2022) proposed that digital government is conducive to efficient resource management, so it can help improve the current use of natural resources. Destek et al. (2024) found that digitalization of the public sector can reduce resource rich countries' dependence on natural resources. Tang et al. (2025) also verified the positive impact of digital government construction on the improvement of enterprise energy efficiency based on empirical research in China, and Jiang et al. (2024) also reached a relatively consistent conclusion in their study.

Carbon dioxide emissions mainly come from the production and consumption behavior of human society. The production and consumption in the reproduction cycle play a decisive role in carbon dioxide emissions. For a long time, China's industrial development has been mainly driven by the secondary industry, which has not only promoted rapid economic growth but also led to a rapid increase in energy consumption that mainly relies on fossil fuels, resulting in a significant increase in carbon emissions. When *per capita* GDP exceeds a certain threshold, people's attention to environmentally sustainable development will prompt them to take measures to reduce carbon dioxide emissions (Wang et al., 2024). However, for China, which is currently in a transitional period, scholars tend to study the main factors affecting carbon emissions from the perspective of government or institutions (Yang et al., 2022). Under the socialist market economy system with Chinese characteristics, the government plays an important role in economy operation. Through the mutual cooperation between various levels of government and the combination of policy tools, it generates important expectations and guidance for the economic behavior of market micro entities, changes their carbon footprint. Some studies believed that China's fiscal decentralization distorts the incentive mechanisms of local governments, leading to excessive use of fossil fuels for short-term economic performance and resulting in severe carbon emissions (Zhao et al., 2023). However, the results of Cai et al. (2025) shown that fiscal decentralization significantly aids carbon reduction, but stronger environmental regulations have not effectively slowed emission growth, creating a "green paradox."

In recent years, with the rapid development of the digital economy, some studies have also examined the government digital attention and its impact effects. For example, the study by Zhang et al. (2024) found that government attention to digital technology can promote regional digital economic development; Li and Yue (2025) also found that government digital attention promotes digital economy output efficiency through data openness mechanism and data flow mechanism. However, previous literature still lacks research on the relationship between government digital attention and carbon reduction. In fact, the government attention to the digital economy and digital technology can help promote low-carbon governance, stimulate low-carbon transformation of enterprises, and also influence public low-carbon attention, thereby reducing regional carbon emissions. Neglecting this factor will inevitably hinder the investigation of the main factors of regional carbon emissions, especially for us to explore how the improvement of government governance capacity affects carbon reduction in the digital economy.

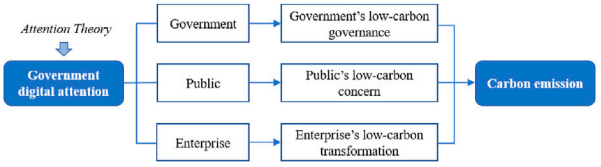


FIGURE 1
Impact mechanism framework.

3 Influence mechanism analysis

Attention theory provides a good explanatory framework for examining the impact of government digital attention on carbon dioxide emissions. In government decision-making, the attention of decision-makers is often seen as a scarce resource. The allocation of attention by the government demonstrates the importance placed on specific affairs, guiding the focus of attention of social entities (enterprises, residents). In the era of digital economy, government digital attention reflects the government's inclusion of digital economy development into the decision-making agenda (such as reflecting digital economy and digital technology in government work reports), emphasizing the use of digital technology to achieve social governance. This not only affects the efficiency of government governance, but also affects production and consumption activities in the economy, such as green economy and carbon dioxide emissions.

The carbon emissions in the real economy mainly come from production and consumption activities, involving three main entities: government, public, and enterprises. On the one hand, as the macro-regulator, various policies promulgated by the government will affect the behavior of micro-subjects and change their carbon footprint. Moreover, as a part of the huge national machine, the carbon emissions generated by the government's own operation cannot be ignored. On the other hand, public life generates carbon dioxide emissions through transportation and heat consumption, accounting for a relatively large proportion of the total carbon emissions in China. In addition, the energy input of China's manufacturing enterprises is still mainly concentrated in fossil fuels, which generates a large amount of carbon emissions. Government digital attention will have a certain impact on the government, the public and enterprises. It will promote carbon reduction from three aspects: government low-carbon governance, the public low-carbon concern and enterprise low-carbon transformation, as shown in Figure 1.

3.1 Government low-carbon governance

Government digital attention can help the government integrate various information resources using digital technology. This helps to better identify green violations, strengthen government green governance, and promote carbon reduction. Specifically, government digital attention will increase the utilization of digital technology and promote the digital transformation of the government itself (Peng et al., 2024). On the one hand, traditional government is often restricted by problems such as

small information volume and blurred sources of information. There is a "blind area" of low-carbon governance, resulting in the government's inability to fully identify social events that violate carbon emissions. The government uses digital technologies such as the Internet to collect and process environmental behavior data of more microeconomic entities, promote information sharing, and provide guarantee for the government to accurately identify carbon emission violations (Bayat and Kawalek, 2023). On the other hand, digital information systems can be used to monitor government workflows and expose corrupt practices, greatly strengthening the hierarchical accountability within the state apparatus (Shim and Eom, 2008); Moreover, in the application of digital technology, the disclosure of government governance information also helps to strengthen the supervision of civil society and media over the government, leading to an increase in external diagonal accountability (Agostino et al., 2021). The strengthening of the accountability system has changed the traditional situation of chaotic and decentralized governance, and effectively implemented environmental protection issues. Effectively controlling the "black box" operation of enterprises, social organizations, and other organizations in the context of excessive carbon emissions also helps the government achieve low-carbon governance.

In addition, as a large national organizational system, the carbon dioxide generated by the operation of the government itself accounts for an indispensable part of carbon emissions. Low carbon governance by the government can effectively guide energy conservation and emission reduction within government departments. More importantly, low-carbon governance by the government can release positive environmental signals, enabling businesses and the public to optimize their own behavior and reduce carbon emissions in production and consumption. Therefore, the following hypothesis is proposed in this paper:

Hypothesis 1. Government digital attention helps to achieve low-carbon governance and promote carbon reduction.

3.2 Public low-carbon concern

Government digital attention can encourage more social entities to participate in social governance, raise public awareness of low-carbon environmental protection, and motivate them to reduce carbon emissions. Due to the single perspective and limited subject of traditional government decision-making, single-center government intervention cannot fundamentally solve externality problems. Many carbon reduction policies do not resonate well in society, resulting in low governance efficiency and slow progress of carbon emission reduction. Government digital attention will strengthen the use of modern information technology and form a structured innovation in digital governance, which can help lower the threshold of public participation in governance, and achieve cooperate working (Xing and Yao, 2022). While ensuring the effectiveness of decision-making, it helps strengthen the public's awareness of environmental protection and then realize the public's low-carbon concern. In addition, digital governance is conducive to improving governance transparency and strengthening internal and external accountability. This will motivate the government to shift its focus to providing public services to the public and form a common interest with the public. While the public has environmental rights, it also enhances environmental awareness and forms an inherent driving force for carbon reduction (Zhao et al., 2023). More importantly, as a populous country, the proportion of carbon emissions generated by the public to total emissions continues to rise with the improvement of living standards (Yuan et al., 2024). The public's concern to low-carbon will effectively control the carbon emissions caused by lifestyle and economic activities, thereby promoting carbon reduction. Therefore, the following hypothesis is proposed in this paper:

Hypothesis 2. Government digital attention can guide public low-carbon concerns, thereby helping to promote carbon reduction.

3.3 Enterprise low-carbon transformation

Government digital attention can optimize the allocation of enterprise attention through "active induction", promote enterprise innovation and improve production methods, and achieve low-carbon transformation. On the one hand, the measures taken by the government to achieve established social goals are a prominent background for the allocation of corporate attention, as these measures are crucial to the operation of enterprises (Nambisan et al., 2019). Enterprises identify business opportunities by evaluating changes in government policies (Tuggle et al., 2010), and develop targeted development plans accordingly. Government digital attention not only promotes the process of government digital transformation, but also helps to reduce the distance between the government and enterprises, and reduce the difficulty for enterprises to understand policies. When the government releases policies related to environmental protection, enterprises will closely monitor information related to the environment, generating motivation for low-carbon transformation. The government ultimately achieves "initiative guidance" (Wang et al., 2022). On the other hand, if a balance is struck between low-carbon transformation and economic growth, the economic risks of transformation failure will greatly reduce the initiative of enterprises in low-carbon transformation. The government's focus on digital technology enables the full utilization of data empowerment attributes and unleashes the vitality of the digital economy. By integrating data resources and optimizing government services, the government creates a more fair and high-quality market environment for market entities, which is conducive to attracting external resources (Eklinder-Frick and Åge, 2017). This to some extent reduces the rent-seeking costs of enterprises, enhances their profit margins and levels, and provides financial support for technological innovation (Peng et al., 2024), thereby facilitating the improvement of production models and achieving green transformation. As the main body of market economy, the low-carbon transformation of enterprises represents the transformation of the overall production mode of society, which is crucial for China to achieve carbon peak. Therefore, the following hypothesis is proposed in this paper:

Hypothesis 3. Government digital attention can help promote the low-carbon transformation of enterprises, thereby promoting carbon reduction in cities.

4 Empirical analysis

4.1 Econometric model construction

Considering that econometric models can help better identify causal relationships between different variables, this paper constructs a panel data econometric model as shown in Formula 1 with the city's carbon emissions as the dependent variable and the degree of government digital attention as the independent variable, to empirically examine the impact of government digital attention on carbon reduction. The panel data used is data from 246 cities in China from 2006 to 2018.

$$Carbon_{it} = \alpha_0 + \beta Digital_Government_{it} + \gamma_m X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (1)$$

In Formula 1, i and t represent region and year respectively; *Carbon* represents the carbon emissions of the city. In this paper, carbon emissions generated by electricity, gas and liquefied petroleum gas, transportation and heat consumption are added together to get the carbon emission amount of the city. α is the constant term; *Digital_Government* is the core independent variable, indicating the degree of government digital attention; β is the corresponding estimated coefficient, indicating the effect of government digital attention on carbon emissions; X represents the control variables that may affect carbon dioxide emissions. γ is the corresponding estimated coefficient. It is worth noting that when using panel data that includes time and region dimensions, it is necessary to consider the impact of unobservable features in time and region on the estimation results. These features may not change over time or region, but are related to the dependent variable. Therefore, the model constructed is a two-way fixed effects model that includes time (λ) and city (μ), which can effectively control the influence of unobservable factors; and ε is a random error term.

4.2 Index election

4.2.1 Carbon dioxide emissions

In this paper, it is believed that regional carbon emissions include not only carbon emissions generated by direct energy consumption (such as gas and liquefied petroleum gas, etc.), but also carbon emissions generated by transportation, as well as carbon emissions generated by electricity and heat consumption.

(1) Carbon emissions from direct consumption of energy such as coal gas and liquefied petroleum gas are measured according to the baseline method (carbon emission conversion factor) provided by the *IPCC Guidelines for National Greenhouse Gas Inventories*', combined with the scale of energy consumption of prefecture-level cities (data sourced from the *China City Statistical Yearbook*).

(2) We use the various energy scales consumed by the transportation sector published in the *China Statistical Yearbook* to calculate the energy consumption per unit of passenger and freight traffic of different transportation modes. Then we the calculate transportation energy consumption and carbon emission of each city by combining the passenger and freight traffic of various transportation modes in the *China City Statistical Yearbook*.

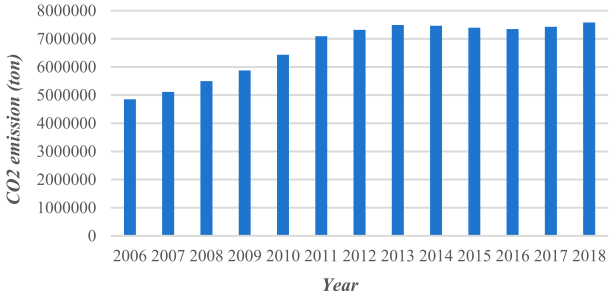


FIGURE 2
China's carbon dioxide emissions (unit: ton).

(3) Carbon emissions of each city's electric energy consumption is equivalent to baseline emission factor of power grid released by six regional power grids in North China, Northeast China, East China, Central China, Northwest China and South China over the past years multiplied by the city's electric energy consumption.

(4) Carbon emissions from urban heat energy consumption are mainly generated by the raw coal consumed in the heating process of the boiler room. The minimum standard of thermal efficiency of coal-fired industrial boilers stipulated in *GB/T152317-2009 Energy-saving Monitoring of Coal-fired Industrial Boilers* is between 65% and 78%. In addition, since China's current central heating boilers are mainly small and medium-sized coal-fired boilers, the thermal efficiency value of 70% is used to calculate. The average low calorific value of raw coal is 20,908 kJ/kg. The amount of raw coal needed can be calculated by using heat supply, thermal efficiency and heat coefficient of raw coal. Then converting raw coal into standard coal coefficient (0.7143 kg of standard coal/per kg), the amount of energy consumed by central heating can be calculated. Finally, according to the IPCC method, the carbon emission coefficient per kilogram of coal is 2.53 kg CO2/kg, and the carbon emissions generated by central heating in various cities are calculated using the amount of raw coal consumed for heat energy.

On this basis, this paper sums up the above four types of carbon dioxide emissions, and obtains the carbon dioxide emissions of each city. Figure 2 depicts the temporal trend of CO2 emissions at the city level in China from 2006 to 2018. It can be observed that during the study period, China's CO2 emissions still showed a certain increasing trend. However, after 2012, this growth trend stopped and China's carbon dioxide emissions entered a stable stage, indicating that the corresponding carbon emission control policies have achieved positive results.

4.2.2 Government digital attention

This paper mainly adopts the method of text mining to quantify the text information in the government work report, so as to measure the government digital attention. In China, the work report of a local government is an important document that reflects its work priorities and focus of attention, and is one of

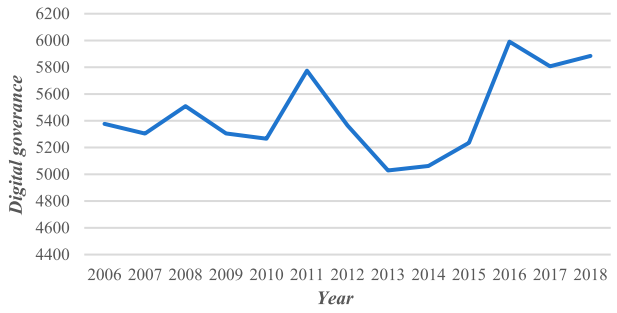


FIGURE 3
Digital attention of governments.

the most authoritative guidelines for the work of local governments. Based on the availability of data, we obtained the terms of digital application concern and digital technology concern from the government work reports of 246 cities in China from 2006 to 2018. The initial text data are sourced from government portal websites of every city.

On the whole, government digital attention is reflected in the degree to which the government pays attention to and uses digital technology in governing economic activities. The keywords related to digital technology in the government work report include *B2B, B2C, C2B, O2O, NFC payment, industrial digitalization, third-party payment, industrial Internet, Internet finance, Internet medical care, financial technology, open banking, quantitative finance, rural big data cloud platform, rural big data, data center, digital service system, digital supply chain, digital finance, digital economy, digital agriculture, digital RMB, Internet of things, online entertainment, unmanned farming, unmanned cars, unmanned retail, unmanned agriculture, unmanned banking, information industry, mobile Internet, mobile payment, government service platform, government application system, smart city, smart agriculture, smart village, smart medical care, smart pension, smart storage, smart wear, smart grid, smart supply chain, intelligent environmental protection, intelligent computing, intelligent home, intelligent transportation, intelligent customer service, intelligent energy, autonomous driving*, etc.

We used computer crawling technology to crawl these keywords in the government work report, and added them up by city and year to obtain the total frequency of government digital attention. Then, we compared it with the total frequency of words in the government work report to obtain the index of local government digital attention. Figure 3 depicts the level of digital attention of Chinese prefecture level municipal governments from 2006 to 2018. It can be observed that during the inspection period, the government continuously strengthened its focus on digital technology and digital economy.

4.2.3 Control variable

To further improve the accuracy of the estimates, we also controlled some other factors that may affect regional carbon emissions, including: (1) regional economic development (*Economy*). The measurement indicator used is the *per capita* income level of the city, which is the ratio of the city's gross domestic product to the total population. (2) The opening of the city (*Open*). The measurement index adopted is the actual amount of foreign capital utilized by cities during the investigation period. (3) Urban Innovation (*Patent*). We mainly use the number of city patent applications granted to measure it. (4) Industrial structure (*Second_rate*). We use the proportion of the total output value of the city's secondary industry to GDP to measure the urban industrial structure. (5) Fiscal decentralization (*Fiscal*). Based on the perspective of fiscal revenue decentralization, the *per capita* local fiscal revenue/(*per capita* local fiscal revenue + *per capita* central fiscal revenue) at the provincial level is used to measure fiscal decentralization. (6) Educational development (*Education*). We use the number of college and undergraduate students in each city to measure it. (7) Environmental governance (*Governance*). We choose the industrial pollution control investment of each city as a measure of the degree of environmental regulation. (8) Internet development (*Internet*). This paper selects the number of Internet broadband access users in each prefecture-level city to measure the level of Internet development. The data for the control variables mentioned above are all sourced from the *China City Statistical Yearbook*. Table 1 reports descriptive statistical results for the above variables.

4.3 Analysis and discussion of estimated results

4.3.1 Estimated results of the benchmark regression model

We estimated the econometric model shown in Formula 1 using Stata 17 software, and the estimation results were obtained as shown in columns (1) - (6) of Table 2. Column (1) shows the results without control variables and fixed effects, the Column (2) shows the results without control variables and with time fixed effects, and the Column (3) shows the results without control variables and with city and time fixed effects; the Column (4) shows the results with control variables but without any fixed effects; Column (5) shows the results with control variables and time fixed effects; Column (6) shows the results after adding control variables and fixed effects of time and city. According to the estimated results shown in column (6), the influence coefficient of the government digital attention on carbon emissions is significantly negative, indicating that the government's attention on the digital technology is conducive to promoting carbon dioxide emission reduction, which is consistent with the expectation.

4.3.2 Endogeneity tests

4.3.2.1 Instrumental variable method

To avoid endogeneity estimation bias caused by potential causal relationships, we used instrumental variable method to estimate the model shown in Formula 1. We subtract the average government digital attention index of all cities within the same province from the government digital attention index of city *i* for year *t*, and take the third power of the difference as the instrumental variable for the degree of government digital attention. The advantage of this method is that it can utilize the information contained in the heteroscedasticity of errors without relying on external variables. Columns (1) and (2) in Table 3 represent the estimated results for the first and second stage respectively. It can be found that the *Cragg-Donald Wald F Statistic* is 3052.26, which is larger than the

TABLE 1 Descriptive statistics of variables.

Variable name	Observations	Mean	sd	Minimum	Maximum
Digital Governance	2,920	8.5601	0.4417	0.6931	9.7044
Carbon	2,925	5.9677	1.1185	2.1437	9.1895
Economy	2,925	10.4173	0.7276	8.1312	15.6718
Open	2,925	9.7423	2.0451	0.0000	14.1520
Patent	2,925	6.8112	1.8777	1.6094	12.1521
Second_rate	2,920	3.8896	0.2859	0.0000	6.3428
Fiscal	2,920	0.4977	0.2713	0.0544	8.3902
Education	2,925	10.3779	1.5630	0.0000	13.9108
Governance	2,925	12.2330	0.7973	8.1786	14.1637
Internet	2,925	12.8910	1.0880	9.2104	15.8567

Note: The above variables are logarithmically processed except for the proportional variables.

TABLE 2 Results of baseline regression model.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.0625*** (10.15)	4.0498*** (10.07)	7.3381*** (53.86)	−3.1178*** (−6.55)	−6.9078*** (−14.98)	5.7098*** (14.02)
Digital_Governance	0.2228*** (4.77)	0.1835*** (3.92)	−0.0236* (−1.83)	−0.0253 (−0.85)	−0.0164 (−0.60)	−0.0250** (−2.02)
Economy				0.3884*** (13.64)	0.7458*** (24.83)	0.0553* (1.87)
Open				0.0326*** (3.41)	−0.0342*** (−3.73)	0.0072 (1.01)
Patent				−0.1098*** (−6.24)	−0.1789*** (−10.87)	−0.1207*** (−9.20)
Second_rate				0.2326*** (4.87)	0.0528 (1.18)	0.0538** (2.20)
Fiscal				0.8899*** (14.64)	0.2170*** (3.48)	0.0504*** (2.60)
Education				−0.1477*** (−12.50)	−0.0803*** (−7.24)	−0.0314*** (−3.36)
Governance				−0.0861*** (−4.77)	−0.0770*** (−4.49)	−0.0279** (−2.14)
Internet				0.0198 (0.73)	0.2426*** (9.12)	−0.0245 (−1.33)
Observations	2,920	2,920	2,920	2,911	2,911	2,911
City Fixed Effect	No	No	Yes	No	No	Yes
Time Fixed Effect	No	Yes	Yes	No	Yes	Yes
R-square	0.0077	0.0322	0.9435	0.6072	0.6771	0.9475

Note: *, ** and *** are significant at 10%, 5% and 1% levels respected; The value in parents indicates the *t* value.

critical value of 10% bias in *Stock-Yogo weak ID test*, so the null hypothesis that the instrumental variable is a weak instrumental variable is rejected. In addition, the estimation coefficient of instrumental variables in the first stage is significant at the 1%, and it can be judged that there is no weak instrumental variable problem. In the results of the second stage shown in column (2), the effect of government digital attention on carbon dioxide emissions is still significantly negative, which is also consistent with the results of the benchmark regression above.

4.3.2.2 Controlling the joint fixed effect

The fixed effects on time and region were added to the benchmark regression model to control for the influence of unobservable features at the time and region levels. However, some important factors may still be missed, which will lead to the endogenous bias of the estimation results. Here, we will further control for the time-region joint fixed effects to reduce the interference of unobservable features that vary simultaneously with time and region on the estimation results. The estimated results considering the joint fixed effect are shown in column (3) of Table 3. The results also show that the effect of government digital attention on carbon dioxide emissions is significantly negative.

4.3.3 Robustness tests

4.3.3.1 Replacing the measurement method of carbon dioxide

To verify the robustness of the benchmark regression model, we use the following two methods to replace the dependent variable in

TABLE 3 Results of endogeneity tests.

	(1)	(2)	(3)
Constant	8.3647*** (40.96)	−6.7846*** (−12.36)	5.5732*** (3.46)
Digital_Governance		−0.0169** (−2.43)	−0.0245* (−1.98)
IVaverage3	0.0239*** (55.25)		
Control Variables	Yes	Yes	Yes
Observations	2,730	2,730	2,911
City Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
City-Time Joint Fixed Effect	No	No	Yes
R-square		0.6673	0.9476
Cragg-Donald Wald F statistic	3052.26		

TABLE 4 Robustness test results.

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.6977*** (5.89)	0.1016*** (10.72)	15.7869*** (150.20)	6.3577*** (10.23)	5.7097*** (8.33)	5.7098*** (7.08)
Digital_Governance	−0.0258* (−1.76)	−0.0003** (−2.03)	−0.0037*** (−3.16)	−0.0006*** (−2.67)	−0.0250** (−2.06)	−0.0250** (−2.53)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,911	2,911	2,911	1,573	2,911	2,911
City Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
R-square	0.7332	0.8295	0.9944	0.9629	0.9475	0.9475

Formula 1. On the one hand, selecting the carbon dioxide emissions per unit of GDP and *per capita* carbon dioxide emissions per unit of GDP as alternative indicators to exclude the influence of economic aggregate. The estimated results are shown in columns (1) and (2) of Table 4; On the other hand, we selected the carbon dioxide emission data observed by the satellite as an alternative index, and the estimated results are shown in column (3) of Table 4. It can be seen from the estimated results that no matter what measurement index is used, the coefficients are significantly negative, and our estimation results have good robustness.

4.3.3.2 Replacing the measurement method of government digital attention

Here, *National Pulse Network Government Index* is selected as an alternative indicator to measure the degree of government digital attention. The estimated results are shown in column (4) of Table 4. It can be seen that the new digital government index has a significant negative impact on carbon dioxide emissions.

4.3.3.3 Using clustering robust standard error

Considering that our panel data may have structural features at the same city or province level, we used robust standard errors for city and province clustering in estimating the econometric model of Formula 1 to improve the robustness and accuracy of the estimation results. The estimated results are shown in columns (5) and (6) of Table 4. We can observe that the influence coefficient of government digital attention degree on carbon dioxide emissions is still significantly negative, and our estimation results are robust.

4.4 Impact mechanism tests

This paper has pointed out that the influence path of government digital attention on carbon dioxide emission mainly includes three aspects: government digital attention may boost government low-carbon governance, enhance the public's low-carbon attention, and promote enterprise low-carbon transformation. Here, we will continue to use econometric models to empirically test these potential impact mechanisms. Specifically, we used a two-step mediation effect model. That is, on the basis of Formula 1, we further constructed an econometric model as shown in Formula 2:

$$Mechanism_{it} = \alpha_0 + \beta Digital_Government_{it} + \gamma_m X_{it} + \lambda_t + \mu_i + \varepsilon_{it} \quad (2)$$

In Formula 2, *Mechanism* represents mechanism variables (including government low-carbon governance, public low-

TABLE 5 Test results of impact mechanism.

	(1)	(2)	(3)	(4)
Constant	−7.0134*** (−5.64)	2.0586** (2.45)	2.0027*** (3.38)	1.9784*** (3.95)
Digital_Governance	0.1185** (2.26)	0.1460* (1.95)	0.2829*** (3.80)	−0.0260* (−1.71)
Control Variables	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,911	1826	1826	2,911
City Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
Time Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
R-square	0.5049	0.6729	0.5948	0.9399

carbon attention, and enterprise low-carbon transformation). The meanings of other variables are consistent with Formula 1. In terms of the mechanism variables, firstly, we selected the number of environmental protection administrative punishment cases in each city to measure the government's low-carbon governance. The estimated results of government digital attention degree on government's low-carbon governance are shown in column (1) of Table 5. Secondly, in terms of public concern about low carbon, we used *low carbon* and *carbon dioxide* as keywords to calculate the *Baidu Index* from 2011 to 2018 as indicator[3]. The estimated results of government digital attention on public low-carbon concern are shown in columns (2) and (3) of Table 5; Thirdly, for low-carbon transformation of enterprises, considering the availability of data at the city level, we converted the total gas consumption, liquefied petroleum gas consumption and electricity consumption of the whole society into coal volume and sum it up. We then calculated the ratio of coal consumption and added value of the secondary industry in China, and chose this index to measure the enterprises' low-carbon transformation. The smaller the index is, the better the low-carbon transformation effect of the enterprise is. The estimated results are shown in column (4) of Table 5.

It can be seen from the estimated results that government digital attention has a significant positive impact on government's low-carbon governance, indicating that the higher the government digital attention, the better its low-carbon governance performance. It is consistent with the statement of Hypothesis 1. According to the results in column (2) and (3), government digital attention has a significant positive impact on public's low-carbon concern. Government digital attention can enable multiple subjects to participate in governance and transmit positive signals to strengthen the public's awareness of carbon emission reduction, which is consistent with Hypothesis 2. Moreover, the results in column (4) show that government digital attention has a negative impact on the coal consumption of enterprises, the higher the government's digital attention, the lower the proportion of coal consumption of enterprises. Government digital attention can promote the low-carbon transformation of enterprises, this also confirms the Hypothesis 3.

3 Baidu index was officially released in 2011. We lack the data from 2006 to 2010 here.

4.5 Extended analysis

4.5.1 Heterogeneity of carbon dioxide emission sources

In fact, all aspects of social production and life will produce a certain amount of carbon dioxide emissions, which is also reflected in the measurement method of carbon dioxide in this paper. On the one hand, due to the high cost of clean energy, fossil fuels such as coal gas, natural gas, and liquefied petroleum gas remain the main fuels for industrial production today. This has led to high carbon dioxide emissions from transportation and coal-fired power generation, making it an important area for low-carbon governance in China. The government will actively increase its attention and use of digital technology, strengthen low-carbon governance and public concern in these fields, so as to effectively reduce carbon dioxide emissions in these areas. On the other hand, for the carbon dioxide generated by urban heat energy, these mainly come from the energy consumption generated by the heating of small boiler rooms in the city in order to meet people's daily life. In China, these thermal energy supplies that are closely related to people's lives cannot be reduced in the short term. Government digital attention may not be able to have a direct impact on carbon dioxide in these areas.

In this paper, carbon dioxide emissions are divided into three aspects: carbon dioxide from direct energy consumption and transportation, carbon dioxide from electric energy consumption and carbon dioxide from heat consumption. The impact of government digital attention on them are estimated respectively, so as to identify the heterogeneity. The estimated results are shown in columns (1), (2) and (3) of Table 6.

As can be seen from the estimated results, government digital attention has significant negative effects on carbon dioxide from direct energy consumption and transportation, and electric energy consumption. It indicates that carbon dioxide generated by direct energy consumption and transportation, and electric energy consumption are important areas of governance. According to the estimated results shown in column (3), the estimated coefficient between government digital attention and carbon dioxide from heat consumption is still not significant at the 10%, indicating that government digital attention cannot have a direct effect on carbon dioxide from heat consumption in the short term. The results are consistent with our expectations.

TABLE 6 Heterogeneity results of carbon dioxide emissions sources.

	(1)	(2)	(3)
Constant	1.1281** (1.97)	5.6224*** (12.31)	6.1605*** (7.49)
Digital_Governance	−0.0011** (−2.06)	−0.0338** (−2.43)	0.0100 (0.40)
Control Variables	*Yes*	*Yes*	*Yes*
Observations	2,911	2,911	2,911
City Fixed Effect	*Yes*	*Yes*	*Yes*
Time Fixed Effect	*Yes*	*Yes*	*Yes*
R-square	0.9274	0.9358	0.9407

4.5.2 Impact of the marketization

The degree of marketization determines the regional resource allocation efficiency to a large extent, which may have an impact on carbon emission reduction effect of government digital attention. Especially for China, which is in the period of economic transformation, if the government controls too many resources and excessively intervenes in the behavior of market players, market competition cannot be played. This will not only cause the government to lose the impetus for digital transformation, but also lead to many high-pollution, high-energy-consuming enterprises unable to withdraw from the market. This then will certainly reduce the impact of government digital attention on carbon dioxide reduction.

Based on this, this paper will identify the impact of government digital attention on carbon dioxide emission reduction under different marketization degrees. We used the index of the degree of marketization (*Market*) of China's provinces, and divided the samples into high degree of marketization and low degree of marketization according to the median, so as to investigate the impact of government digital attention on carbon dioxide emission reduction in different samples respectively. The final results are shown in columns (1) and (2) of Table 7. Moreover, we also adopted the method in the form of interaction terms to incorporate the interaction terms of government digital attention and marketization degree index into the model. The estimated results are shown in column (3).

As can be seen from Table 7, in areas with a high degree of marketization, government digital attention has a significant negative effect on carbon dioxide emissions. While in areas with a low degree of marketization, the impact of government digital attention is not significant. The degree of marketization does indeed affect the carbon reduction effect of government digital attention. According to the results shown in column (3), the estimated coefficient of the interaction term is significantly negative, indicating that the degree of marketization can positively regulate the government digital attention and carbon dioxide emission reduction.

4.5.3 The impact of regional heterogeneity

Due to the comprehensive influence of historical factors, geographical environment and policy factors, China's regional economic and social development presents a typical spatial gradient pattern. There are significant spatial differences in economic development level and governance capacity in eastern, central and western regions. On the one hand, the difference in economic development often determines the difference in the decision-making orientation of local governments. The development of digital economy in the eastern region is relatively high, and the government attaches more importance to the application of digital technology. The government is more willing and capable of using digital technology for governance. On the other hand, the eastern region has a dense population distribution and a huge manufacturing volume, facing more serious carbon emission problems. Hence, their urgency of low-carbon transition is relatively high. We believe that government digital attention may have a significant impact on carbon emission reduction in the eastern region, but not in the central and western regions.

We identified regional heterogeneity by separately estimating the impact of government digital attention on carbon dioxide emissions reduction in the eastern, central, and western regions. The results are shown in Table 8, where columns (1), (2) and (3) represent the estimated results for the eastern, central and western regions respectively.

As for the estimation results of spatial heterogeneity shown in Table 8, government digital attention has a significant positive impact on carbon dioxide emission reduction in the eastern region, while the effect in the central and western regions are not significant. It verifies the existence of spatial heterogeneity of carbon dioxide emission reduction influenced by government digital attention, which is consistent with our expectation.

TABLE 7 Results of considering the regional marketization.

	(1)	(2)	(3)
Constant	6.3231*** (11.46)	4.4879*** (6.33)	5.7397*** (14.08)
Digital_Governance	−0.1400*** (−2.59)	−0.0101 (−0.76)	−0.0399** (−2.36)
Digital_Governance × Market			−0.0018** (−2.29)
Control Variables	*Yes*	*Yes*	*Yes*
Observations	1,618	1,293	2,911
City Fixed Effect	*Yes*	*Yes*	*Yes*
Time Fixed Effect	*Yes*	*Yes*	*Yes*
R-square	0.9634	0.9665	0.9475

TABLE 8 Results of regional heterogeneity.

	(1)	(2)	(3)
Constant	4.0729*** (4.47)	6.5136*** (11.27)	4.5831*** (4.92)
Digital_Governance	−0.0864*** (−2.69)	−0.0027 (−0.20)	−0.0138 (−0.46)
Control Variables	Yes	Yes	Yes
Observations	961	1,179	771
City Fixed Effect	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
R-square	0.9559	0.9507	0.9232

5 Conclusion and policy implications

This paper is based on attention theory and examines the impact of government digital attention on regional carbon reduction within the framework of government-public-enterprise. The following conclusions have been drawn: (1) During the study period, government digital attention has a significant negative impact on carbon dioxide emissions, indicating that the government attention to digital technology can further promote carbon dioxide emission reduction in the region. (2) Results of the impact mechanism test show that government digital attention can improve the government's low-carbon governance, strengthen the public's low-carbon attention, and encourage enterprises' low-carbon transformation. (3) Government digital attention has a significant negative effect on carbon dioxide from direct energy consumption, and transportation, electric energy consumption, but has no significant effect on the carbon dioxide from heat energy consumption. The degree of marketization helps to strengthen the carbon reduction effect of government digital attention. The effect of government digital attention on carbon dioxide emissions in the eastern region is significantly negative, while the effect in the central and western regions are not significant.

The policy implications of this research conclusion are as follows: (1) The government should accelerate the popularization of digital technologies such as the Internet of things, cloud computing, and big data, increase attention to digital technologies, promote government digital transformation, and enhance the digital governance capabilities. That is, the government should pay more attention to digital technology in the future work. They should give full play to the functions of the Internet of things, sensors and other public data collection, establish governance databases and data cockpits, providing guarantees for integrating data resources and accurately identifying carbon violations. In addition, the construction of digital government should be accelerated. On the one hand, by providing the public with more convenient and information-based services, the public can improve their trust in government decision-making and participation in joint decision-making, so as to lay the foundation for the public's low-carbon concern. On the other hand, we can improve the digital economy policy and optimize the business environment, so as to stimulate the motivation of enterprises' low-carbon transformation. (2) It is necessary to further dredge the transmission channels of government's digital attention to promote carbon dioxide emission reduction through government low-carbon governance, public low-carbon attention and enterprise low-carbon transformation. Specifically, government can establish a digital file management system, promote digital examination and approval system, establish a digital assessment and evaluation platform. Government can also establish digital platforms so that the public can participate in government decision-making anytime and anywhere. Through data opening and sharing, the public can understand the work of the government. (3) Government can disclose relevant ecological civilization information to enterprises, such as environmental monitoring data, environmental protection policies, environmental impact assessment reports, etc. At the same time, government can strengthen digital publicity and education, conveying government intentions and policy connotations to enterprises through digital media. It will help guide enterprises to allocate attention to ecological civilization, and improve their responsibility awareness in ecological civilization.

This article has made many attempts and extensions to the research on the carbon reduction effect of government digital attention, but it cannot be denied that there are also certain shortcomings. The government's digital attention reflects its emphasis on the development of the digital economy and the use of digital technology in decision-making, which is both a broad concept and highly subjective. This article mainly extracts the frequency of words related to digital technology from government work reports to identify the government's digital concerns. Although this has good applicability in China, it still cannot reflect all the content of the government's digital concerns, such as the actual adoption and investment of digital technology by the government, which may also have an impact on carbon reduction in the economy. In the future, we will continue to expand our research on the connotation of government digital attention, in order to have a more comprehensive understanding of the new models and impact effects of government governance in the digital economy era.

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

RH: Formal Analysis, Funding acquisition, Investigation, Writing–review and editing. KS: Conceptualization, Data curation, Methodology, Funding acquisition, Writing–original draft.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This work was funded by the Jiangsu University Philosophy and Social Science Research Project "Research on the Relationship between the Evolution of Independent Innovation Capability and Risk Perception in High tech Enterprises" (Project Number: 2023SJYB0662) and the Youth Fund Project of the Humanities and Social Sciences Research Project of the Ministry of Education "Research on the Mechanism of Coordinated Guidance of Green

Finance Policies on the Low Carbon Transformation of Manufacturing Industry between Supply and Demand" (Project Number: 23YJC790113), Jiangsu Provincial Social Science Fund Youth Project "Research on the Path of Empowering Jiangsu's' Specialized, Refined, Unique and New 'Enterprises with Digital Intelligence Integration to Enhance Resilience" (Project Number: 23EYC023).

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 author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Agostino, D., Saliterer, I., and Steccolini, I. (2021). Digitalization, accounting and accountability: a literature review and reflections on future research in public services. *Financial Account. Manag.* 38 (2), 152–176. doi:10.1111/faam.12301

Bayat, A., and Kawalek, P. (2023). Digitization and urban governance: the city as a reflection of its data infrastructure. *Int. Rev. Adm. Sci.* 89 (1), 21–38. doi:10.1177/00208523211033205

Cai, Z., Ding, X., Zhou, Z., Han, A., Yu, S., Yang, X., et al. (2025). Fiscal decentralization's impact on carbon emissions and its interactions with environmental regulations, economic development, and industrialization: evidence from 288 cities in China. *Environ. Impact Assess. Rev.* 110, 107681. doi:10.1016/j.eiar.2024.107681

Castro, C., and Lopes, C. (2022). Digital government and sustainable development. *J. Knowl. Econ.* 13, 880–903. doi:10.1007/s13132-021-00749-2

Chen, R., and Liu, D. C. (2022). Research on the innovation path of government digital transformation under the new development pattern of 'double cycle'. *Reform Econ. Syst.* (1), 28–34. (in Chinese).

Danish, B. M. A., Mahmood, N., and Zhang, J. W. (2019). Effect of natural resources, renewable energy and economic development on CO2 emissions in BRICS countries. *Sci. Total Environ.* 678, 632–638. doi:10.1016/j.scitotenv.2019.05.028

Destek, M. A., Hossain, M. R., Manga, M., and Destek, G. (2024). Can digital government reduce the resource dependency? Evidence from method of moments quantile technique. *Resour. Policy* 99, 105426. doi:10.1016/j.resourpol.2024.105426

Eklinder-Frick, J., and Åge, L. J. (2017). Perspectives on regional innovation policy: from new economic geography towards the IMP approach. *Ind. Mark. Manag.* 61, 81–92. doi:10.1016/j.indmarman.2016.07.005

Gil-Garcia, J. R., Helbig, N., and Ojo, A. (2014). Being smart: emerging technologies and innovation in the public sector. *Gov. Inf. Q.* 31, 11–I8. doi:10.1016/j.giq.2014.09.001

Guo, Y. F., and Lin, B. (2022). Influencing factors and multiple paths of construction ability of digital government: qualitative comparative analysis based on 31 Chinese provinces. *Procedia Comput. Sci.* 199, 1213–1220. doi:10.1016/j.procs.2022.01.154

Hamish, S., Aaron, G., Valtteri, K., Michelle, R., and Val, H. (2021). Mechanisms of service ecosystem emergence: exploring the case of public sector digital transformation. *J. Bus. Res.* 137, 100–115. doi:10.1016/j.jbusres.2021.08.008

Han, F., and Zhang, D. (2024). Government digitalization and its influence on government functions transformation adopting a Structural Functionalism perspective: evidence from county-level governments in China. *Heliyon* 17 (10), e37267. doi:10.1016/j.heliyon.2024.e37267

Jiang, Z., Yuan, C., and Xu, J. (2024). The impact of digital government on energy sustainability: empirical evidence from prefecture-level cities in China. *Technol. Forecast. Soc. Change* 209, 123776. doi:10.1016/j.techfore.2024.123776

Lee, J. N., Ham, J., and Choi, B. (2016). Effect of government data openness on a knowledge-based economy. *Procedia Comput. Sci.* 91, 158–167. doi:10.1016/j.procs.2016.07.053

Li, E., Chen, Q., Zhang, X., and Zhang, C. (2023). Digital government development, local governments' attention distribution and enterprise total factor productivity: evidence from China. *Sustainability* 15, 2472. doi:10.3390/su15032472

Li, X., and Yue, S. J. (2025). Does the government digital attention improve China's digital economy output efficiency: accelerator or inhibitor. *Econ. Analysis Policy* 85, 607–625. doi:10.1016/j.eap.2024.12.020

Luca, T., Marijn, J., Michele, B., and Giuliano, N. (2021). Digital government transformation: a structural equation modelling analysis of driving and impeding factors. *Int. J. Inf. Manag.* 60, 102356. doi:10.1016/j.ijinfomgt.2021.102356

Luna-Reyes, L. F., and Gil-Garcia, J. R. (2014). Digital government transformation and internet portals: the co-evolution of technology, organizations, and institutions. *Gov. Inf. Q.* 31 (4), 545–555. doi:10.1016/j.giq.2014.08.001

Mergel, I., Noella, E., and Nathalie, H. (2019). Defining digital transformation: results from expert interviews. *Gov. Inf. Q.* 36 (4), 101385. doi:10.1016/j.giq.2019.06.002

Nambisan, S., Wright, M., and Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: progress, challenges and key themes. *Res. Policy* 48 (8), 103773. doi:10.1016/j.respol.2019.03.018

Peng, Z., Huang, Y., Liu, L., Xu, W., and Qian, X. (2024). How government digital attention alleviates enterprise financing constraints: an enterprise digitalization perspective. *Finance Res. Lett.* 67, 105883. doi:10.1016/j.frl.2024.105883

Rahman, M. M., Sultana, N., and Velayutham, E. (2022). Renewable energy, energy intensity and carbon reduction: experience of large emerging economies. *Renew. Energy* 184, 252–265. doi:10.1016/j.renene.2021.11.068

Shim, D. C., and Eom, T. H. (2008). E-government and anti-corruption: empirical analysis of international data. *Int. J. Public Adm.* 31 (3), 298–316. doi:10.1080/01900690701590553

Sohail, R. C., Hu, G. W., Si, W. F., and Pasha, A. T. (2020). Synthesizing e-government maturity model: a public value paradigm towards digital Pakistan. *Transforming Gov. People Process Policy* 14 (3), 495–522. doi:10.1108/tg-11-2019-0110

Tang, J., Li, W., Hu, J., and Ren, Y. (2025). Can government digital transformation improve corporate energy efficiency in resource-based cities? *Energy Econ.* 141, 108043. doi:10.1016/j.eneco.2024.108043

Tuggle, C. S., Sirmon, D. G., Reutzel, C. R., and Bierman, L. (2010). Commanding board of director attention: investigating how organizational performance and CEO duality affect board members' attention to monitoring. *Strategic Manag. J.* 31 (9), 946–968. doi:10.1002/smj.847

Wang, Q., Ren, F., and Li, R. (2024). Exploring the impact of geopolitics on the environmental Kuznets curve research. *Sustain. Dev.* 32 (3), 1700–1722. doi:10.1002/sd.2743

Wang, X. C., Li, Y., Tian, L. W., and Hou, Y. (2022). Government digital initiatives and firm digital innovation: evidence from China. *Technovation* 119, 102545. doi:10.1016/j.technovation.2022.102545

Xian, Y., Wang, H., Zhang, Z., Yang, Y., and Zhong, Y. (2025). Driving factors and reduction paths dynamic simulation optimization of carbon dioxide emissions in China's construction industry under the perspective of dual carbon targets. *Environ. Impact Assess. Rev.* 112, 107789. doi:10.1016/j.eiar.2024.107789

Xing, Q., and Yao, W. (2022). Digital governance and its benchmarking college talent training under the rural revitalization in China: a case study of Yixian County (China). *Public Health* 10, 984427. doi:10.3389/fpubh.2022.984427

Yang, C., Gu, M., and Albitar, K. (2024). Government in the digital age: exploring the impact of digital transformation on governmental efficiency. *Technol. Forecast. Soc. Change* 208, 123722. doi:10.1016/j.techfore.2024.123722

Yang, X., Wang, J., Cao, J., Ren, S., Ran, Q., and Wu, H. (2022). The spatial spillover effect of urban sprawl and fiscal decentralization on air pollution: evidence from 269 cities in China. *Empir. Econ.* 63, 847–875. doi:10.1007/s00181-021-02151-y

Yu, C., Gao, D., and Sun, H. (2025). The impact of digital government services on manufacturing productivity: China's pilot city insights. *Finance Res. Lett.* 73, 106600. doi:10.1016/j.frl.2024.106600

Yuan, B., Zhong, Y. P., Li, S. S., and Zhao, Y. H. (2024). The degree of population aging and living carbon emissions: evidence from China. *J. Environ. Manag.* 353, 120185. doi:10.1016/j.jenvman.2024.120185

Yuan, Y. P., Dwivedi, Y. K., Tan, G. W., Cham, T. H., Ooi, K. B., Aw, E. C., et al. (2023). Government digital transformation: understanding the role of government social media. *Gov. Inf. Q.* 40 (1), 101775. doi:10.1016/j.giq.2022.101775

Zhang, C., Wang, C., Jin, H., Xu, M., Balezentis, T., and Agnusdei, L. (2025). The impact of green finance on energy transition and carbon emission targets: exploring the double threshold and spatial spillover effects among the regions. *Struct. Change Econ. Dyn.* 73, 1–10. doi:10.1016/j.strueco.2024.12.012

Zhang, K., Cao, B., Guo, Z., Li, R., and Li, L. (2024). Research on the impact of government attention on the digital economy of Chinese provinces. *Innovation Green Dev.* 3 (2), 100118. doi:10.1016/j.igd.2023.100118

Zhang, L., and Zhang, X. (2025). Impact of digital government construction on the intelligent transformation of enterprises: evidence from China. *Technol. Forecast. Soc. Change* 210, 123787. doi:10.1016/j.techfore.2024.123787

Zhao, B., Wang, K., and Xu, R. (2023). Fiscal decentralization, industrial structure upgrading, and carbon emissions: evidence from China. *Environ. Sci. Pollut. Res.* 30, 39210–39222. doi:10.1007/s11356-022-24971-w

Zhao, S. L., Teng, L. J., Vincent, E. A., and Hu, H. (2023). Impacts of digital government on regional eco-innovation: moderating role of dual environmental regulations. *Technol. Forecast. Soc. Change* 196, 122842. doi:10.1016/j.techfore.2023.122842

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 20 February 2025
DOI 10.3389/fenvs.2025.1519286

Check for updates

OPEN ACCESS

EDITED BY
Ji Zheng,
The University of Hong Kong, Hong Kong SAR, China

REVIEWED BY
Xuetao Sun,
Ocean University of China, China
Chen Li,
Shanghai University of Engineering Sciences, China
Zheng Wang,
Jiangxi Administration Institute, China

*CORRESPONDENCE
Donglin Chen,
chendl@whut.edu.cn

RECEIVED 30 October 2024
ACCEPTED 24 January 2025
PUBLISHED 20 February 2025

CITATION
Chen Y, Chen D, Gao C and Wei X (2025) The inverted U-shaped impact of the digital economy on indirect household carbon emissions — an empirical study based on CFPS. *Front. Environ. Sci.* 13:1519286. doi: 10.3389/fenvs.2025.1519286

COPYRIGHT
© 2025 Chen, Chen, Gao and Wei. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The inverted U-shaped impact of the digital economy on indirect household carbon emissions — an empirical study based on CFPS

Ying Chen[1,2], Donglin Chen[1,2]*, Chenfeng Gao[1,2] and Xiaochao Wei[1,2]

[1]School of Economic, Wuhan University of Technology, Wuhan, Hubei, China, [2]Hubei Provincial Research Center for E-Business Big Data Engineering Technology, Wuhan, Hubei, China

Introduction: In the era of the booming digital economy and global efforts to reduce carbon emissions, this study investigates how digital economy growth impacts indirect household carbon emissions (IHCEs). Understanding this relationship is critical, as the digital economy has the potential to both drive and mitigate carbon emissions, depending on its stage of development and regional context.

Methods: Using panel data from the 2014–2018 China Family Panel Studies (CFPS), a fixed effects model is applied to analyze the relationship between digital economy growth and IHCEs. The study examines regional variations, levels of digital economy development, and consumption categories to identify heterogeneous effects.

Results: The findings reveal an inverted U-shaped relationship between the digital economy and IHCEs. Initially, IHCEs rise due to increased consumption of energy-intensive products, but as digital technologies mature, emissions decline due to improved efficiency and sustainable consumption. Heterogeneity analysis shows that the inverted U-shaped relationship is more pronounced in less developed digital economy regions, while in advanced regions, the relationship is less significant. Regionally, the eastern region, with its advanced infrastructure and green technologies, effectively curbs IHCEs, whereas the central region experiences increased emissions, and the western region exhibits the inverted U-shaped pattern. In terms of consumption, the digital economy significantly impacts housing and food-related emissions, while other categories show mixed or minor effects.

Discussion: These findings highlight the dual role of the digital economy in both driving and mitigating carbon emissions. Policymakers should adopt region-specific strategies, invest in digital infrastructure, and promote sustainable consumption practices to leverage the digital economy for carbon reduction. The study underscores the importance of managing expectations and addressing discrepancies between digital economy growth and its environmental impacts, offering valuable insights for achieving sustainable development goals.

KEYWORDS

digital economy, household carbon emissions, consumption carbon emissions, inverted U-shape, carbon mitigation

1 Introduction

Consumer consumption activities play a major role in global warming, responsible for nearly 70% of the greenhouse gases emitted from household use (Ma et al., 2022). In several Western countries, household carbon emissions account for 70%–80% of total emissions across all sectors (Hertwich and Peters, 2009; Baiocchi et al., 2010), while in China, residential consumption contributes to over 50% of total carbon emissions. Therefore, understanding and mitigating carbon emissions from household consumption is critical for achieving global emission reduction targets and ensuring sustainable development. Given the rapid economic growth and rising living standards, household carbon emissions in China are expected to continue increasing, highlighting the urgency of addressing this issue. (Sharif et al., 2019).

China's digital economy has experienced rapid growth, reaching a valuation of 53.9 trillion yuan in 2023—a 3.7 trillion yuan increase from the previous year—and accounting for over 42.8% of the national GDP, according to the 2024 Development Report on China's Digital Economy by the China Academy of Information and Communication Technology. This expansion has not only lowered the costs of economic activities and improved operational efficiency but also significantly reshaped the landscape of production, distribution, and consumption across the national economy (Goldfarb and Tucker, 2019).

However, the impact of the digital economy on household carbon emissions remains complex and dual-faceted. On one hand, it enhances consumer choice by offering extensive information and unparalleled convenience, which can lead to a comparative mindset, impulsive purchases (Ding et al., 2022; Luo et al., 2022), greater household waste (Frick and Matthies, 2020), and increased overall consumption—factors that ultimately drive production activities and elevate carbon emissions (Wiedmann et al., 2020). On the other hand, it also stimulates green technological innovations, broadens the range of available low-carbon products, optimizes the supply structure, and promotes eco-friendly household consumption, thereby supporting a transition to more sustainable practices (Sarfraz et al., 2022). Furthermore, the digital economy has the potential to significantly lower household carbon emissions by encouraging low-carbon consumption behaviors (Gong et al., 2020; Kim et al., 2020; Li et al., 2021b). Therefore, the digital economy functions as a double-edged sword, with the capacity to both increase and decrease carbon emissions.

Despite the broader discussions around the digital economy's influence on carbon emissions, its specific effects on household consumption-related emissions are underexplored. Most existing research has either focused on the detrimental or beneficial aspects of the digital economy, but a comprehensive analysis of its dual impact on household carbon emissions remains lacking. This study seeks to fill this gap by examining the relationship between the digital economy and household carbon emissions, focusing on household-level consumption and its underlying mechanisms. Using the entropy weight method to measure the progress of the digital economy and leveraging household tracking survey data, we employ an econometric model to identify the key factors driving increases or decreases in household carbon emissions.

The marginal contributions of this study in the field of the relationship between the digital economy and household carbon emissions are reflected in the following aspects: First, from a theoretical perspective, this study provides an in-depth analysis of the dual impact of the digital economy on household carbon emissions, revealing the dynamic change process and the transmission path of household consumption. This analysis fills the gap in the existing literature, enriches the relevant theoretical framework, and lays a solid foundation for future research. Second, from a methodological standpoint, this study constructs a scientific econometric model, using households as the unit of analysis, to systematically capture the nonlinear relationship between the digital economy and household carbon emissions from the consumption side. This methodological innovation offers a new perspective and paradigm for research in this field, significantly enhancing the reliability and scientific rigor of the study. Finally, from a practical perspective, this study provides policymakers with targeted decision-making support, helping to formulate regional and sectoral policies that promote the synergistic development of the digital economy and the "dual carbon" goals. It also offers market insights for businesses and social organizations, guiding enterprises to adjust strategies, develop low-carbon products, and encouraging social organizations to actively engage in the transformation toward sustainable consumption, thus promoting coordinated economic and environmental development.

The structure of this paper is organized as follows: Section 2 provides a review of the existing literature, while Section 3 outlines the theoretical framework and research hypotheses. Section 4 describes the empirical research design in detail. In Section 5, we present the findings on the impact of the digital economy on IHCEs, with an exploration of heterogeneity across different dimensions. Finally, Section 6 summarizes the research and offers key recommendations and conclusions. The study framework is depicted in Figure 1.

2 Literature review

This study examines the existing literature on the methodologies used to calculate carbon emissions from household consumption, explores the factors that influence these emissions, and analyzes the role of the digital economy in shaping emission patterns.

To accurately assess carbon emissions associated with household consumption, a precise and reliable calculation methodology is essential. The consensus in the literature identifies household consumption emissions as comprising two primary components: direct household carbon emissions (DHCEs), which result from a household's direct energy use, and indirect household carbon emissions (IHCEs), which stem from the consumption of non-energy goods and services, including their production and processing stages (Ivanova et al., 2016). Evidence consistently suggests that IHCEs exceed DHCEs in magnitude and can be measured with relative ease (Yin et al., 2020). The commonly employed methods for calculating IHCEs include the emission coefficient method (Eggleston et al., 2006), input-output models (Song et al., 2019; Zhang et al., 2020; Guo et al., 2022), the consumer lifestyle approach (Bin and Dowlatabadi, 2005; Wei et al., 2007; Feng et al., 2011; Xu et al., 2016), and life cycle assessment (Heinonen and

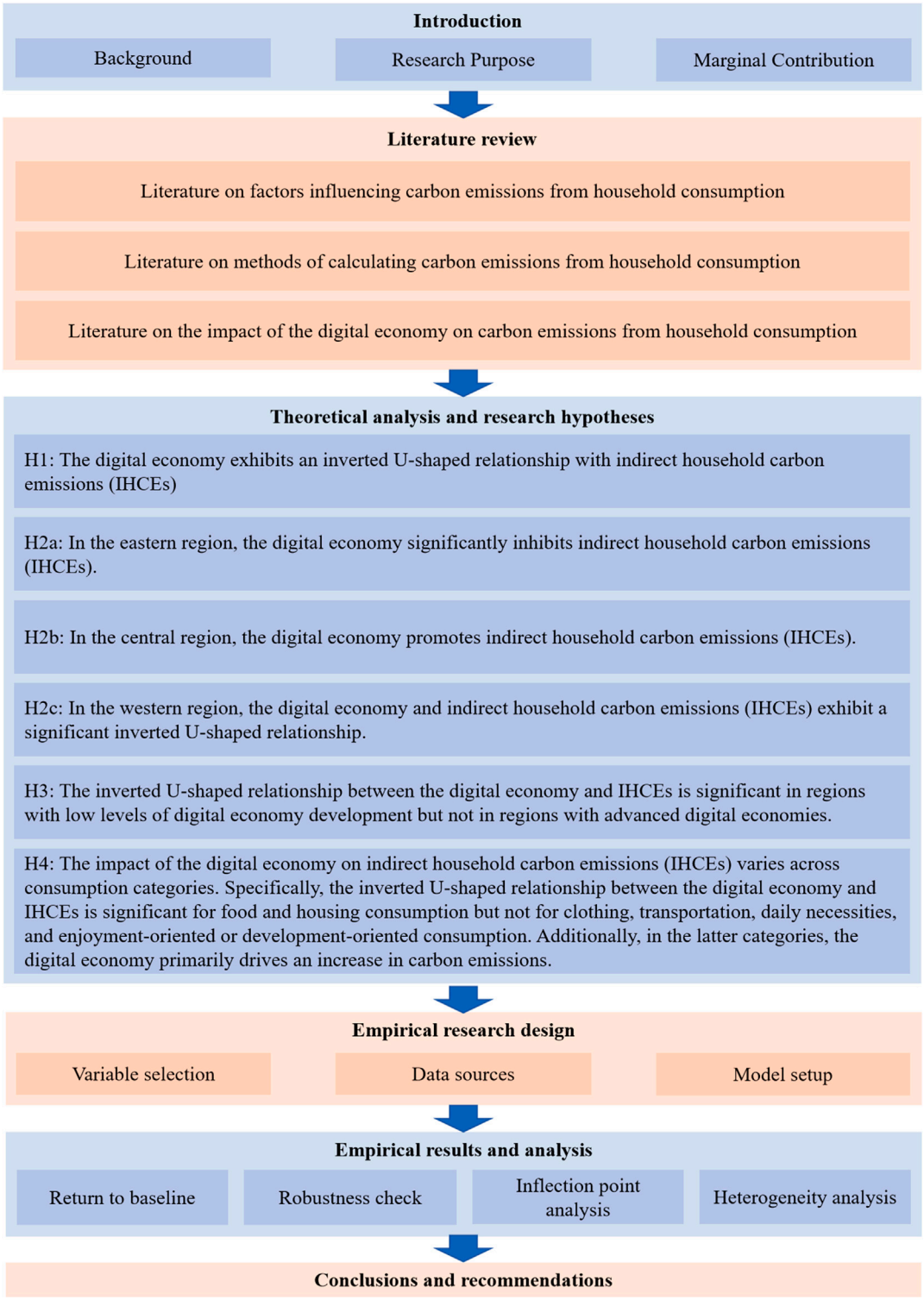


FIGURE 1
The research framework of this paper.

Junnila, 2011; Shirley et al., 2012; Kim et al., 2019). These methodologies provide a robust foundation for quantifying household consumption emissions and are instrumental in understanding the drivers and implications of such emissions in various contexts.

Household carbon emissions are shaped by various factors that influence consumption behaviors. Among these, education plays a significant yet complex role. While higher education levels can improve energy awareness and encourage environmentally conscious behaviors, thereby reducing emissions (Brand et al.,

2013; Cao et al., 2019), other studies suggest that education may elevate aspirations for a better quality of life, leading to greater reliance on modern energy sources and increased emissions (Büchs and Schnepf, 2013; Liu et al., 2013). Similarly, geographical differences significantly affect emissions, with urban households generally exhibiting distinct patterns compared to their rural counterparts (Wang et al., 2021). For example, in China, smaller household sizes are associated with higher *per capita* carbon emissions, with IHCEs being more strongly affected than DHCEs (Zhang et al., 2023). Demographic factors such as an aging population are also noteworthy, as studies link the rising proportion of elderly individuals to an increase in overall household emissions (Fan et al., 2021; Zheng et al., 2022). Furthermore, access to credit influences consumption patterns and emissions, with the most pronounced effects observed in higher income groups that leverage long-term secured credit to increase their consumption (Xu and Han, 2017). Finally, income and wealth are crucial determinants, as wealthier households and regions typically exhibit higher consumption levels, resulting in a positive correlation between income and carbon emissions (Mi et al., 2020).

The relationship between the digital economy and carbon emissions is inherently complex, reflecting both mitigating and exacerbating effects. On one hand, numerous studies argue that the digital economy fosters low-carbon development by improving resource efficiency, facilitating the adoption of green technologies, and enabling more sustainable consumption practices (Bieser and Hilty, 2018; Zhang et al., 2022). On the other hand, some research indicates that the digital economy exacerbates emissions by promoting higher consumption levels and expanding carbon footprints through digital finance and mobile payments (Li et al., 2021a; Wang et al., 2022). Recent studies also suggest that the digital economy may exhibit an inverted U-shaped relationship with emissions, where initial stages of growth lead to increased emissions, but advanced stages contribute to emission reductions (Li and Wang, 2022; Lei et al., 2023; Yin X et al., 2023; Hou et al., 2024). However, conflicting evidence exists, with some studies finding no discernible effect of the digital economy on carbon emissions (Jin and Yu, 2022).

While existing research has predominantly focused on indirect aspects of the digital economy, such as internet usage, digital finance, and mobile payments, its direct effects on household consumption emissions remain underexplored. Emerging evidence highlights both the potential of digital technologies to mitigate emissions and the risks of exacerbating them. For example, Du et al. (2024) demonstrate that while digital economy growth may increase direct emissions, it simultaneously reduces IHCEs. Similarly, Yin Z et al. (2023) find that mobile payments significantly reduce household consumption emissions, although the effects vary across different emission types. Digital technologies also facilitate the decarbonization of consumer preferences by fostering environmental awareness and promoting innovations in green products (Zhang and Wei 2023). However, the emission-increasing effects of digital advancements should not be overlooked. Mobile payment systems, for instance, encourage higher spending and consumption, which can expand household carbon footprints (Li et al., 2024). Additionally, while digital finance promotes eco-friendly purchasing habits, it often leads to higher overall emissions by augmenting income and expenditure, particularly through its effects on employment and consumption in China (Pu and Fei, 2022; Qin et al., 2022; Feng et al., 2023).

Despite significant progress in understanding the measurement and determinants of household consumption emissions, critical gaps persist regarding the impact of the digital economy on IHCEs. Existing studies primarily focus on either its mitigating or exacerbating effects, offering limited empirical evidence for the existence of an inverted U-shaped relationship between the digital economy and household emissions. Furthermore, the heterogeneity of this relationship across different contexts, including geographical regions and income groups, remains underexplored.

This study seeks to address these gaps by analyzing the dual effects of digital economy development on household carbon emissions, encompassing both its potential to reduce and increase emissions. It aims to elucidate the inverted U-shaped relationship between digital economy growth and IHCEs, quantify the inflection point of this relationship, and explore its variability across different contexts. These findings are expected to contribute to the "dual-carbon" objectives by providing actionable insights into how the digital economy can advance sustainable development. By employing innovative methodologies and offering novel perspectives, this study enriches the theoretical framework on the interplay between carbon emissions and the digital economy, providing valuable guidance for both researchers and policymakers.

3 Theoretical analysis and research hypotheses

3.1 The dual impact mechanism of the digital economy on household carbon emissions

The expansion of the digital economy presents a complex duality, with the potential to both exacerbate and mitigate indirect household carbon emissions (IHCEs). On the one hand, the digital economy has significantly increased the flexibility of household consumption patterns. Consumers now have more convenient access to abundant product information, enabling them to fulfill their consumption desires with greater precision. As the digital economy continues to expand, the explosive growth of information exposes consumers to a wider range of choices. However, this phenomenon often triggers a comparison mentality, which increases impulsive purchasing behavior and ultimately leads to a rise in IHCEs. Additionally, the increasing popularity of digital financial products has enhanced household liquidity, encouraging higher household expenditures and thereby driving up carbon emissions.

On the other hand, the digital economy is also expected to improve resource utilization efficiency and promote green consumption, thus contributing to a reduction in IHCEs. For example, the rise of the sharing economy has optimized the use of idle resources, effectively reducing waste in the production process. The widespread adoption of shared bicycles has transformed commuting habits, reducing reliance on traditional high-carbon transportation methods and lowering carbon emissions. Moreover, the internet economy has reshaped consumers' perceptions of sustainability. Online platforms that

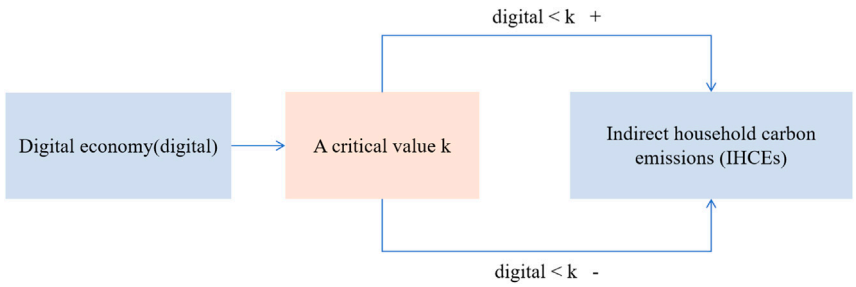


FIGURE 2
Relationship between the level of development of the digital economy and the impact of indirect household carbon emissions (IHCEs).

encourage virtual low-carbon behaviors have helped raise individual awareness of environmental impacts, thereby fostering low-carbon lifestyles and strengthening green consumption practices. For instance, Alipay's "Ant Forest" initiative incentivizes users to engage in environmentally friendly consumption habits. These examples illustrate the dual impact of the digital economy on IHCEs and provide a deeper understanding of the relationship between the digital economy and carbon emissions.

3.2 The dynamic relationship between digital economy development and household carbon emissions and hypothesis

During the initial stages of digital economy development, several factors contribute to increased household consumption and rising IHCEs. The rapid growth of online shopping and the widespread adoption of digital payment methods have provided consumers with unprecedented convenience and access to a vast array of product choices. Simultaneously, improved liquidity has further stimulated consumption expenditures. These factors collectively drive an increase in total household consumption, which inevitably leads to higher IHCEs. Furthermore, the rapid dissemination and abundance of information in the digital economy can result in overconsumption, further exacerbating the carbon emissions problem.

However, as the digital economy matures, its impact on IHCEs may evolve. The development of sharing economy models, emphasizing resource sharing and optimal utilization, effectively reduces resource waste and associated emissions. Additionally, the internet economy raises environmental awareness among consumers, encouraging them to choose eco-friendly products. These changes may result in a gradual decline in IHCEs, suggesting an inverted U-shaped relationship between digital economy development and IHCEs. Initially, the digital economy exerts a positive effect on emissions, followed by a negative effect as it advances. This dynamic relationship reflects the intricate interplay between IHCEs and the growth of the digital economy, as illustrated in Figure 2.

Hypothesis H1. Based on this, we propose Hypothesis H1: The digital economy exhibits an inverted U-shaped relationship with indirect household carbon emissions (IHCEs).

3.3 Heterogeneity analysis of the impact of the digital economy on household carbon emissions and hypothesis

3.3.1 Impact analysis and hypotheses from the perspective of regional differences

The eastern region, characterized by its advanced economy, high development level, and robust digital economy infrastructure, provides a unique foundation for understanding the relationship between the digital economy and IHCEs. From a theoretical perspective, industrial structure optimization theory posits that the eastern region's strong technological innovation capabilities enable enterprises to deeply integrate digital technologies into production and operational processes, facilitating intelligent and green transformations. Additionally, the region's comprehensive carbon emission regulatory framework, grounded in externality theory, ensures that enterprises internalize the external costs of carbon emissions through stringent environmental standards and policies, effectively reducing emissions during production. Against this backdrop, the incremental carbon emissions resulting from digital economy development in the eastern region are relatively insignificant. As the digital economy deepens, its inhibitory effect on IHCEs becomes increasingly evident. For example, digital technologies have driven intelligent logistics innovations in e-commerce, optimizing distribution routes and reducing energy consumption during transportation, thereby lowering IHCEs.

Hypothesis H2a. In the eastern region, the digital economy significantly inhibits indirect household carbon emissions (IHCEs).

In contrast, the central region lags behind the eastern region in economic development and the transformation of consumption patterns. Traditional consumption behaviors remain deeply entrenched. According to the theory of unbalanced regional development, the initial stages of digital economy development in the central region, characterized by inadequate digital infrastructure and limited technological application capabilities, provide minimal promotion of low-carbon household consumption. As the digital economy penetrates further, residents' consumption habits gradually shift toward new consumption patterns, such as online shopping. This shift aligns with consumer behavior theory, which posits that increased exposure to consumption information stimulates demand, driving the development of related industries. Consequently, IHCEs are likely to rise significantly. During the

research period, however, the digital economy in the central region has not yet reached a stage where large-scale energy-saving technologies or comprehensive shifts in consumption concepts have been realized. Therefore, IHCEs are expected to remain on an upward trajectory.

Hypothesis H2b. In the central region, the digital economy promotes indirect household carbon emissions (IHCEs).

The western region, with its traditional industrial foundation, is undergoing a critical phase of economic transformation and industrial restructuring, facing numerous challenges. During the initial stages of digital economy development, low levels of digital technology adoption hinder enterprises' ability to digitally transform production processes, resulting in slow improvements in energy efficiency. Additionally, the inertia of traditional production models, coupled with insufficient attention to environmental management, exacerbates carbon emissions. Over time, however, government policies promoting environmental protection technologies, coupled with increasing public awareness of green consumption, are expected to mitigate emissions. As residents adopt greener behaviors, such as purchasing energy-efficient appliances and utilizing sustainable transportation, IHCEs are likely to decline. Consequently, the relationship between digital economy development and IHCEs in the western region may exhibit a significant inverted U-shaped pattern.

Hypothesis H2c. In the western region, the digital economy and indirect household carbon emissions (IHCEs) exhibit a significant inverted U-shaped relationship.

3.3.2 Impact analysis and hypotheses from the perspective of the level of digital economy development

Regions with low levels of digital economy development, characterized by underdeveloped economies and inefficient industrial structures, often experience rapid increases in IHCEs during the initial stages of digital economy growth. For example, the rise of e-commerce stimulates consumption and drives the development of associated industries, such as logistics and transportation, resulting in higher emissions due to limited technological advancements and environmental protections. As the digital economy develops further, investments in energy-saving technologies and stricter environmental policies help suppress and ultimately reduce IHCEs, forming a distinct inverted U-shaped relationship. In contrast, regions with advanced digital economies, optimized industrial structures, and strong environmental regulations integrate sustainability concepts early, mitigating the inverted U-shaped effect.

Hypothesis H3. The inverted U-shaped relationship between the digital economy and IHCEs is significant in regions with low levels of digital economy development but not in regions with advanced digital economies.

3.3.3 Impact analysis and hypotheses from the perspective of consumption categories

Based on observations of real-world consumption markets and the mechanisms of the digital economy, different consumption categories exhibit unique characteristics and development logics. Compared to basic living needs, the digital economy exerts a more significant impact on enjoyment-oriented and development-oriented consumption (such as household equipment, art, education, and entertainment), often resulting in increased carbon emissions in these areas (Du et al., 2024). For enjoyment-oriented and development-oriented consumption, the digital economy's impact is more pronounced due to its role in enhancing information dissemination, driving product innovation, and transforming consumption patterns. For instance, the rise of online art exhibitions and smart educational equipment has enriched the consumer experience but also introduced more energy-intensive processes, thereby increasing carbon emissions. In the areas of food and housing consumption, the digital economy initially focuses on breaking spatial and temporal limitations on consumption and improving convenience, which stimulates consumption growth and drives increased carbon emissions in related industries. Subsequently, with technological advancements and industrial upgrades, measures aimed at environmental protection and resource efficiency begin to take effect, leading to an inverted U-shaped trend where carbon emissions initially rise and then fall. By contrast, in areas such as clothing, transportation, and daily necessities, consumption behaviors are constrained by traditional habits, fixed demand structures, and the realities of infrastructure. Even with the penetration of the digital economy, it is difficult to achieve fundamental changes in these consumption patterns or related carbon emissions. As a result, the digital economy has an insignificant impact on IHCEs in these categories.

Hypothesis H4. The impact of the digital economy on indirect household carbon emissions (IHCEs) varies across consumption categories. Specifically, the inverted U-shaped relationship between the digital economy and IHCEs is significant for food and housing consumption but not for clothing, transportation, daily necessities, and enjoyment-oriented or development-oriented consumption. Additionally, in the latter categories, the digital economy primarily drives an increase in carbon emissions.

4 Empirical research design

4.1 Variable selection

4.1.1 Explanatory variable

The dependent variable is the logarithm of IHCEs (lnC). The measurement of Indirect household carbon emissions (IHCEs) involves calculating the carbon emissions produced during the production of eight broad categories of daily consumption items: food, clothing, transportation and communication, pharmaceutical products, household equipment and supplies, culture, education and entertainment, housing, and other purposes. The household's main eight consumption categories and their corresponding production sectors are shown in Table 1. The indirect carbon emissions from household consumption were calculated using the following formula (Equations 1–4):

$$CE_i = CEP_i \times CEC \tag{1}$$

TABLE 1 The main eight consumption items of households and their related production industry sectors.

Consumption categories	Related consumption products
Food	Agriculture, Forestry, Animal Husbandry, Fishery and Water Conservancy; Processing of Food from Agricultural Products; Manufacture of Foods; Manufacture of Liquor, Beverages and Refined Tea
Clothing	Manufacture of Textile; Manufacture of Textile, Wearing Apparel and Accessories; Manufacture of Leather, Fur, Feather and Related Products and Footwear
Transportation and communication	Manufacture of Computers, Communication and Other Electronic Equipment; Transport, Storage and Post
Pharmaceutical manufacturing	Manufacture of Medicines
Consumption of household equipment and supplies	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products; Manufacture of Furniture; Manufacture of Rubber and Plastics Products; Manufacture of Metal Products; Manufacture of Electrical Machinery and Apparatus
Culture, Education and Entertainment	Manufacture of Paper and Paper Products; Printing and Reproduction of Recording Media; Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities
Housing	Manufacture of Non-metallic Mineral Products; Production and Supply of Electric Power and Heat Power; Production and Supply of Gas; Production and Supply of Water; Construction
Others	Manufacture of Tobacco Wholesale, Retail Trade and Hotel, Restaurants

TABLE 2 Indicator system for evaluating the level of development of the digital economy.

Tier 1 indicators	Tier 2 indicators	Variable	Tier 3 indicators
Level of development of The digital economy (digital)	Digital infrastructure	x1	Internet users per 100 population (users/100 population)
		x2	Mobile phone subscribers per 100 population (subscribers/100 population)
	Digital industrialization	x3	Revenue from telecommunication services (in millions of dollars, in logarithms)
		x4	Share of persons working in computer services and software in % of persons working in urban units (%)
	Industrial digitization	x5	Total postal operations *per capita* (million yuan)
		x6	Express business *per capita* (pieces)
	Digital services and governance	x7	Digital Financial Inclusion Index
		x8	Science and technology expenditures as a percentage (%)

$$CI_i = CE_i / G_i \tag{2}$$

$$\mathbf{IHCEs} = \sum_{i=1}^{n} CI_i \times consume_j \tag{3}$$

$$\mathbf{lnC} = \mathbf{ln}\,(\mathbf{IHCEs}) \tag{4}$$

where CE_i represents the scale of carbon emissions of the ith industry, CEP_i represents the energy consumption of the ith industry, and CEC represents the carbon emission coefficient of various energy sources consumed by the corresponding industry. CI_i represents the carbon emission intensity per unit of GDP for the ith industry, G_i represents the value added by the ith industry, and CE_i represents the carbon emissions of the ith industry. We then classify and analyze the household consumption expenditure items of each industry. By multiplying the amount of household expenditure on item j, consumej, by the carbon emission intensity per unit of value added of the ith industry to which it belongs, CI_i, we compute the carbon emissions generated by each household consumption expenditure. The carbon emissions of all consumption items are summed to obtain the total indirect carbon emissions from household consumption (IHCEs). Finally, we take the logarithm of this total to obtain the logarithmic value of IHCEs (lnC).

4.1.2 Core explanatory variables

The degree of digital economic development (digital) is the primary explanatory variable in this study, and the precise computation method is based on the research by Zhao et al. (2020). In this paper, eight variables are selected to construct the digital economic development index from four aspects: digital infrastructure, digital industrialization, industrial digitization, and digital services and governance. The assessment indexes are weighted using the entropy weighting method to produce a comprehensive assessment index of China's digital economic development level (refer to Table 2).

4.1.3 Control variable

To ensure a comprehensive and robust analysis of the impact of digital economy development on indirect household carbon emissions (IHCEs), this paper incorporates a set of carefully selected control variables at both the individual and household levels, addressing potential confounding factors that influence household consumption and emissions. At the individual level, age (the age of household decision-makers) is included to reflect generational differences in consumption patterns and

TABLE 3 Description of variables.

Variable	Sample size	Averages	Standard deviation	Minimum	Maximum
lnC	4,170	8.113	0.828	6.067	10.23
digital	4,170	0.116	0.0907	0.0266	0.567
digital^2	4,170	0.0218	0.0465	0.000709	0.322
age	4,170	54.65	11.91	17	85
gender	4,170	0.531	0.499	0	1
marriage	4,170	0.875	0.331	0	1
education	4,170	7.4	4.766	0	16
urban	4,170	0.479	0.5	0	1
familysize	4,170	3.269	1.487	1	13
child	4,170	0.101	0.149	0	0.667
old	4,170	0.177	0.311	0	1
house_debts	4,170	0.137	0.344	0	1
nonhousing_debts	4,170	0.113	0.317	0	1
lfamilyincome	4,170	9.59	0.757	6.685	11.52

environmental awareness, as younger decision-makers may adopt energy-intensive lifestyles while older ones might prioritize thriftier consumption. Gender (male = 1, female = 0) accounts for observed differences in consumption preferences, as male decision-makers often exhibit less inclination toward frequent purchases compared to females. Marriage (with spouse = 1, without spouse = 0) captures the effect of household composition, as married households typically exhibit higher resource demands. Education, measured by years of schooling (primary school = 6, lower secondary school = 9, upper secondary school = 12, tertiary and above = 16), is included to reflect the dual effect of education: enhancing income and aspirations for higher living standards while also potentially raising environmental awareness.

At the household level, urban (urban = 1, rural = 0) is controlled for to address structural disparities in access to goods and services and consumption patterns. Familysize reflects economies of scale in resource usage, where larger households often achieve higher efficiency in consumption *per capita*. The child dependency ratio (child) and elderly dependency ratio (old) (calculated as the ratio of children and elderly dependents to total household members, respectively) account for the impact of demographic structures on consumption priorities, such as expenditures on education or healthcare. House_debts (with housing loans = 1, without housing loans = 0) and nonhousing_debts (with non-housing loans = 1, without non-housing loans = 0) are included to measure financial constraints and their influence on household spending patterns, as households with debt obligations may prioritize essential consumption over discretionary or green purchases. Lastly, lfamilyincome (the logarithmic value of *per capita* net household income) is incorporated to capture the income effect, as wealthier households tend to consume more goods and services, which directly influences their carbon emissions.

These control variables are critical for isolating the effect of digital economy development on IHCEs by accounting for demographic, financial, and structural heterogeneities across households. For detailed definitions and summary statistics of these variables, see Table 3.

4.2 Data sources

This study utilizes data from multiple authoritative and nationally representative sources to analyze household consumption and carbon emissions. The core dataset is derived from the China Family Panel Studies (CFPS) for the years 2014, 2016, and 2018. CFPS, conducted by Peking University, is a nationally representative, longitudinal household survey that covers urban and rural households across 25 provinces, representing approximately 95% of China's population. Its comprehensive design ensures representativeness across regional, economic, and demographic dimensions, making it a robust data source for analyzing household behaviors. The dataset includes detailed information on eight distinct categories of household expenditure, ranging from food and housing to transportation and education. The CFPS data for 2020 were excluded from this study for two primary reasons. First, the 2020 dataset lacks detailed data on household consumption, making it inconsistent with earlier rounds of the survey. Second, the COVID-19 pandemic had an unprecedented impact on household consumption patterns, which would have introduced biases and inconsistencies into the analysis. By focusing on pre-pandemic years, this study ensures that the data accurately reflect typical household consumption behavior under stable economic and social conditions.

Energy consumption data, including energy equivalent standard coal coefficients and energy carbon emission coefficients, are sourced from the China Energy Statistics Yearbook and the IPCC Guidelines for National Greenhouse Gas Inventories, two widely recognized and authoritative sources. These datasets provide the energy equivalent standard coal coefficients and energy carbon

TABLE 4 Impact of the level of development of the digital economy on IHCEs: baseline regression results.

Variable	(1)	(2)	(3)	(4)
	lnC	lnC	lnC	lnC
digital	0.794*	2.357***	2.364***	1.940**
	(0.437)	(0.900)	(0.903)	(0.869)
$digital^2$		−3.146**	−2.907**	−2.868***
		(1.487)	(1.457)	(1.461)
age			−0.010***	−0.005***
			(0.001)	(0.001)
gender			−0.125***	−0.062***
			(0.028)	(0.023)
education			0.054***	0.028***
			(0.003)	(0.003)
marriage			0.316***	0.160***
			(0.048)	(0.039)
urban				0.175***
				(0.031)
familysize				0.110***
				(0.010)
lfamilyincome				0.453***
				(0.017)
house_debts				0.059*
				(0.033)
nonhousing_debts				0.054
				(0.035)
child				0.030
				(0.087)
old				−0.033
				(0.043)
city/year fixed	yes	yes	yes	yes
Constant	8.021***	7.907***	7.833***	3.132***
	(0.054)	(0.080)	(0.123)	(0.193)
Observations	4,170	4,170	4,170	4,170
R^2	0.176	0.177	0.317	0.476

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors clustered at the household level are reported in parentheses. The same applies to all subsequent tables.

emission coefficients, which are essential for converting energy consumption into carbon emissions. The accuracy and reliability of these coefficients are critical for ensuring robust and precise calculations of household carbon emissions. Additionally, value-added data for non-industrial sectors are obtained from the National Bureau of Statistics. Since value-added data for industrial sub-sectors have not been updated since 2007, this study estimates the values for 2014, 2016, and 2018 by applying growth rates from 2008 to 2018 to the 2007 baseline, with calculations performed using data from the CSMAR database. The growth rate adjustments for industrial sub-sector value-added are based on the "factory price index of industrial products," also sourced from CSMAR. For evaluating digital economic development, data from the China City Statistical Yearbook and statistical yearbooks of

prefectural-level cities are utilized. Missing data points are interpolated using linear and annual average methods. A one-to-one correspondence between household sample data and city-level digital economy metrics is established, resulting in the selection of 1,157 households surveyed across 2014, 2016, and 2018.

4.3 Model setup

Citing R.F.J. Haans et al. (2016), this study constructs two models: Model (5), which includes the primary terms of the explanatory variables, and Model (6), which includes the secondary terms of the explanatory variables. These models are used to examine the inverted U-shaped relationship between IHCEs and the development level of the digital economy. The econometric model is specified as follows (Equations 5, 6):

$$ln\,C_{it} = \alpha_0 + \alpha_1 digital_{it} + \sum_{j=2}^{j=14} \alpha_j Control_{it} + provinc_i + year_t + \varepsilon_{it} \quad (5)$$

$$ln\,C_{it} = \beta_0 + \beta_1 digital_{it} + \beta_2 digital_{it}^2 + \sum_{j=3}^{j=15} \beta_j Control_{it} + provinc_i + year_t + \varepsilon_{it} \quad (6)$$

where lnC_{it} represents the logarithm of household i's IHCEs in year t Digitalit represents the level of digital economic development in household i's city in year t. Controlit is a set of control variables including household decision maker and household characteristics variables, $province_i$ and $year_t$ represent province and year fixed effects, and ε_{it} is an unobservable observable error term.

5 Empirical results and analysis

5.1 Return to baseline

To enhance the robustness of the test results, this study adopts a stepwise methodology that incorporates provincial and temporal fixed effects, the digital economy, its squared term, and additional control variables into the regression model. Table 4 details the outcomes, with each column representing the logarithmic value of IHCEs as the dependent variable. A benchmark regression using the entire sample assesses the impact of the digital economy on IHCEs. Column (1) displays results based exclusively on the core explanatory variable, "digital". The significantly positive coefficient indicates that as the digital economy advances, the rate of increase in IHCEs also rises. Column (2) introduces the squared term of the digital economy ($digital^2$), revealing an inverted U-shaped relationship between the digital economy and IHCEs. Specifically, the coefficient for "digital" remains significantly positive, while the coefficient for "$digital^2$" is significantly negative. Columns (3), (4), and (5) sequentially incorporate individual, household, and regional control variables. The results continue to show a significantly positive coefficient for "digital" and a significantly negative coefficient for "$digital^2$", with only slight variations in magnitude and significance. These results substantiate the inverted U-shaped relationship between IHCEs and the digital economy. These results substantiate the inverted U-shaped relationship between IHCEs and the digital economy, suggesting that initially, as the digital economy fosters greater efficiency and consumption, it leads to higher carbon emissions. However, at a certain level of digital development, the relationship reverses due to the potential for more sustainable practices, such as increased efficiency in energy use and the promotion of green technologies. In other words, while the digital economy accelerates growth in carbon emissions at first, its later stages contribute to emissions reductions through innovation and improved resource management.

Column (3) presents the results for individual-level control variables, revealing a significant negative correlation between the age of the household decision-maker and IHCEs. This indicates that older individuals are more likely to display thriftier and more environmentally conscious consumption behaviors. This could be because older individuals may prioritize longevity, financial security, and sustainability, which influence their purchasing decisions and reduce their carbon footprint. However, this association does not hold in Column (4), where the coefficient becomes insignificant. This could indicate that other factors, such as income or family size, might overpower the effect of age on consumption behavior in this specific model, or that age-related effects are moderated by different contextual variables. Male decision-makers experience a slower rate of increase in IHCEs compared to their female counterparts. This difference is likely due to a lower inclination toward purchasing among men, leading to lower consumption and, consequently, fewer carbon emissions. The purchasing behaviors of men may differ from those of women due to socialized norms or differing attitudes toward consumption, which could contribute to this lower rate of increase in emissions. Furthermore, male decision-makers may prioritize cost-effective choices, leading to lower overall consumption. There is a statistically significant correlation between educational attainment and IHCEs. While higher education generally leads to better job prospects and higher income, the increased consumption associated with these higher earnings may counteract the environmental awareness gained through education, resulting in higher carbon emissions. Higher levels of education can often lead to greater financial affluence, which typically translates into greater consumption of goods and services, many of which are energy-intensive and contribute to higher carbon emissions. This highlights a complex relationship between income, consumption, and education. Moreover, the environmental awareness fostered through education may not always translate directly into more sustainable consumption patterns, especially when the financial means to consume more are available. Married households, compared to single-person households, generally exhibit higher carbon emissions due to increased consumption demands driven by larger household sizes. Moreover, their greater economic resources enable the purchase of more goods and services, many of which contribute to higher carbon emissions. Households with decision-makers in good health generally experience higher growth rates in indirect consumption-related carbon emissions. This is likely due to the reduction in healthcare expenditures, which allows for increased spending on other consumption goods and services, typically associated with higher carbon emissions. It is important to note that this effect is only significant in Model (3), indicating that the relationship may be sensitive to the inclusion of other variables or the specific model specification. It is worth noting

TABLE 5 Robustness test: inverted U-shaped relationship test results.

Variable	Lower bound	Upper bound
Interval	0.027	0.567
Slope	1.786	−1.314
t-value	2.227	−1.324
P>|t|	0.013	0.093

that this result is only significant in model (3), which suggests that this relationship may be influenced by other variables or vary by model setting. At the household level, regression coefficients for household size, total mortgage, the log of non-mortgage financial liabilities, and urban attributes are all positive and significant. In contrast, coefficients for child dependency and elderly dependency are not significant. A possible reason for this is that larger households typically exhibit higher emissions due to increased resource consumption associated with a larger family size. Similarly, households with substantial mortgages or non-mortgage liabilities tend to prioritize consumption over environmental concerns, driven by financial pressures, thereby contributing to higher emissions. Urban households, with their greater purchasing power and access to energy-intensive goods, also experience higher IHCEs. These findings align with the proposed hypotheses and earlier results.

5.2 Robustness check

5.2.1 Inverted U-shaped relationship test

This study examines the U-shaped relationship between the development level of the digital economy and industrial greenhouse gas emissions (IHCEs). Relying solely on the significance of the quadratic term's coefficient to establish this relationship lacks sufficient rigor.

First, the U-shaped curve has endpoints with positive and negative slopes, indicating that the curve trends both upward and downward. Second, the main explanatory variables in the model have positive primary coefficients, while the quadratic coefficients are negative, suggesting that the curve rises initially and then declines. Third, the inflection point of the curve should fall within the range defined by the core explanatory variables, specifically the digital economy development level examined in this study.

Table 5 and Figure 3 present the outcomes of the three-step U-test. The graphical representation reveals a curve exhibiting both upward and downward trends, characterized by an initial positive slope followed by a negative one. This pattern implies that the influence of digital economic growth on carbon emissions associated with household consumption is neither exclusively stimulatory nor purely inhibitory. As detailed in Table 3, the coefficients for "digital" and "digital2" are positive and negative, respectively, and are statistically significant at the 1% level. This finding suggests that the effect of digital economy development on household consumption-related carbon emissions initially promotes an increase, which subsequently transitions to a suppressive effect. The inflection point of 0.338 signifies a pivotal threshold in the development of the digital economy. Prior to this inflection point, advancements in digital economic infrastructure are associated with an increase in household consumption carbon emissions. However, once this threshold is surpassed, further development in the digital economy begins to moderate additional increases in these emissions. This observation supports the first Hypothesis H1. Initially, the digital economy's impact on household consumption is predominant, overshadowing its role in fostering green consumption behaviors and failing to effectively promote sustainable practices. As the digital economy progresses, heightened household consumption—both in volume and frequency—intensifies the growth rate of IHCEs. Nevertheless, during the later stages of digital economy maturation, the availability of environmentally friendly products and heightened

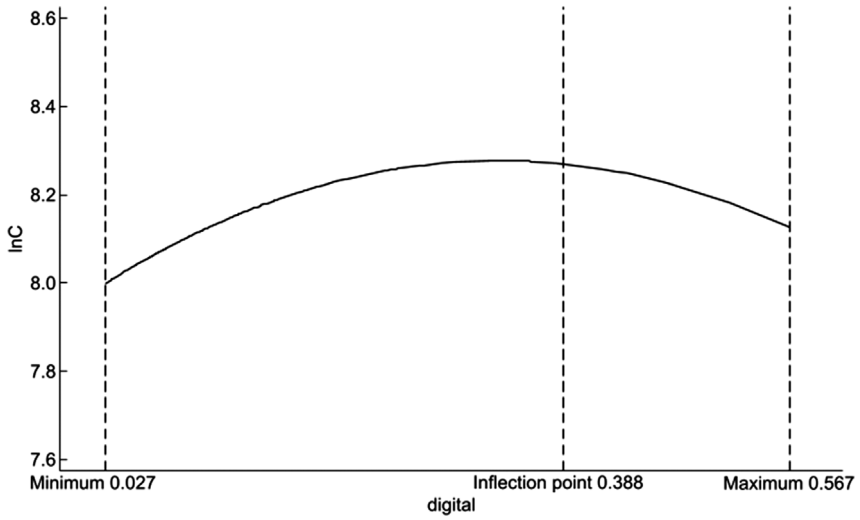


FIGURE 3
Inverted U-shaped relationship between the digital economy and household consumption carbon emissions.

TABLE 6 Robustness tests: main explanatory variable measures with substitutions.

Variable	(1)	(2)
	lnC	lnC
digital	1.831**	1.701**
	(0.914)	(0.866)
digital^2	−2.563*	−2.454*
	(1.471)	(1.422)
control variable	no	yes
city/year fixed	yes	yes
Constant	6.873***	2.935***
	(0.081)	(0.190)
Observations	4,170	4,170
R^2	0.227	0.510

TABLE 7 Results of heterogeneity test (subregion).

Variable	East	East	Central	Central	West
	lnC	lnC	lnC	lnC	lnC
digital	−1.545	−1.062**	2.914	2.054***	7.130***
	(1.160)	(0.525)	(2.693)	(0.776)	(2.662)
digital^2	0.791		−2.200		−11.182*
	(1.696)		(6.988)		(5.749)
control variable	yes	yes	yes	yes	yes
city/year fixed	yes	yes	yes	yes	yes
Constant	3.817***	3.771***	2.266***	2.321***	3.215***
	(0.297)	(0.282)	(0.340)	(0.315)	(0.375)
Observations	1886	1886	1,306	1,306	978
R^2	0.477	0.477	0.485	0.485	0.436

awareness of green and low-carbon consumption practices contribute to a deceleration in the growth rate of IHCEs.

5.2.2 Replacement of core explanatory variable measures

To enhance the reliability of the estimation results, this paper conducted a stability test. Specifically, the logarithm of *per capita* indirect household carbon emissions (IHCEs) was used as an explanatory variable instead of the logarithm of total IHCEs. The results, presented in Table 6, show that the coefficient for the digital economy variable is positive, while the coefficient for the squared digital economy variable is negative. All estimated coefficients remain significant after adjusting the explanatory variables. This confirms that the relationship between household carbon emissions and the digital economy remains inverted, thereby validating the robustness of the baseline regression.

5.3 Inflection point analysis

Where does China's digital economy development currently fall on the inverted U-shaped curve? Previous analyses have identified an inverted U-shaped relationship between IHCEs and the level of digital economy growth. The question arises: will the ongoing advancement in digitalization lead to a reduction or an escalation in IHCEs? This study leverages empirical estimations to pinpoint the inflection point on this inverted U-shaped curve.

Based on the logarithm of total IHCEs, the inflection point for digital economic development is determined to be 0.338. For the logarithm of average *per capita* IHCEs, the inflection point is slightly higher at 0.347, as derived from various measurement methodologies (see Tables 3–5). Currently, with a mean score of 0.116, China's level of digital economic development is positioned to the left of this inflection point. Furthermore, only 3.71% of cities with sample households have surpassed the inflection point in digital economy development, suggesting that most cities have yet to reach it. These results imply that the digital economy in China is still in its developmental phase. Given the mean digital economy development score of 0.116, it is evident that China's digital economy remains on the lower segment of the inverted U-shaped curve. Therefore, the continued growth of the digital economy is anticipated to further increase IHCEs, and accelerating digital economy development may be crucial for mitigating these emissions.

TABLE 8 Heterogeneity test results (by level of digital economy development).

Variable	Low level of digital economy development	High level of digital economy development
digital	lnC	lnC
	12.888**	1.183
digital^2	(5.596)	(1.428)
	−71.805**	−1.410
control variable	(33.792)	(1.923)
	yes	yes
city/year fixed	yes	yes
Constant	2.733***	2.897***
	(0.314)	(0.377)
Observations	2,914	1,256
R^2	0.446	0.506

5.4 Heterogeneity analysis

5.4.1 By region

The analysis divides the country into three distinct regions: the eastern, central, and western regions. Each region has unique characteristics that shape the relationship between the digital

TABLE 9 Results of heterogeneity tests (by type of household consumption).

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnC_food	lnC_dress	lnC_trco	lnC_med	lnC_daily	lnC_eec	lnC_house	lnC_other
digital	1.570	−0.970	0.347	−1.625	−0.434	7.853**	3.515***	0.572
	(0.972)	(1.270)	(1.031)	(2.015)	(1.909)	(3.304)	(1.359)	(1.587)
$digital^2$	−2.378*	0.108	−0.555	1.671	−0.007	−8.905	−5.829***	−1.954
	(1.423)	(1.892)	(1.697)	(3.312)	(3.088)	(5.726)	(2.099)	(2.906)
control variable	yes	yes	yes	yes	yes	yes	yes	yes
city/year fixed	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.865***	0.978***	2.166***	−0.285	−0.578	2.768***	2.112***	−2.657***
	(0.217)	(0.299)	(0.276)	(0.415)	(0.378)	(0.739)	(0.274)	(0.369)
Observations	4,160	3,903	4,119	3,757	4,122	2,372	4,154	3,503
R^2	0.494	0.378	0.398	0.157	0.261	0.178	0.307	0.314

Note: lnC_food, lnC_dress, lnC_trco, lnC_med, lnC_daily, lnC_eec, lnC_house, and lnC_other represent the logarithms of carbon emissions from food consumption, clothing consumption, transportation consumption, medical and healthcare consumption, household equipment and supplies consumption, cultural and entertainment consumption, housing consumption, and other consumption, respectively.

economy and indirect household carbon emissions (IHCEs). In the eastern region, boasting advanced digital infrastructure and a robust economic foundation, the digital economy significantly curbs IHCEs. As per Hypothesis H2a, the region's strong technological innovation, driven by industrial structure optimization, enables enterprises to integrate digital tech into production, reducing emissions. Also, a comprehensive carbon emission regulatory framework, based on externality theory, ensures environmental sustainability. This may have pushed the region past the inverted U - shaped curve's inflection point, nullifying the digital economy's initial positive impact on emissions. Turning to the central region, Hypothesis H2b holds true. Here, traditional consumption patterns are deeply ingrained. In the early days of digital economy development, limited digital infrastructure and tech application capabilities meant little promotion of low - carbon consumption. As digital penetration grows, new consumption patterns like online shopping emerge, driving up IHCEs as related industries expand. The western region, with its traditional industrial base, is in a phase of transformation. Initially, low digital technology adoption and traditional production inertia led to more emissions during digital economy growth. But as per Hypothesis H2c, with government - promoted environmental tech and rising public green awareness, the relationship between the digital economy and IHCEs forms an inverted U - shape. As seen in Table 7, these trends confirm Hypotheses H2a, H2b, and H2c, highlighting the diverse impacts of the digital economy on IHCEs across different regions.

5.4.2 By level of digital economy development

Samples are stratified based on the level of digital economy development. Those below the mean are classified as having a low level of digital economy development, while those above the median are categorized as having a high level of digital economy development. As indicated in Table 8, the inverted U - shaped relationship between household carbon emissions and digital economy development is pronounced in low - development areas. However, in high - development regions, this relationship is not statistically significant. A reasonable explanation for this is as follows. In areas with underdeveloped digital economies, household expenditures are mainly concentrated on essential goods and services such as food, clothing, and housing. These consumption activities generally result in relatively low carbon emissions. When the digital economy starts to develop in these areas, for example, the rise of e − commerce stimulates consumption and drives the development of related industries like logistics and transportation. Due to limited technological capabilities and imperfect environmental protection measures at this stage, indirect household carbon emissions (IHCEs) increase rapidly. Nevertheless, with the further development of the digital economy, increased investment in energy - saving technologies and the implementation of stricter environmental policies help to suppress and eventually reduce IHCEs, thus forming a distinct inverted U - shaped relationship. In contrast, in regions with advanced digital economies, characterized by strong economic growth, advanced technology, and optimized industrial structures, the concept of sustainable development has been integrated into development strategies from the early stage. Although households in these areas may tend to consume high - carbon - emission goods and services such as automobiles, air travel, and electronics, and residents may prefer luxurious and high - consumption lifestyles, the well - established energy - saving and emission - reduction systems and strict environmental regulations in these regions encourage both enterprises and consumers to prioritize environmental protection. As a result, the inverted U - shaped effect between household carbon emissions and digital economy development is weakened. In conclusion, Hypothesis H3 is confirmed.

5.4.3 By type of household consumption

This study delves into the influence of the digital economy on carbon emissions, meticulously examining eight different categories

of household consumption. As presented in Table 9, a notable finding is that there exists an inverted U - shaped relationship between the digital economy and indirect household carbon emissions (IHCEs), with this correlation being mainly shaped by housing and food consumption. For clothing, medical care, transportation, home goods and equipment, education, entertainment, and other categories, a positive U - shaped relationship with carbon emissions is observed, yet it lacks statistical significance. This divergence can be attributed to multiple factors. In the early stages of the digital economy, as living standards rise, consumption increases, thereby driving up IHCEs, especially in food and housing. For instance, more people might choose larger houses or dine out more frequently. However, as the digital economy matures, the easy access to and sharing of information has promoted healthy eating concepts. People consume less high - calorie and high - fat foods, reducing carbon emissions from food consumption. Meanwhile, in the housing sector, the digital economy has enabled households to access more eco - friendly housing options and construction materials, cutting down on related emissions. In line with Hypothesis H4, which posits that the digital economy's impact on IHCEs varies across consumption categories, with an inverted U - shaped relationship significant for food and housing but not for other categories where it mainly drives emission increases. Up to this point, Hypothesis H4 is verified.

6 Conclusions and recommendations

In the global context of advancing carbon reduction efforts and promoting sustainable development, the digital economy, as an emerging and highly influential force, is reshaping socio-economic structures comprehensively. Against this backdrop, the relationship between the digital economy and indirect household carbon emissions (IHCEs) has garnered significant attention. However, previous studies have not fully explored the mechanisms through which the digital economy impacts IHCEs, nor the variations of this impact across regions, levels of digital economic development, and consumption categories. To address these gaps, this study focuses on the critical issue of how digital economic development influences IHCEs. To achieve precise and representative conclusions, this research employs data from the 2014–2018 China Family Panel Studies (CFPS). This dataset covers households across different regions and economic levels in China, providing comprehensive and reliable information to build a solid foundation for analysis. Using rigorous econometric modeling and empirical methods, this study conducts an in-depth multidimensional analysis, yielding the following key findings:

(1) An Inverted U-shaped Relationship between the Digital Economy and IHCEs. The relationship between the digital economy and IHCEs exhibits a significant inverted U-shaped pattern, as validated by robustness checks. In the early stages of digital economic development, improved accessibility to goods and services, coupled with expanded consumer choices, drives significant increases in the consumption of energy-intensive products, thereby raising IHCEs. This occurs because, in its initial stages, the digital economy primarily stimulates consumption growth, while its energy-saving and carbon-reducing benefits remain underutilized. As digital technologies mature, resource allocation becomes more efficient, and sustainable consumption concepts gain traction. Enterprises leverage digital technologies to improve production efficiency and reduce resource waste, while consumers are more inclined to choose low-carbon products, leading to a gradual decline in IHCEs. This finding enriches the theoretical understanding of the relationship between the digital economy and environmental sustainability, offering policymakers critical evidence for formulating stage-specific policies that align digital economic growth with carbon reduction objectives.

(2) Regional Differences in the Digital Economy's Impact. The impact of the digital economy on IHCEs varies significantly across regions. In the Eastern region, supported by advanced digital infrastructure and a high level of digitalization, enterprises efficiently adopt green production technologies, and residents are more likely to embrace low-carbon lifestyles. Consequently, the digital economy in the Eastern region exhibits a strong carbon-reducing effect. In contrast, the Central region, with its relatively underdeveloped digital infrastructure, experiences increased emissions as industries consume more energy and emit more carbon during the transition to new consumption patterns like online shopping. Meanwhile, in the Western region, carbon emissions initially rise due to industrial transformation challenges. However, as technological progress accelerates and environmental awareness improves, the digital economy and IHCEs in the Western region gradually exhibit an inverted U-shaped relationship.

(3) Heterogeneity by Digital Economic Development Levels. The impact of the digital economy on IHCEs also varies significantly based on the level of digital economic development. In regions with low levels of digital economic development, IHCEs and the digital economy exhibit a pronounced inverted U-shaped relationship. During the initial phase, rapid growth in new industries, such as e-commerce, stimulates consumption and drives industrial expansion. However, due to inadequate technology and insufficient environmental measures, carbon emissions increase rapidly. As the digital economy advances, increased investments in energy-saving technologies and improved environmental policies help curb and eventually reduce emissions. Conversely, in regions with high levels of digital economic development, the inverted U-shaped relationship is less pronounced. These regions, characterized by advanced economies, optimized industrial structures, and strict environmental regulations, integrate sustainability concepts into economic and consumption models early on, preventing significant rises in carbon emissions.

(4) Sectoral Heterogeneity in the Digital Economy's Impact on IHCEs. A deeper analysis by consumption categories reveals significant heterogeneity in the digital economy's impact on IHCEs. In the food and housing sectors, the digital economy demonstrates a clear inverted U-shaped relationship with

IHCEs. During the early stages, the convenience brought by digital technologies stimulates demand, leading to industrial expansion and increased emissions. As digital technologies mature, industries accelerate their green transformation, reducing energy consumption and carbon emissions. However, in sectors such as transportation, household equipment, and cultural and recreational activities, the theoretical inverted U-shaped relationship is not significant. In the clothing and healthcare sectors, a positive U-shaped relationship emerges but lacks strong significance. These findings highlight the uneven progress in emission reductions across industries, revealing the untapped potential of the digital economy for reducing emissions.

To fully realize the potential of the digital economy in reducing IHCEs, policymakers should design targeted, region-specific, and sector-focused strategies based on the study's findings. The following recommendations are proposed:

(1) Promoting Sustainable Development Based on the Inverted U-shaped Relationship. Given the inverted U-shaped relationship between the digital economy and IHCEs, policymakers should focus on guiding consumption during the early stages of digital economic development. On one hand, public education campaigns can enhance consumer awareness and preferences for low-carbon products, discouraging excessive consumption of energy-intensive goods. On the other hand, subsidies and tax incentives should support the development and application of energy-saving and carbon-reducing technologies, accelerating technological and industrial transformation. During the mature stages of the digital economy, policies should encourage enterprises to continue innovating and leveraging digital technologies to optimize resource allocation while promoting sustainable consumption concepts. These efforts will align the digital economy with low-carbon development goals.

(2) Regional Differentiation Policies to Promote Balanced Development. To address regional disparities in the digital economy's impact on IHCEs, region-specific strategies are essential. In the Eastern region, policymakers should strengthen the digital economy's role in promoting low-carbon development by encouraging enterprises to engage in green technological innovation and integrating digital technologies into green production processes. In the Central region, investments in digital infrastructure should be accelerated to attract digital economy enterprises, facilitate the digital transformation of traditional industries, and reduce industrial energy consumption. In the Western region, efforts should focus on advancing technology and raising environmental awareness by establishing special funds for energy-saving technology research and promoting green consumption practices. These measures will help ensure that the Western region transitions more quickly to the descending phase of the inverted U-shaped curve.

(3) Tailoring Strategies to Digital Economy Development Levels. In regions with low levels of digital economy development, efforts should focus on regulating emerging industries, such as e-commerce, by establishing green development thresholds and encouraging enterprises to adopt environmentally friendly production technologies. As the digital economy advances, investments in energy-saving technologies should increase, and environmental policies should impose stricter carbon emission limits. In regions with high levels of digital economy development, policies should explore the integration of digital economy advancements with green industries. For example, establishing innovation parks with tax incentives can encourage sustainable practices. Supporting green supply chain management and rewarding enterprises for reducing supply chain emissions will further consolidate sustainable development outcomes.

(4) Unlocking Emissions Reduction Potential by Consumption Categories. Policies should prioritize emissions reductions in the food and housing sectors, where the digital economy demonstrates clear potential for impact. Early-stage green planning should guide industrial expansion, while incentives for environmentally friendly production processes and materials can further support these efforts. For sectors such as transportation, household equipment, and cultural activities, policies should encourage the development of low-carbon technologies and products. For example, subsidies for new energy vehicle production and research on digital emissions reduction pathways in these sectors could drive progress. In the clothing and healthcare sectors, businesses using sustainable materials and processes should receive subsidies, and public awareness campaigns should promote environmentally conscious consumption. These measures will unlock the full potential of the digital economy in reducing IHCEs across all consumption categories.

By implementing these policy measures, governments can maximize the digital economy's potential to reduce IHCEs while fostering sustainable and inclusive economic growth. The findings provide valuable guidance for policymakers and researchers seeking to align digital economic development with environmental sustainability goals.

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

YC: Data curation, Software, Writing–original draft, Writing–review and editing. DC: Supervision, Writing–review and editing. CG: Methodology, Supervision, Writing–review and editing. XW: Funding acquisition, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by the National Natural Science Foundation of China [grant number 72271192].

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 author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Baiocchi, G., Minx, J., and Hubacek, K. (2010). The impact of social factors and consumer behavior on carbon dioxide emissions in the United Kingdom: a regression based on Input–Output and geodemographic consumer segmentation data. *J. Ind. Ecol.* 14, 50–72. doi:10.1111/j.1530-9290.2009.00216.x

Bieser, J. C. T., and Hilty, L. M. (2018). Indirect effects of the digital transformation on environmental sustainability: methodological challenges in assessing the greenhouse gas abatement potential of ICT. *EPiC Ser. Comput.* 52, 68–53. doi:10.29007/lx7q

Bin, S., and Dowlatabadi, H. (2005). Consumer lifestyle approach to US energy use and the related CO2 emissions. *Energy Policy* 33, 197–208. doi:10.1016/S0301-4215(03)00210-6

Brand, C., Goodman, A., Rutter, H., Song, Y., and Ogilvie, D. (2013). Associations of individual, household and environmental characteristics with carbon dioxide emissions from motorised passenger travel. *Appl. Energy* 104, 158–169. doi:10.1016/j.apenergy.2012.11.001

Büchs, M., and Schnepf, S. V. (2013). Who emits most? Associations between socio-economic factors and UK households' home energy, transport, indirect and total CO2 emissions. *Ecol. Econ.* 90, 114–123. doi:10.1016/j.ecolecon.2013.03.007

Cao, J., Ho, M. S., Li, Y., Newell, R. G., and Pizer, W. A. (2019). Chinese residential electricity consumption: estimation and forecast using micro-data. *Resour. Energy Econ.* 56, 6–27. doi:10.1016/j.reseneeco.2017.10.003

Ding, N., Gu, L., and Peng, Y. (2022). Fintech, financial constraints and innovation: evidence from China. *J. Corp. Finance* 73, 102194. doi:10.1016/j.jcorpfin.2022.102194

Du, Z., Xu, J., and Lin, B. (2024). What does the digital economy bring to household carbon emissions? – From the perspective of energy intensity. *Appl. Energy* 370, 123613. doi:10.1016/j.apenergy.2024.123613

Eggleston, H. S., Buendia, L., Miwa, K., Ngara, T., and Tanabe, K. (2006). 2006 IPCC Guidelines for national greenhouse gas Inventories. Available at: https://www.osti.gov/etdeweb/biblio/20880391 (Accessed August 30, 2024).

Fan, J., Zhou, L., Zhang, Y., Shao, S., and Ma, M. (2021). How does population aging affect household carbon emissions? Evidence from Chinese urban and rural areas. *Energy Econ.* 100, 105356. doi:10.1016/j.eneco.2021.105356

Feng, S., Liu, J., and Xu, D. (2023). Digital financial development and indirect household carbon emissions: empirical evidence from China. *Environ. Dev. Sustain.* 26, 23401–23435. doi:10.1007/s10668-023-03603-4

Feng, Z.-H., Zou, L.-L., and Wei, Y.-M. (2011). The impact of household consumption on energy use and CO2 emissions in China. *Energy* 36, 656–670. doi:10.1016/j.energy.2010.09.049

Frick, V., and Matthies, E. (2020). Everything is just a click away. Online shopping efficiency and consumption levels in three consumption domains. *Sustain. Prod. Consum.* 23, 212–223. doi:10.1016/j.spc.2020.05.002

Goldfarb, A., and Tucker, C. (2019). Digital economics. *J. Econ. Lit.* 57, 3–43. doi:10.1257/jel.20171452

Gong, X., Zhang, J., Zhang, H., Cheng, M., Wang, F., and Yu, N. (2020). Internet use encourages pro-environmental behavior: evidence from China. *J. Clean. Prod.* 256, 120725. doi:10.1016/j.jclepro.2020.120725

Guo, F., Zheng, X., Wang, C., and Zhang, L. (2022). Sharing matters: household and urban economies of scale for a carbon-neutral future. *Resour. Conserv. Recycl.* 184, 106410. doi:10.1016/j.resconrec.2022.106410

Haans, R. F. J., Pieters, C., and He, Z. (2016). Thinking about U: theorizing and testing U - and inverted U -shaped relationships in strategy research. *Strateg. Manag. J.* 37, 1177–1195. doi:10.1002/smj.2399

Heinonen, J., and Junnila, S. (2011). Implications of urban structure on carbon consumption in metropolitan areas. *Environ. Res. Lett.* 6, 014018. doi:10.1088/1748-9326/6/1/014018

Hertwich, E. G., and Peters, G. P. (2009). Carbon footprint of nations: a global, trade-linked analysis. *Environ. Sci. Technol.* 43, 6414–6420. doi:10.1021/es803496a

Hou, J., Li, W., and Zhang, X. (2024). Research on the impacts of digital economy on carbon emission efficiency at China's City level. *PloS One* 19, e0308001. doi:10.1371/journal.pone.0308001

Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A., et al. (2016). Environmental impact assessment of household consumption. *J. Ind. Ecol.* 20, 526–536. doi:10.1111/jiec.12371

Jin, X., and Yu, W. (2022). Information and communication technology and carbon emissions in China: the rebound effect of energy intensive industry. *Sustain. Prod. Consum.* 32, 731–742. doi:10.1016/j.spc.2022.06.004

Kim, H. B., Iwamatsu, T., Nishio, K., Komatsu, H., Mukai, T., Odate, Y., et al. (2020). Field experiment of smartphone-based energy efficiency services for households: impact of advice through push notifications. *Energy Build.* 223, 110151. doi:10.1016/j.enbuild.2020.110151

Kim, J., Jang, M., and Shin, D. (2019). Examining the role of population age structure upon residential electricity demand: a case from korea. *Sustainability* 11, 3914. doi:10.3390/su11143914

Lei, X., Ma, Y., Ke, J., and Zhang, C. (2023). The non-linear impact of the digital economy on carbon emissions based on a mediated effects model. *Sustainability* 15, 7438. doi:10.3390/su15097438

Li, T., Jiang, Y., and Zhao, Y. (2024). Does mobile payment foster low-carbon lifestyles? Evidence from Alipay's "collecting five blessings" campaign. *J. Clean. Prod.* 463, 142513. doi:10.1016/j.jclepro.2024.142513

Li, T., and Ma, J. (2021a). Does digital finance benefit the income of rural residents? A case study on China. Quant. *Finance Econ.* 5, 664–688. doi:10.3934/QFE.2021030

Li, X., Zhang, D., Zhang, T., Ji, Q., and Lucey, B. (2021b). Awareness, energy consumption and pro-environmental choices of Chinese households. *J. Clean. Prod.* 279, 123734. doi:10.1016/j.jclepro.2020.123734

Li, Z., and Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: evidence city-level empirical data in China. *J. Clean. Prod.* 351, 131570. doi:10.1016/j.jclepro.2022.131570

Liu, W., Spaargaren, G., Heerink, N., Mol, A. P. J., and Wang, C. (2013). Energy consumption practices of rural households in north China: basic characteristics and potential for low carbon development. *Energy Policy* 55, 128–138. doi:10.1016/j.enpol.2012.11.031

Luo, S., Sun, Y., and Zhou, R. (2022). Can fintech innovation promote household consumption? Evidence from China family panel studies. *Int. Rev. Financ. Anal.* 82, 102137. doi:10.1016/j.irfa.2022.102137

Ma, R., Zheng, X., Zhang, C., Li, J., and Ma, Y. (2022). Distribution of CO2 emissions in China's supply chains: a sub-national MRIO analysis. *J. Clean. Prod.* 345, 130986. doi:10.1016/j.jclepro.2022.130986

Mi, Z., Zheng, J., Meng, J., Ou, J., Hubacek, K., Liu, Z., et al. (2020). Economic development and converging household carbon footprints in China. *Nat. Sustain.* 3, 529–537. doi:10.1038/s41893-020-0504-y

Pu, Z., and Fei, J. (2022). The impact of digital finance on residential carbon emissions: evidence from China. *Struct. Change Econ. Dyn.* 63, 515–527. doi:10.1016/j.strueco.2022.07.006

Qin, X., Wu, H., and Li, R. (2022). Digital finance and household carbon emissions in China. *China Econ. Rev.* 76, 101872. doi:10.1016/j.chieco.2022.101872

Sarfraz, M., Ivascu, L., Abdullah, M. I., Ozturk, I., and Tariq, J. (2022). Exploring a pathway to sustainable performance in manufacturing firms: the interplay between innovation capabilities, green process, product innovations and digital leadership. *Sustainability* 14, 5945. doi:10.3390/su14105945

Sharif, A., Raza, S. A., Ozturk, I., and Afshan, S. (2019). The dynamic relationship of renewable and nonrenewable energy consumption with carbon emission: a global study with the application of heterogeneous panel estimations. *Renew. Energy* 133, 685–691. doi:10.1016/j.renene.2018.10.052

Shirley, R., Jones, C., and Kammen, D. (2012). A household carbon footprint calculator for islands: case study of the United States Virgin Islands. *Ecol. Econ.* 80, 8–14. doi:10.1016/j.ecolecon.2012.04.027

Song, K., Qu, S., Taiebat, M., Liang, S., and Xu, M. (2019). Scale, distribution and variations of global greenhouse gas emissions driven by U.S. households. *Environ. Int.* 133, 105137. doi:10.1016/j.envint.2019.105137

Wang, J., Dong, X., and Dong, K. (2022). How digital industries affect China's carbon emissions? Analysis of the direct and indirect structural effects. *Technol. Soc.* 68, 101911. doi:10.1016/j.techsoc.2022.101911

Wang, S., Sun, S., Zhao, E., and Wang, S. (2021). Urban and rural differences with regional assessment of household energy consumption in China. *Energy* 232, 121091. doi:10.1016/j.energy.2021.121091

Wei, Y.-M., Liu, L.-C., Fan, Y., and Wu, G. (2007). The impact of lifestyle on energy use and CO2 emission: an empirical analysis of China's residents. *Energy Policy* 35, 247–257. doi:10.1016/j.enpol.2005.11.020

Wiedmann, T., Lenzen, M., Keyßer, L. T., and Steinberger, J. K. (2020). Scientists' warning on affluence. *Nat. Commun.* 11, 3107. doi:10.1038/s41467-020-16941-y

Xu, X., and Han, L. (2017). Diverse effects of consumer credit on household carbon emissions at quantiles: evidence from urban China. *Sustainability* 9, 1563. doi:10.3390/su9091563

Xu, X., Han, L., and Lv, X. (2016). Household carbon inequality in urban China, its sources and determinants. *Ecol. Econ.* 128, 77–86. doi:10.1016/j.ecolecon.2016.04.015

Yin, X., Hao, Y., Yang, Z., Zhang, L., Su, M., Cheng, Y., et al. (2020). Changing carbon footprint of urban household consumption in Beijing: Insight from a nested input-output analysis. *J. Clean. Prod.* 258, 120698. doi:10.1016/j.jclepro.2020.120698

Yin, X., Zhang, J., and Ji, J. (2023). Nonlinear impact of digital economy on carbon intensity: the moderating role of low-carbon regulation. *Environ. Sci. Pollut. Res.* 30, 122346–122363. doi:10.1007/s11356-023-30770-8

Yin, Z., Wang, T., and Jiang, J. (2023). The impact of mobile payment on carbon consumption of Chinese households: evidence from household carbon footprint. *Account. Econ. Res.* 37, 99–116. doi:10.16314/j.cnki.31-2074/f.2023.01.006

Zhang, H., Shi, X., Wang, K., Xue, J., Song, L., and Sun, Y. (2020). Intertemporal lifestyle changes and carbon emissions: evidence from a China household survey. *Energy Econ.* 86, 104655. doi:10.1016/j.eneco.2019.104655

Zhang, J., and Wei, Z. (2023). Can the digital economy drive the low-carbon transformation of household consumption? Empirical evidence based on CFPS. *Mod. Finance Economics-Journal Tianjin Univ. Finance Econ.* 43, 3–19. doi:10.19559/j.cnki.12-1387.2023.09.001

Zhang, W., Liu, X., Wang, D., and Zhou, J. (2022). Digital economy and carbon emission performance: evidence at China's city level. *Energy Policy* 165, 112927. doi:10.1016/j.enpol.2022.112927

Zhang, Y., Wang, F., and Zhang, B. (2023). The impacts of household structure transitions on household carbon emissions in China. *Ecol. Econ.* 206, 107734. doi:10.1016/j.ecolecon.2022.107734

Zhao, T., Zhang, Z., and Liang, S. (2020). Digital economy, entrepreneurship, and high-quality economic development: empirical evidence from urban China. *J. Manag. World* 36, 65–76. doi:10.19744/j.cnki.11-1235/f.2020.0154

Zheng, H., Long, Y., Wood, R., Moran, D., Zhang, Z., Meng, J., et al. (2022). Ageing society in developed countries challenges carbon mitigation. *Nat. Clim. Change* 12, 241–248. doi:10.1038/s41558-022-01302-y

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 21 February 2025
DOI 10.3389/fenvs.2025.1443405

Check for updates

OPEN ACCESS

EDITED BY
Mobeen Ur Rehman,
Keele University, United Kingdom

REVIEWED BY
Mohamed R. Abonazel,
Cairo University, Egypt
Maham Furqan,
Oregon State University, United States

*CORRESPONDENCE
Youhui Li,
liyouhui19901018@163.com

RECEIVED 04 June 2024
ACCEPTED 16 January 2025
PUBLISHED 21 February 2025

CITATION
Li Y, Chen B, Guo L and Kang J (2025) Analysis of the impact of the digital economy system on carbon emissions and carbon footprint from the perspective of high-quality development. *Front. Environ. Sci.* 13:1443405. doi: 10.3389/fenvs.2025.1443405

COPYRIGHT
© 2025 Li, Chen, Guo and Kang. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Analysis of the impact of the digital economy system on carbon emissions and carbon footprint from the perspective of high-quality development

Youhui Li[1,2]*, Beichuan Chen[3], Lifeng Guo[1] and Jie Kang[1]

[1]College of Mathematics and Statistics, Yulin University, Yulin, Shaanxi, China, [2]Graduate School, Woosong University, Daejeon, Republic of Korea, [3]College of Mathematics and Statistics, Yunnan University of Finance and Economics, Kunming, Yunnan, China

The application of digital technology and the emergence of new economic forms have accelerated economic and social dynamic circulation, and the digital economy industry has achieved positive results in enhancing regional carbon emission efficiency. Therefore, exploring the carbon footprint of the digital economy system and the new development model of "dual circulation" from the perspective of high-quality development is important to ensure its healthy development. This study is based on the theory of high-quality development. It uses panel models, spatial econometric models, and other methods for empirical analysis of the level of digital economy development and carbon emission efficiency in more than 25 provinces in China and also of their impact effects. The results indicated that under the post-epidemic situation, the digital economy level of various provinces in China has improved to varying degrees, especially in the Beijing, Tianjin, Hebei, and Pearl River Delta regions, where the improvement effect is significant. The carbon emission efficiency showed a decreasing trend from east to west in the spatial dimension. The digital economy was significantly positively correlated with carbon emission efficiency at the 1% level. In comparison, the negative effects of urbanization level and government macro intervention variables were significant at the 5% and 10% levels. The adjustment of industrial structure, energy technology, and development of the digital economy had significant spatial spillover effects and heterogeneity. When the digital economy improved carbon emission efficiency, a certain degree of peripheral inhibition was observed. From the perspective of high-quality development, the digital economy needs to focus on the "simultaneous realization and maintenance" of economic and ecological benefits and actively adjust the industrial structure and energy optimization based on regional differences.

KEYWORDS

digital economic system, carbon emissions, panel model, spatial spillover effects, industrial structure, carbon footprint

1 Introduction

Faced with the current trend of digital transformation and development in the world economy, its scale anddepth of development are also constantly deepening and expanding. As an important lever to enhance economic development and build new competitive advantages and new patterns, it has obvious advantages in leveraging China's market advantages and domestic demand potential. The research and application of digital technology such as big data, artificial intelligence (AI), and cloud computing are continuously promoting technological innovation, and new economic formats are emerging one after another. The dynamic cycle system of economic development is also constantly being optimized (Yu and Zhu, 2023; Han et al., 2022). The report of the 20th National Congress of the Communist Party of China proposed accelerating the digital economy development (DED) and stimulating the deep and multi-domain development of digital technology through the deployment of economic network infrastructure (Hussain et al., 2022). Digital economy has become a new engine for promoting economic and social high-quality development (HQD). As an economic system based on digital technology, it covers a wide range of connotations. In the China Digital Economy Development Report (2022), the extent of industrial digitization in China exceeded 80% in 2021. As a new direction of industrial development, digital economy is closely related to carbon emissions (CEs) (Ren et al., 2022). According to relevant data, there are differences in the carbon footprint (CFP) of industrial activities in China in the 21st century, and the ecological deficit caused by the scarcity in productive land area is more obvious, making it difficult to compensate for the CFP of the industrial space (Hertwich, 2021). With the increasing severity of global climate change, reducing CEs and achieving sustainable economic development have become urgent issues that need to be addressed by countries and regions. The digital economy accelerates the penetration and integration of digital technology and digital elements into deeper and wider fields by continuously upgrading network infrastructure and information tools such as intelligent machines. It also promotes the transformation of the economic form from industrial economy to smart economy, thereby bringing about a change in the overall economic operation mode. In the context of carbon peak and carbon neutrality, high-energy-consuming industries urgently need to be transformed and upgraded, and residents' consumption patterns need to be optimized urgently. Therefore, combining digital economy with green development is the only way and key technology to promote the "dual carbon" goal and high-quality economic development (Chen et al., 2024). In the 14th Five Year Plan and 2035 Vision Goal Outline, it is also proposed to that the intelligence level of cities be improved, digital management and operation of cities be promoted, and the concept of "low-carbon" cities be advanced (Saeed et al., 2023). Therefore, conducting research on China's provincial level is in line with the requirements of China's development strategy and an important part of adapting to future economic development. There are differences in industrial structure, resource endowment, and technological level among different provinces. At the provincial level, research can provide a scientific basis for the development of each province, improve resource utilization efficiency, and serve as a crucial strategic support for achieving China's long-term carbon neutrality goals.

Within different economic circles, the impact of DED on CEs varies, and the spatial boundary effects that it presents also differ to some extent. Among them, the development of digital industries, digital innovation capabilities, and digital inclusive finance are important factors regarding the impact of the digital economy on urban CEs. The digital economy has driven the development of information and communication technology, while remote sensing technology, Internet of Things devices, and online data analysis tools have improved the efficiency of economic activities. Digital transformation may lead to changes in energy consumption patterns, which can help automate CE trading markets. The relationship between the digital economy and emission efficiency depends on multiple factors, especially the application of digital technology and the policy environment in which it operates. To maximize the use of the digital economy to improve emission efficiency, it is necessary to strategically plan and adjust energy use and emissions, while encouraging responsible technology use and innovation. Related studies have shown that there is significant spatial heterogeneity in the development of China's digital economy, and the development pattern has shifted from a "multi-point" sporadic distribution to a "clustered" aggregation form. However, the gap in development levels among cities has not improved (Wang and Zhong, 2023). The digital economy, with the Internet and big data as its main components, has become an important booster for China's HQD. The integration of digital technology provides an opportunity for economic green and low-carbon transformation (LCT), and carbon emission efficiency (CEE) and CFP are related to factors such as energy structure, industrial upgrading, and technological innovation. Exploring the relationship between DED and CE is of great practical significance in handling the difficulties posed by global climate change to the dual circulation pattern. Most studies only concentrate on the CE effect of energy consumption (EC) in the digital industry, which tends to overlook the technology spillover situation in the digital industry, making it difficult to present actual results. In this context, this study combines theoretical analysis with empirical testing to explore the empirical impacts of DED on CE through theoretical model design and econometric data collection. This study innovatively utilizes the perspective of HQD to enrich the empirical content of the relationship between the two. In addition, the refinement of variable indicator data and the consideration of mediating variables from multiple perspectives can also provide theoretical support and policy recommendations for achieving sustainable HQD.

2 Literature review

Digital economy is an essential endogenous driving force for driving urban economic development. Yu et al. discussed panel data of Chinese cities from 2011 to 2019 and examined the impact of DED level on carbon reduction. Digital economy had an inhibitory effect on the development of CE, showing significant heterogeneity, and it could effectively intervene in CE by regulating green energy efficiency (Yu et al., 2022). Zhong et al. conducted a research on the relationship between agricultural CE and economic HQD using

panel data, spatial Durbin model (SDM), and mediation effect (ME) models. At present, the carbon intensity level of agriculture in China is still relatively high, and adjustment of agricultural technology could effectively play an intermediary role. Therefore, the application and DED in agricultural technology should be strengthened in the later stage (Zhong et al., 2022). Tan et al. focused on the ME of industrial structure upgrading (ISU) on the correlation between digital economy and low-carbon sustainable development (LCSD) and tested it using urban regression models. ISU could provide an external positive environment for the DED and reduce CE (Tan et al., 2024). In response to the LCT of the manufacturing economy, T. Wu combined qualitative and quantitative analyses, using theoretical and empirical methods to perform an analysis on 30 provinces in China. Digital economy could reduce CE, and its integration with technology-intensive manufacturing could effectively leverage the multiplier effect of carbon reduction (Wu et al., 2023). Wang et al. explored the relationship between digital economy and urban LCSD from a climate perspective using panel data and fixed-effects (FE) models. Promoting digital economy could effectively promote urban LCSD, and the flow of innovative factors was an important influencing factor. The influence of digital economy in urban LCSD has increased (Wang et al., 2022). Cui et al. innovatively analyzed the relationship between productive capital stock and CE from the perspective of China's information and communication technology calculation. Wireless communication in information technology could indirectly reduce CE through DE, and a non-linear connection was observed between DE and CE. The degree of influence mechanism was related to the type of wireless communication (Cui et al., 2023). The framework of the Environmental Kuznets Curve assumption, the relationship between CE and natural resource exploitation, globalization index, economic growth, and population aging presented an inverted U-shaped relationship. Strengthening the sustainable development goals under multiple objectives had important practical significance. Shang et al. used the Tapio decoupling model to explore the relationship between carbon dioxide and driving factors, and they employed parallel deep learning algorithms to design a perceptual neural network. They constructed a partial least squares regression model to analyze the driving factors. The results indicated that the variable importance of urbanization rate in predicting the output had a strong inhibitory effect on CFP growth, and the marginal effect relationship between CFP and economic growth had stages (Shang and Luo, 2021). Regarding the EC and CEs of 5G mobile networks, Li et al. developed a data-driven framework and coordinated the working status of 5G batteries using DeepEnergy energy-saving methods and deep reinforcement learning neural networks. The results indicated that this method had great potential in reducing CEs, and its integration with solar energy systems could further promote the development of energy-efficient telecommunications (Li et al., 2023). Based on the perspective of ecological environment improvement research, Wang et al. explored the impact and mechanism of green finance on the economic and social green development space under panel data from 30 provinces and cities in China (2011–2020) through FEs and moderation effects models. The results indicated that the development of green finance in China has significantly expanded the green development space of the economy and society. The improvement of the ecological environment played an important intermediary and regulatory role, which could achieve high-quality and sustainable development of the economy and society (Wang et al., 2023).

Green development is an important part of the transformation and upgrading of other enterprises. Gao et al. analyzed the energy-saving and CE reduction ability of the digital economy from the perspective of technological structure transformation using a bidirectional FE model and an ME model. The improvement of green technology efficiency could reduce EC (Gao and Peng, 2023). Patterson et al. analyzed CE using machine learning techniques and found that reducing the EC of machine learning is of great significance in reducing the total CE (Patterson et al., 2022). Müller L J et al. analyzed the CFP raw materials and found that capturing CO_2 carbon sources can significantly reduce their emissions and that accelerating the optimization of CFP indicator evaluation methods can analyze CO_2 under different energy demands (Müller et al., 2020). Valls-Val K et al. believed that from the perspective of CE evaluation content, CFP should strengthen the analysis of the impact of different key elements on it, further improve the emission coefficient database, and develop reasonable processing tools, which was a long and arduous task (Valls-Val and Bovea, 2021). Wood et al. believed that the formulation of strategies for CFP control needs to consider trade composition and driving factors, among which greenhouse gases are crucial for analyzing the industrial and agricultural sectors (Wood et al., 2020). Mi et al. analyzed the CFP of 10 households with different income groups in China using multi-regional input–output analysis and found that CFP showed regional differences and that economic growth can improve carbon inequality (Mi et al., 2020). Shahbaz et al. considered the potential relationship between digital economy and energy transition and used panel data from 72 countries between 2003 and 2019 to study the impact of the digital economy on renewable EC and power generation structure. They analyzed the mediating role of government governance, indicating that the digital economy stimulated the transition to renewable energy by enhancing government governance capabilities (Shahbaz et al., 2022). The market-oriented trading mechanism is an important means for the Chinese government to control environmental pollution. Xuan et al. used a differential model to explore the impact of CE trading policies on CE reduction. The results indicated that CE trading policies, economic development, technological research level, and opening up to the outside world could significantly reduce CE intensity (Xuan et al., 2020). Adams et al. found that when analyzing the relationship between the economy and EC of countries with high geopolitical risks from 1996 to 2017, the uncertainty index had a co-integration relationship between EC, economic growth, geopolitical risks, economic policy uncertainty, and CE. There was a one-way causal relationship between CE and geopolitical risks, making significant adjustments to energy policies to better adapt to economic policy uncertainty and geopolitical risks (Adams et al., 2020).

Most previous studies demonstrated that the evaluation of CFP requires the support of a large amount of data, and there are differences in the standards for CE selection among different industries and regions. CFP is closely related to carbon reduction, and it is difficult to accurately evaluate CFP solely through macro-surveys conducted by DE. Therefore, the research

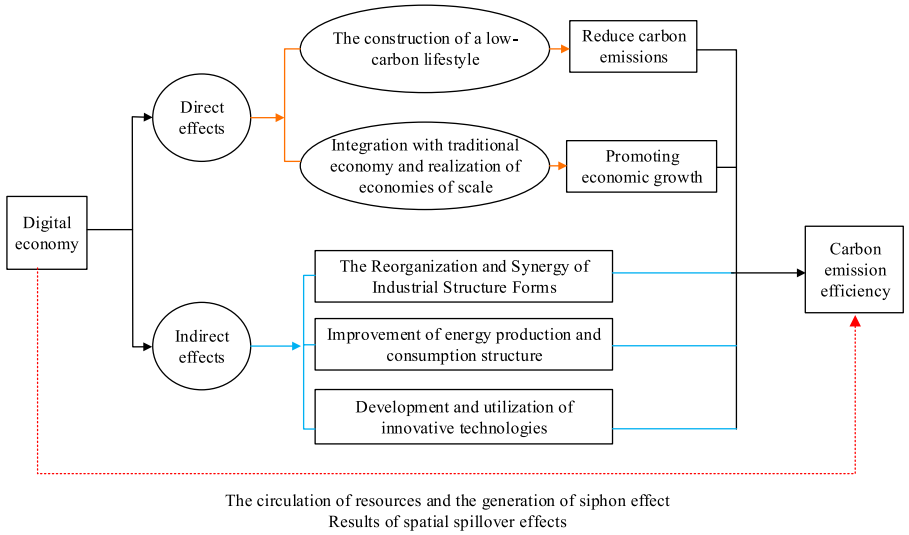


FIGURE 1
Impact mechanism of DED and CEE from the perspective of HQD.

mainly focuses on carbon reduction, indirectly demonstrating the impact of CFP. This paper analyzes the correlation between digital economy and carbon reduction efficiency (CRE) from multiple aspects and considers the impact of various mediating variables on urban CFP, which can effectively provide the reference value for urban HQD.

3 The impact mechanism of DED on CEE from the aspect of HQD

Digital economy has accelerated the development of information-related industries and also promoted digital technology penetration and integration in traditional industries, causing a huge improvement in the degree of economic intelligence. On the one hand, digital technology relies on intelligent information technology to improve scientific decision-making efficiency, while reducing CE while improving energy utilization efficiency. For example, the dynamic assessment of market data by digital technology platforms can facilitate a more comprehensive analysis of the trajectory and supply–demand dynamics of the energy economy. This, in turn, enables the formulation of macro-level policies that regulate energy market transactions (Luo et al., 2023). On the other hand, the upgrading and transformation of traditional industries through digital technology can reduce the clustering of high pollution emission industries, stimulate the vertical flow of production factors, and improve resource allocation efficiency. The enhancement of green consumption concepts can also help reduce the CE intensity. The advent of the post-pandemic era has caused damage to China's domestic production and business activities, and coupled with the severe external global economic background, the concept of a new development pattern of dual circulation has emerged. The impact mechanism of DED and CEE from the perspective of HQD is shown in Figure 1.

From the perspective of direct impacts, the digital economy industry has obvious environmentally friendly characteristics, which make people's work and production activities no longer limited to specialized time and space, and low-carbon lifestyles are gradually becoming a new fashion. The integration of digital economy and traditional industries can reduce production costs and develop economies of scale and scope, to a certain extent reduce waste of resource investment, and create a good economic development environment (Zhu et al., 2022). From the perspective of indirect impacts, digital economy can reduce CEE through industrial energy structure adjustment and optimization, energy utilization intensity reduction, technological progress, and other aspects. Specifically, the application and development of AI and Internet of Things technology have changed the traditional mode of industrial economic operation, and their design of resource allocation efficiency and restructuring of industrial organization has enhanced the EC structure. The reduction in the use of fossil fuels and non-renewable energy, as well as the development and utilization of clean energy and new energy industries, can effectively improve CEE and reduce the irreversible damage of energy to the environment. The technological innovation wave triggered by digital economy can effectively stimulate the transformation of EC structure (Xu et al., 2024a; Gazman, 2023). Given the CE spatial spillover effects (SSE), the acceleration of information technology circulation speed and the flow of production factors by digital economy can greatly achieve the balanced development of CEE at the spatial level.

4 The spatiotemporal characteristics and analysis of DED and CE

4.1 Indicator measurement setting

This paper adopts the entropy weight approach to calculate indicator data. The entropy value is inversely proportional to the amount of information it contains. Moreover, the method is easy to carry out and can reduce data evaluation errors caused by human

TABLE 1 DED indicator system.

Digital economy			Unit	Indicator attribute
Level I indicators	Secondary indicators	Third level indicators		
DI	Electronic information equipment manufacturing industry	Investment in communication equipment and computer services	RMB 100 mn	+
		Mobile phone production	10,000 units	+
		Production of computer and integrated circuit equipment	One billion yuan	+
	Telecommunications industry	Internet broadband access	10,000 households	+
		Mobile phone exchange capacity	Kilometer	+
		Long-distance optical cable line length	RMB 100 mn	+
	Software data technology service-related categories	Information technology service revenue	RMB 100 mn	+
		Industrial output	RMB 100 mn	+
ID	Industry	The proportion of sales revenue from industrial innovation products	%	+
		Technical renovation expenses	Ten thousand yuan	+
	The third industry	Value added of the service industry	RMB 100 mn	+
		Number of Internet users	Ten thousand people	+
		Social retail consumer goods	RMB 100 mn	+
		Cultural, educational, and entertainment consumption	Element	+
	Agriculture	Electricity consumption	Billions of hours	+
		Investment in fixed assets investment such as electricity and gas	RMB 100 mn	+
	Infrastructure fixed assets investment	Transportation	RMB 100 mn	+
		Computer services and software	RMB 100 mn	+
		Health and social work	RMB 100 mn	+
	Digital talent	Higher education institutions	Individual	+
		Number of professional awards	People	+

factors. According to the positive and negative attributes of the indicators, different index calculation methods are designed, as shown in Equation 1.

$$\begin{cases} I_P = \dfrac{X_i - X_{\min}}{X_{Max} - X_{\min}} \\ I_{IP} = \dfrac{X_{Max} - X_i}{X_{Max} - X_{\min}} \end{cases}. \quad (1)$$

In Equation 1, I_P and I_{IP} represent the calculation expressions of positive and negative indicator indices, respectively. X_i is the raw data for the i-th indicator in a certain region, respectively. X_{Max} and $X_{\min}$ are the maximum and minimum of the indicator data, respectively (Sharma et al., 2022). Subsequently, the indicator data are normalized, information entropy and redundancy are calculated, and finally the weight result w_j of the indicator data is obtained, as shown in Equation 2.

$$w_j = \frac{d_j}{\sum_{i=1}^{n} d_j}. \quad (2)$$

In Equation 2, j denotes the item indicator of the evaluation object. d_j is the redundancy of indicator j. n is the number of indicators. When calculating the CE level, this study refers to the energy CE coefficient in the IPCC National Greenhouse Gas Emission Inventory, 2006, and uses macro-data to convert the CE coefficient of various energy sources. Equation 3 represents the CE expression of energy heat generation C_i.

$$C_i = \frac{44}{12} O_i H_i C_i^0. \quad (3)$$

In Equation 3, O_i is the low calorific value of fossil fuels, H_i is the carbon oxidation factor of fossil fuels, and C_i^0 is the energy carbon dioxide coefficient. DED focuses on economic infrastructure digital economy application. Therefore, based on the consideration of the

connotation and related indicators of CFP, this study selects indicator systems from three dimensions: infrastructure construction, digital industrialization (DI), and industrial digitization (ID). Table 1 lists the components of the constructed DED indicator system.

The selected digital economy indicator data are all from the National Statistical Yearbook and the statistical yearbooks of various local provinces. Parts of the industrial data are taken from the China Industrial Economic Statistical Yearbook. Missing data are filled in using interpolation (Kirikkaleli and Oyebanji, 2022).

4.2 Empirical model setting

This study designs a panel regression model to empirically model the relationship between selected DED data and CEE, as shown in Equation 4.

$$CPE_{i't} = \alpha_0 + \alpha_1 X_{i't} + \alpha_k \sum_{k=1}^{n} C_{ki't} + \mu_{i'} + \varphi_t + \varepsilon_{i't}. \quad (4)$$

In Equation 4, t represents the year, i' represents the province, $CPE_{i't}$ is CEE, $X_{i't}$ is the dependent variable, $C_{i't}$ is the control variable (CV), and α is the estimated coefficient. $\mu_{i'}$ and φ_t represent unobservable provincial and temporal effects, respectively. $\varepsilon_{i't}$ is a random perturbation term. $\varepsilon_{i't}$ is a random perturbation term. k represents the number of explanatory variables, including the constant term (intercept). n represents the sample size, which is the number of observed values. When conducting empirical analysis on the relationship between the digital economy and CE efficiency, the study can assume that there is no sequence correlation or heteroscedasticity in the data, no complete multicollinearity between independent variables, and no missing variable data in the model. Individual differences are random and independent of the explanatory variables. This study selects CEE as the independent variable. Based on the research content of previous scholars, the dependent variable is divided into five main dimensions: population size (Pop), urbanization level (URB), government macro intervention (GI), level of opening-up (L-open), and financial support (FS). The rise in Pop causes an increase in total EC, and the improvement in URB means that energy efficiency and demand will also increase. GI will affect the formulation of market policies, and both excessive intervention and loose policies will affect resource allocation. L-open means two different situations: learning carbon reduction technologies and pollution transfer (Jiang et al., 2022; Li et al., 2022). For the convenience of data statistics, this study uses the proportion of deposit and loan balances of financial institutions to represent the FS level. The higher the level of capital circulation, the more it reflects the rationality of resource allocation. The variable comes from the Urban Statistical Yearbook and the Financial Statistical Yearbook. Descriptive statistical results of variable data are shown in Table 2.

4.3 Mediation model setting

In the process of mechanism verification, an ME model is constructed to discuss the influence mechanism of digital economy on CEE. The model setting is shown in Equation 5.

$$\begin{cases} CEE = \alpha_0 + \alpha_1 de_{i't} + \sum_{k=1}^{n} \delta_k C_{ki't} + \mu_{i'} + \varphi_t + \varepsilon_{i't} \\ M_{it} = b_0 + b_1 de_{i't} + \sum_{k=1}^{n} \theta_k C_{ki't} + \mu_{i'} + \varphi_t + \varepsilon_{i't} \end{cases}. \quad (5)$$

In Equation 5, $M_{i't}$ is a mediator variable, δ is the total effect estimation coefficient, b is the index of influencing factors, and θ is the effect of mediating variables on CEE after controlling for the influence of DE. This study introduces spatial correlation coefficients to analyze CEE and uses Moran scatter plots (MSP) to show the data's spatial correlation. Among them, spatial distribution and correlation analysis are used to demonstrate the connection and clustering trend of variable value (Addai et al., 2022; Dabbous and Tarhini, 2021). Its mathematical expression is shown in Equation 6.

$$\begin{cases} I = \left[\sum_{l=1}^{n'}\sum_{p=1}^{n'} W_{lp}(x_l - \bar{x})(x_p - \bar{x})\right] \Big/ \left[S^2 \sum_{l=1}^{n'}\sum_{p=1}^{n'} W_{lp}\right] \\ I_l = Z_l \sum_{p=1}^{n'} W_{lp} Z_{lp} \end{cases}. \quad (6)$$

In Equation 6, I is spatial auto-correlation. I_l is local auto-correlation. n' is the number of spatial units. x_l, x_p is the CE quantity of urban unit l, p. $\bar{x}$ denotes the mean variable. W_{lp} refers to the adjacency space weight matrix. Z_{lp} is the standardized form of the sample space. When I_l is positive, the spatial difference between l, p and its neighboring cities is small, and when *vice versa*, the spatial difference is large. S represents the observed value. When its value is 0, it indicates that the sample space units exhibit randomness in spatial distribution (Khan et al., 2024). This study selects five indicators, namely, advanced industrial structure (AIS), rational structure of production (RSP), energy-resource structure (ES), energy intensity (EI), and technical progress (TP), as mediating variables, as exhibited in Table 3.

5 Empirical result analysis

5.1 Panel effect testing

Panel data refer to taking multiple cross-sections on a time series and simultaneously selecting sample observations on the cross-sections. It can reflect the heterogeneity of data in time and space to a certain extent, and it can better estimate dynamic behavior compared to simple time-series data. The stationarity of sequence variables is an important basis for affecting model performance, and directly conducting regression analysis on non-stationary variables may lead to spurious regression problems. The study hypothesizes that the cross-sectional sequence of panel data has different unit root processes. The study takes 30 provinces other than Xizang from 2000 to 2021 as the research object, and the data are from "China Statistical Yearbook," "China Urban Statistical Yearbook," and "China Financial Statistical Yearbook." A few missing values are filled with multiple imputation. The outliers in the experimental data have been removed. To verify whether the selected variables have a high correlation, the study uses the coefficient of variance

TABLE 2 Descriptive statistical results of variable data.

Variable	Index	Mean	Standard deviation	Maximum	Minimum
Independent variable	CEE	55.689	42.150	321.025	6.235
Dependent variable	DE	0.125	0.106	0.746	0.008
	DI	0.087	0.101	0.732	0.009
	ID	0.163	0.121	0.851	0.008
CV	Pop	4623.144	2811.318	12648.531	564.71
	URB	56.258	13.698	88.926	25.981
	GI	23.177	9.678	65.137	7.685
	L-open	5.329	5.124	42.056	0.001
	FS	2.687	1.115	7.334	0.944

TABLE 3 Descriptive statistical results of mediator variable data.

Variables	Index	Mean	Standard deviation	Maximum	Minimum
Mediating variables	AIS	1.082	0.589	5.320	0.491
	RSP	11.263	18.236	265.178	−68.253
	ES	98.743	50.124	277.439	2.33
	EI	2.165	1.162	8.025	0.602
	TP	42165.289	76436.177	726549	81.335

TABLE 4 Results of multicollinearity analysis.

Variable	VIF
Ln-DE	2.93
Ln-DI	2.64
Ln-ID	2.61
Ln-Pop	2.26
Ln-URB	2.17
Ln-GI	1.27
Ln-L-open	1.00
Ln-FS	2.12

inflation for multicollinearity testing. The results are shown in Table 4.

The results in Table 4 indicate that the variance inflation factor values of each variable do not exceed 10 and the maximum VIF value among the variables does not exceed 3. This indicates that there is no multicollinearity among the control variables and a certain correlation exists between them and CEE. The ADF test is used to test the stationarity of sequence variables affecting CEs, and the results are shown in Table 5.

If there is a unit root process in the sequence, it will be non-stationary and lead to spurious regression in regression analysis. In Table 5, Ln-CEE is the explanatory variable, while Ln-DE, Ln-DI, Ln-ID, Ln-Pup, Ln-URB, Ln-GI, Ln-L-open, and Ln-FS are dependent variables. The results in the table indicate that the critical values of ADF tests for different variables are stable at 5% and 10%, indicating that the corresponding variable difference sequence is a stationary sequence. Subsequently, the regression model proposed in the study is subjected to the Breusch–Pagan LM test, and the dependence of cross-sectional data is analyzed. The results are shown in Table 6.

In Table 6, the LM test results indicate that the variable data do not reject the null hypothesis of structural mutation unit root process at the 5% significance level, indicating that there is no cross-sectional dependence in the data. At the same time, when conducting the Gregory–Hansen co-integration test on the ADF statistic, the results indicate that there is no structural mutation co-integration at the 1% significance level, and the statistic value is −8.7526, indicating that there is indeed a certain co-integration relationship between CE and influencing factors. This study first analyzes the digital economy composite index of 30 Chinese provinces from 2000 to 2021, as displayed in Figure 2.

The digital economy levels in various provinces have shown varying degrees of improvement after the epidemic, especially in areas such as Beijing, Tianjin, and Hebei (BTH) and the Pearl River Delta (PRD). The results indicate that the digital economy index ranges from 0.2 to 0.3 in Guangdong and Jiangsu, from 0.1 to 0.2 in Sichuan and Shandong, and from 0.3 to 0.4 in Henan. The digital economy improvement in Zhejiang Province is also quite significant. The digital economy level in the western region is still relatively low. Figure 3 shows the CEE results for each province.

TABLE 5 ADF inspection results.

Variable	ADF test value	Critical value		Stability of critical value	
		5%	10%	5%	10%
Ln-DE	−5.8656	−4.1897	−3.5462	Stable	Stable
Ln-DI	−3.4099	−3.2953	−2.6691	Stable	Stable
Ln-ID	−3.6322	−3.8674	−3.4324	Stable	Stable
Ln-Pop	−4.2665	−4.2339	−3.2118	Stable	Stable
Ln-URB	−7.8513	−4.1919	−3.1361	Stable	Stable
Ln-GI	−3.6337	−3.8689	−3.4359	Unstable	Stable
Ln-L-open	−4.2681	−4.2352	−3.2131	Unstable	Stable
Ln-FS	−7.8528	−4.1934	−3.1376	Stable	Stable
Ln-CEE	−7.9127	−4.2326	−3.1622	Stable	Stable

TABLE 6 Breusch–Pagan LM test.

Variable	Breusch–Pagan LM test	
	Statistic	5% critical value
Ln-DE	−3.3791	−3.5638
Ln-DI	−4.1092	−4.5076
Ln-ID	−3.4067	−3.5638
Ln-Pop	−4.3718	−4.4974
Ln-URB	−2.7482	−3.5630
Ln-GI	−4.1473	−4.4992
Ln-L-open	−3.1191	−3.5651
Ln-FS	−4.3945	−4.4493

In Figure 3, CEE shows a reduced tendency in the spatial dimension from east to west. Among them, the CE rate in western regions such as Xinjiang and Gansu has changed from the range of (0.25) in 2000 to the range of (25.50) in 2021. In terms of the time dimension, the CEE of most cities has improved, with significant growth observed in the eastern regions dominated by Jiangsu and Zhejiang and the southwestern regions dominated by Sichuan and Chongqing. The CE rates in Shanghai and Tianjin have exceeded 100, with a significant increase. The study conducts panel regression and robustness tests on the relationship between digital economy and CE efficiency and examines them from two dimensions of the digital economy. The results are shown in Table 7.

Table 7 shows a positive correlation between digital economy and CRE at 1%, with a regression value of 310.289 and the t-value of 9.876. There are also differences in regression analysis between the dimensions of DI, ID, and CRE, with DI significantly improving CRE compared to ID (259.783 > 210.659). On CV, the regression values of Pop, URB, and GI dimensions on the impact of CRE are negative. The URB and GI variables have significant negative effects at 5% and 10%, indicating that population growth and urbanization development rate will accelerate EC to a certain extent, and unreasonable macro interventions may affect the achievement of CRE. Other variables, such as higher FS, indicate a more significant positive effect of CRE, with regression values and t-values reaching 16.334 and 2.146, respectively. The effect of the L-open level on CRE does not exhibit any significant characteristics. The robustness result

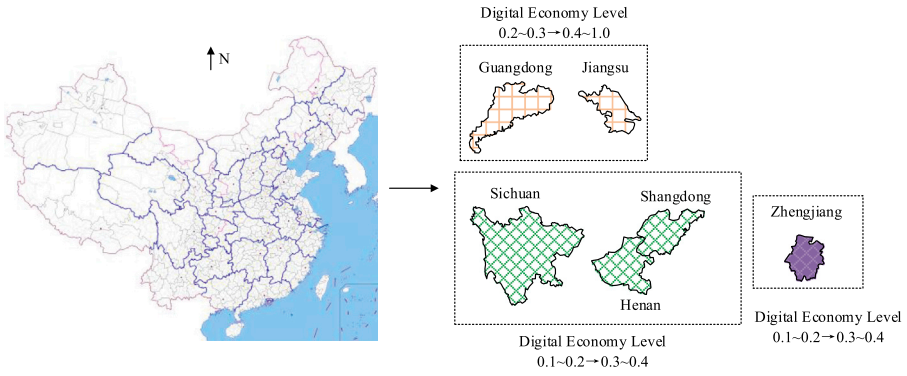


FIGURE 2
Comprehensive index of digital economy in China from 2000 to 2021.

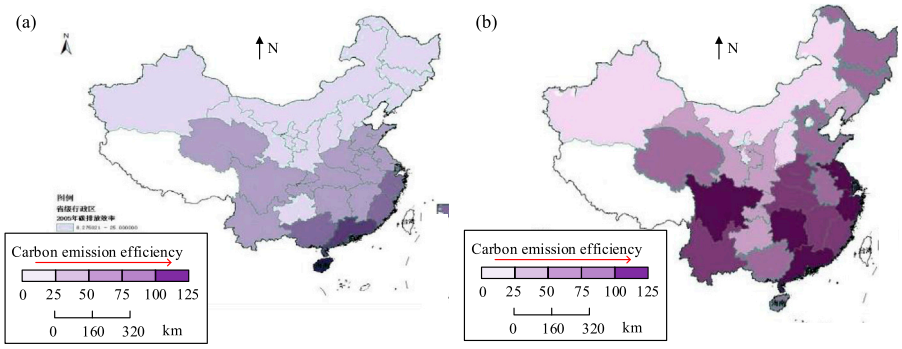


FIGURE 3
CEE of China from 2000 to 2021. **(A)** Year 2000. **(B)** Year 2021.

TABLE 7 Panel regression test results (t-value).

Variable	CEE			Robust test
	Independent variable	Dependent variable	CV	
DE	310.289*** (9.876)	—	—	5.0952*(−1.679)
DI	—	259.783*** (9.912)	—	0.0456*(−0.326)
ID	—	—	210.659*** (6.234)	0.0192**(−1.653)
Pop	−0.021*** (−3.895)	−0.015*** (−3.674)	−0.005 (−1.258)	−0.0852*(1.829)
URB	−0.593*** (−2.516)	0.013 (0.065)	−0.589** (−2.114)	−0.1021**(0.401)
GI	−0.206 (0.894)	−0.401 (−1.325)	−0.487* (1.657)	−0.1476 (-0.619)
L-open	0.189 (0.867)	0.139 (0.576)	0.176 (0.741)	0.8580**(2.033)
FS	12.006*** (4.895)	11.859*** (4.338)	16.334*** (6.129)	0.4884***(2.298)
Constant term	130.641*** (5.128)	96.234*** (3.565)	62.951** (2.146)	—
Hausman test	16.894 (0.003)	14.023 (0.020)	12.790 (0.048)	—
R-squared	0.508	0.508	0.489	0.129

Note: "*, **, and ***" mean significant statistical differences in variables at 10%, 5%, and 1%, respectively.

is the result of replacing the self-variable and control variable with the previous year's profit growth rate as the dependent variable and then conducting regression analysis on the self-variable and control variable. The robustness test results indicate that the regression results between the digital economy and CE reduction efficiency are consistent with the variable regression results, indicating the feasibility of the results.

5.2 Robustness analysis

To ensure the accuracy of the Hausman test, lagged data on the DED level are utilized as a tool to perform endogeneity robust analysis on variables. Table 8 contains the details of further testing of the model.

In Table 8, the *P* of the regression results on KP-LM are all less than 0.005, indicating no identification error. The results of KP-WF show that the values above the 10% critical value are all greater than 15, showing no weak instrumental variable matter. The above results indicate that the selected model is effective. Table 9 presents the results of robustness testing on the digital economy variables.

The results in the second and third columns of Table 9 indicate that under the selected instrumental variables, digital economy still shows a positive effect with CRE at the 1% level. Under the least squares method, the regression results show that digital economy and CE have an impact at 5% efficiency. This study calculates the efficiency of CE measurement and replaces the independent and dependent variables with the digital economy innovation and entrepreneurship index based on the *per capita* real GDP, and the results are shown in the fifth and sixth columns. The replacement of the dependent and independent variables does not exhibit an obvious effect on the regression between digital economy and CEE, with regression values of 0.052 and 0.715 and a significant positive correlation at the 1% level. Differently, compared to the outcomes in the fifth column, the dependent variable, after being replaced, the regression value of Pop is positive, and the government's macroeconomic regulation shows a negative correlation regression effect. This indicates that

TABLE 8 Endogeneity testing.

Variable	Phase 1	Phase 2
DE	—	−1.589*** (−4.89)
IV	0.006*** (13.697)	—
CV	Yes	Yes
Year FE	Satisfy	Satisfy
Urban FEs	Satisfy	Satisfy
Kleibergen–Paap rk LM statistic (KP-LM)	9.25 [0.002]	9.33 [0.003]
Kleibergen–Paap rk Wald F statistic (KP-WF)	31569{15.29}	22,158{16.23}
Constant term	−0.418 (−5.23)	0.129 (0.364)

Note: the values within [] are *p* values; {} is the critical value at the 10% degree of the weak identification test.

TABLE 9 Robustness test data.

Variable	DE	Dependent variable	Least squares regression results	Replace independent variables	Replace dependent variable	Exclude some data
DE	—	135.289*** (11.86)	198.126** (11.268)	0.052*** (4.267)	0.715*** (6.529)	197.321*** (10.296)
DI	0.000*** (4.126)	−0.001 (−1.265)	−0.001 (−2.167)	−0.000*** (−2.156)	0.021*** (3.698)	−0.014*** (−6.211)
ID	−0.000	0.128 (0.743)	−0.179*** (0.826)	−0.000*** (−2.058)	−1.526*** (−2.976)	0.576*** (3.875)
Pop	0.000***	−0.898*** (−4.236)	−0.765*** (−3.271)	−0.000 (−1.289)	−1.562*** (−3.114)	−0.369*** (−3.106)
URB	0.000***	1.043*** (3.121)	0.296* (1.405)	0.00 (0.354)	−0.307 (−1.236)	0.144 (−1.121)
GI	0.001	17.682*** (11.629)	15.267*** (5.388)	0.007*** (5.899)	16.035*** (4.869)	1.190 (0.749)
Constant term	−0.003 (−1.021)	−1.658 (−0.154)	35.941*** (2.489)	0.061*** (3.471)	3.746 (0.105)	85.167*** (4.863)
R-squared	—	0.627	0.589	0.235	0.458	0.702

government macroeconomic regulation can create a certain economic environment for social innovation and entrepreneurship. The seventh column shows the regression results after excluding certain administrative data. The regression value between digital economy and carbon reduction is 197.321. The above results indicate that the regression results have good robustness.

5.3 Mediation effect analysis

Based on the rationality of the above benchmark content, this study conducts regression tests using AIS and rationalization as mediating variables, as shown in Table 10.

As shown in Table 10, digital economy and AIS have an obvious effect at the 1% level, and the CEE changes significantly. The impact coefficients of digital economy and CEE have decreased, but the significance of RSP on CEE is significantly smaller than that of AIS. The possible reason for this result may be that when AIS occupies a partial mediating position, the updating and upgrading of the EC industry requires a relatively slow process, so the CEE effect demonstrated by rational resource allocation is slower. Table 11 conducts an ME test from the perspective of energy.

Table 11 has a significant inactive relation between digital economy and ES, and a decrease in coal consumption can enhance CRE. The larger EI represents a higher degree of digital economy effect and a smaller carbon reduction impact, showing a more significant negative correlation. The adjustment of ES and EI can have a certain mediating effect, but the DED may lead to an increase in the energy input. Table 12 shows the mediating effects under TP.

The TP results indicate that the digital economy driving effect on technology is obvious. TP has a negative effect on CRE at the 5% level, which may be related to the conversion cycle of technological achievements. Overall, the significant positive effect of the DED on carbon reduction is still quite evident.

5.4 Spatial effect testing and regional heterogeneity analysis

As shown in Table 13, this study roughly divides the sample data into three parts based on geographical space: eastern, central, and western, and conducts heterogeneity testing.

TABLE 10 Mediation effects from the perspective of industrial structure.

Variable	AIS		RSP	
	AIS	CEE	RSP	CEE
DE	2.081***	137.169***	36.297**	223.165***
DI	—	39.969***	—	—
ID	—	—	—	−0.065
Pop	−0.000***	−0.001	−0.001*	−0.003***
URB	−0.007***	0.074	0.085	−0.179
GI	0.003	−8.169***	−0.364***	−0.805***
L-open	0.011***	−0.087	0.154	0.326
FS	0.347***	0.425	5.169***	16.129***
Constant term	0.706*** (3.598)	11.698 (1.052)	−0.497 (−0.052)	38.416*** (2.657)

TABLE 11 Mediation effects from the perspective of energy.

Variable	ES	CEE	EI	CEE
DE	−50.169**	205.136***	0.654***	235.169***
DI	—	−0.321***	—	—
ID	—	—	—	24.68***
Pop	—	—	—	—
URB	0.001	−0.003**	−0.000***	−0.0896***
GI	0.105	−0.184	−0.289***	−1.025***
L-open	0.523**	−0.619***	0.002	−0.856
FS	−0.059	0.258	0.001	0.321
DE	−2.987	12.394***	−0.069***	15.36***
Constant term	90.125***	64.140***	3.258***	136.198

TABLE 12 Mediation effects from the perspective of technological progress.

Variable	TP	CEE
DE	869.257***	348.167***
DI	—	—
ID	—	—
Pop	—	−0.000***
URB	−9.657	−0.529***
GI	−2.334	−0.598***
L-open	−765.288	−0.795***
FS	−164.259	0.254
DE	4.125*	16.234***
Constant term	115.267***	58.437***

TABLE 13 Regional heterogeneity test results.

Variable	East	Middle part	West
DE	336.012*** (5.168)	325.167*** (5.145)	355.661***
DI	−0.039*** (−3.261)	0.011 (0.698)	0.016 (1.306)
ID	−2.674*** (−3.058)	−0.233 (−0.325)	0.024 (−0.077)
Pop	1.306 (1.228)	0.754 (0.899)	−0.306 (−1.479)
URB	−0.165 (−0.389)	−1.688*** (−2.154)	−0.506 (−1.152)
GI	26.159*** (4.412)	−11.075*** (−2.118)	−0.306 (−0.105)
Constant term	279.675*** (3.266)	−14.095 (−0.156)	−19.116 (−0.487)
R-squared	0.512	0.804	0.614

In Table 13, digital economy is significantly correlated with CEE in all three regions at the 1% level, with regression values of 336.012, 325.167, and 355.661, respectively. The most influential region is the eastern area, followed by the central range. The Pop variable and URB have a negative impact on CEE in the east, while they perform slightly worse in the west. The regression value between L-open and central CEE is negative at the 1% level (−1.688). Subsequently, the SSE of digital economy and CEE are analyzed, and the spatial dependency relationship of indicator data is analyzed by introducing a weight matrix approach. Figure 4 shows the MSP of CEE.

As shown in Figure 4, most provinces are located in high- or low-concentration areas, with a good spatial correlation. The Moran index has changed from a dispersed trend to a gathering trend toward the origin, indicating that the CEE between provinces is decreasing. It should be noted that the CEE in the Yangtze River Delta regions such as Jing and Hu is still relatively high. Subsequently, regression tests are conducted using the SDM, as shown in Table 14.

Table 14 indicates that the spatial lag coefficients of CEE under three matrices are −3.165, −3.164, and 3.029. This indicates that

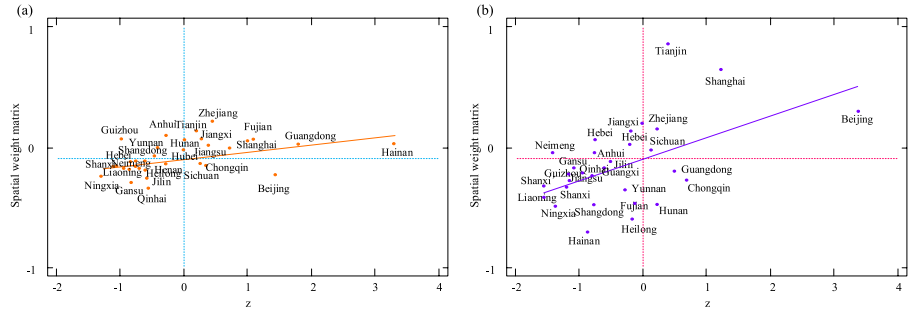


FIGURE 4
MSP of carbon emission efficiency. **(A)** Year 2000. **(B)** Year 2021.

TABLE 14 Spatial regression results.

Variable space weight matrix	Adjacency matrix	Geographic distance matrix	Economic distance matrix (EDM)
DE	−223.567*** (−3.165)	−522.165*** (−3.164)	226.341*** (3.029)
DI	0.038*** (5.016)	0.105*** (3.165)	−0.058*** (−4.126)
ID	3.678***(5.897)	5.896*** (4.361)	−6.856*** (−5.126)
Pop	−0.433 (-0.899)	0.077 (0.054)	0.726 (1.177)
URB	−0.036 (-0.067)	−2.156 (−1.033)	0.226 (0.659)
GI	8.156**(2.036)	2.519 (0.231)	−9.236 (−1.523)
Spatial auto-regressive coefficient	0.405*** (6.896)	0.115 (0.801)	0.285*** (3.644)
Ballistic error impact	135.487*** (16.021)	149.063*** (14.698)	149.367*** (14.966)
R-squared	0.004	0.008	0.254
Log likelihood	−1925.167	−1890.262	−1899.634

digital economy exhibits peripheral inhibition when enhancing CEE. Under the EDM, there is an active relationship between digital economy and CEE at the 1% level. From the perspective of CV, Pop and URB exhibit significant SSE. The spatial coefficient between government macroeconomic regulation and L-open is not significant. Regions with similar economic levels have a positive correlation between CEE and the economic level.

6 Development strategies and carbon reduction regulation strategies for DE

While promoting the process of globalization, digital economy also constructs the development format of global information technology and economic system structure. As an endogenous driving force for economy development, it effectively promotes the rationalization and ISU, reducing the hindrance of spatial distance to production efficiency. This study is based on the HQD perspective and analyzes the CE reduction and CFP impact mechanism under DE. The digital economy level in various Chinese provinces has improved to varying degrees after the epidemic, especially that in BTH, PRD, and other regions are more obvious. The coefficient of influence between digital economy and CEE has decreased, but the significance of RSP on CEE is significantly smaller than that of AIS. The reason may be that when AIS plays a partial mediating role, the upgrading of the EC industry requires a relatively slow process, so the CEE effect demonstrated by rational resource allocation is slower. The adjustment of ES and EI can have a certain mediating effect, but the DED may lead to an increase in the energy input. The regression results show that in various provinces of China, the digital economy is significantly positively correlated with CE reduction efficiency at the 1% level. This result is similar to the research findings by Zhong et al. (2022) and Wu et al. (2023). Zhong believes that the digital economy can effectively reduce agricultural carbon intensity by improving agricultural technology. The ME under technological regulation is consistent with the research results of energy technology regulation on CEE (Zhong et al., 2022). Wu believes that the integration of technology-intensive manufacturing can effectively leverage the multiplier effect of CE reduction. The research found that there is heterogeneity in the development of digital economy and CE in various provinces of China (Wu et al., 2023). The CEE of the digital economy in the three regions of East, Central, and West is significantly correlated at the 1% level, with regression values of 336.012, 325.167, and 355.661, respectively. The regression value between the degree of openness to the outside world and the CEE of the central region has a significant negative effect at the 1% level (−1.688). The SSE results show that the CEE between provinces is

decreasing. When the digital economy improves CEE, there is a surrounding decrease, and the two have a significant positive impact relationship (at the 1% level) under the economic distance matrix. The CEE in eastern China has significantly increased, which is similar to the results of Shahbaz et al. (2022) on the relationship between digital economy and energy transition. There are differences in the energy structure among different regions, which are related to the conversion efficiency and energy emission efficiency of regional economic activities.

Compared to the research of Gao and Peng (2023) that focused on resource-based cities and the heterogeneity results of Yu et al. (2022) that emphasized spatial differences and SSE, this study has a richer content. In addition, this study suggests that the level of urbanization and macro government intervention may accelerate EC and affect CEE. In contrast, Adams et al. (2020) focused on the relationship between different factors (such as geopolitical risks and economic policy uncertainty) and EC and CEE. Tan et al. (2024) found that the rationalization of industrial structure is directly related to the development of digital economy and the decrease in the consumption level, but there is no specific comparison of the strength of the impact of industrial structure rationalization and industrial structure upgrading. This is different from the research that directly points out that the impact of industrial structure rationalization is smaller than that of industrial structure rationalization. The pilot program of low-carbon cities in China has promoted the digital transformation of manufacturing enterprises in pilot cities, and it has significant heterogeneity in enterprises, industries, and regions. It can promote digital transformation by strengthening science and technology fiscal expenditures and alleviating financing constraints (Zhao et al., 2023). Xu et al. (2024b) constructed a performance ranking technique based on ideal solution similarity to analyze the development status of new urbanization. They believed that the new urbanization policies significantly suppressed CE in pilot cities, and economic and population urbanization were important influencing factors, showing an inverted U-shaped relationship with CE. It is important to note that there is regional heterogeneity between these mechanisms. Therefore, when formulating carbon reduction strategies, it is essential to consider the specific local conditions. (Xu et al., 2024b).

However, it should be noted that in the results of this study, the CEE of the Yangtze River Delta region, including Beijing and Shanghai, is still relatively high. To fully tap into the potential of CE reduction, three countermeasures are proposed for research. First, it is imperative to accelerate the industrialization of the digital economy, promote the integration of green industries and traditional economic sectors, and facilitate carbon reduction through the implementation of sustainable development principles. Second, in response to regional development differences, it is necessary to actively adjust the industrial structure, accelerate industrial upgrading, regulate high CFP industries, and pay attention to the simultaneous realization and maintenance of economic and ecological benefits. Furthermore, the circulation and allocation of enterprise resources must be actively promoted. Third, it is essential to prioritize the optimization of energy structure, the enhancement of energy efficiency, and the completion of a green transformation through strategic investment in technological innovation and the transformation of achievements.

In the context of the dual carbon goals, the analysis of the spatiotemporal characteristics of the digital economy and CEE can clearly demonstrate the basic situation of China's DED and CEE, providing some reference for relevant departments to formulate targeted goals and policies for the development of the digital economy and for emission reduction. The impact of the digital economy on CEE and its SSE can also provide some reference for some regions to improve CEE through the development of the digital economy. It should be noted that the research mainly discusses the impact and mechanism of the macro-level digital economy on CE. With the gradual improvement in the classification standards for the digital economy industry, it is necessary to objectively measure the impact of CE on different digital economy industries, construct a more comprehensive and perfect indicator system, and increase the richness of data acquisition. This is an important aspect that needs to be improved in future research.

From the perspective of HQD, digital economy needs to focus on environmental protection factors and emphasize the synergistic progress of economic and ecological benefits. The CFP level of industries in different regions is often correlated to their land-use structure. The adjustment of traditional ES can reduce the CFP of regional units, and the digital industry may cause an increase in the energy in the product service life cycle, an increase in the number of digital devices, and the use of information technology resources, causing a significant increase in the growth rate of CFP. The current energy source for electricity production is still traditional energy sources such as oil and coal. The demand for computing power urgently needs to handle the issue of EC. Emphasizing the digitalization and green synergy of digital economy is an important aspect of building the "dual carbon" goal. To fully tap into the potential of carbon reduction, this study proposes three strategies: to accelerate the DED industrialization, promote the integration of green industries and traditional economy, and use the LCSD concept to help reduce CE. The second is to actively adjust the industrial structure, accelerate industrial upgrading, regulate high-CFP industries in response to regional development differences, pay attention to the "simultaneous realization and maintenance" of economic and ecological benefits, and actively promote the circulation and allocation of enterprise resources. The third is to focus on the adjustment of ES, optimize energy efficiency, and complete the green transformation through technological innovation investment and achievement transformation. Most previous research studies have shown that the assessment of CFP requires much data support, and there are differences in the standards for selecting CE among different industries and regions. The relationship between CFP and carbon reduction is closely related, and it is difficult to accurately assess CFP solely through macro surveys of the digital economy. The research results and existing literature both agree that the digital economy has a positive effect on improving CEE. However, the study analyzes the specific impact of spatial differences, urbanization, government intervention, and industrial structure, which covers a wider and more specific range of factors and provides a reference for policy formulation and analysis of the impact on CEE. By analyzing the digital economy and CRE from multiple perspectives and considering the impact of various mediating variables on urban CFP, this study

can effectively provide reference values for high-quality urban development.

7 Conclusion

The CEE of each province has a decreasing trend in spatial dimensions from the east to the west. In terms of the time dimension, the CEE of most cities has improved, with significant growth observed in the eastern regions dominated by Jiangsu and Zhejiang and the southwestern regions dominated by Sichuan and Chongqing. The regression results demonstrate a significant active correlation between digital economy and CRE at the 1% level, with a regression value of 310.289. The efficiency of DI in improving CER is significantly better than that of ID (259.783 > 210.659). The regression values of Pop, URB, and GI dimensions on the impact of CRE are negative, with URB and GI variables having significant negative effects at 5% and 10%, respectively. This indicates that population growth and the urbanization development rate will accelerate EC to a certain extent, and unreasonable macro interventions may affect the achievement of CRE. However, overall, there are spatial differences (eastern > central > western) and SSEs between the development of the digital economy and CE reduction efficiency, and the CEE among provinces is decreasing.

There are two shortcomings in this research. One is that it is based solely on static simulation analysis to explore the relationship between the development of the digital economy and CE without conducting any long-term dynamic analysis of the relationship between the two. The second is that the selection of indicator data is not comprehensive enough, including the failure to further refine and analyze the industrial digitalization indicators of the secondary industry. It is, thus, recommended that subsequent research studies consider the addition of dynamic modules to explore the impact of the digital economy on the development of total factor productivity. Furthermore, the effects of carbon tax policies, CE trading policies, and other factors on economic structure emissions reduction should be considered. Concurrently, a more comprehensive and detailed indicator system is being constructed to investigate the long-term impact trends of the digital economy and CE.

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: investigation, supervision, and writing–review and editing. BC: investigation and writing–original draft. LG: investigation and writing–original draft. JK: investigation and writing–original draft.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was supported by the Science and Technology Bureau of Yulin City (1504-CXY2022110) and the Education Department of Shaanxi Province (23JK0751).

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Adams, S., Adedoyin, F., Olaniran, E., and Bekun, F. (2020). Energy consumption, economic policy uncertainty and carbon emissions; causality evidence from resource rich economies. *Econ. Anal. Policy* 68, 179–190. doi:10.1016/j.eap.2020.09.012

Addai, K., Serener, B., and Kirikkaleli, D. (2022). Empirical analysis of the relationship among urbanization, economic growth and ecological footprint: evidence from Eastern Europe. *Environ. Sci. Pollut. R.* 29 (19), 27749–27760. doi:10.1007/s11356-021-17311-x

Chen, Y., Ji, X., and Zhao, G. (2024). Does digital infrastructure construction impact urban carbon emission reduction? Evidence from China's smart city construction. *Environ. Sci. Pollut. R.* 31 (27), 39481–39496. doi:10.1007/s11356-024-33799-5

Cui, H., Cao, Y., Feng, C., and Zhang, C. (2023). Multiple effects of ICT investment on carbon emissions: evidence from China. *Environ. Sci. Pollut. R.* 30 (2), 4399–4422. doi:10.1007/s11356-022-22160-3

Dabbous, A., and Tarhini, A. (2021). Does sharing economy promote sustainable economic development and energy efficiency? Evidence from OECD countries. *J. Innov. Knowl.* 6 (1), 58–68. doi:10.1016/j.jik.2020.11.001

Gao, W., and Peng, Y. (2023). Energy saving and emission reduction effects of urban digital economy: technology dividends or structural dividends? *Environ. Sci. Pollut. R.* 30 (13), 36851–36871. doi:10.1007/s11356-022-24780-1

Gazman, V. D. (2023). A new criterion for the ESG model. *Green Low-Carbon Econ.* 1 (1), 22–27. doi:10.47852/bonviewGLCE3202511

Han, D., Ding, Y., Shi, Z., Shi, Z., and He, Y. (2022). The impact of digital economy on total factor carbon productivity: the threshold effect of technology accumulation. *Environ. Sci. Pollut. R.* 29 (37), 55691–55706. doi:10.1007/s11356-022-19721-x

Hertwich, E. G. (2021). Increased carbon footprint of materials production driven by rise in investments. *Nat. Geosci.* 14 (3), 151–155. doi:10.1038/s41561-021-00690-8

Hussain, M., Mir, G. M., Usman, M., Ye, C., and Mansoor, S. (2022). Analysing the role of environment-related technologies and carbon emissions in emerging economies: a step towards sustainable development. *Environ. Technol.* 43 (3), 367–375. doi:10.1080/09593330.2020.1788171

Jiang, S., Chishti, M. Z., Rjoub, H., and Syed, R. (2022). Environmental R&D and trade-adjusted carbon emissions: evaluating the role of international trade. *Environ. Sci. Pollut. R.* 29 (42), 63155–63170. doi:10.1007/s11356-022-20003-9

Khan, A. J., Hameed, W. U., Ahmed, T., Uqbal, J., Aplin, M. J., and Leahy, S. (2024). Green behaviors and innovations: a green hrm perspective to move from traditional to sustainable environmental performance. *Employ. Responsib. Rights J.* 36 (2), 231–248. doi:10.1007/s10672-023-09443-8

Kirikkaleli, D., and Oyebanji, M. O. (2022). Consumption-based carbon emissions, trade, and globalization: an empirical study of Bolivia. *Environ. Sci. Pollut. R.* 29 (20), 29927–29937. doi:10.1007/s11356-022-18495-6

Li, J., Chen, L., Chen, Y., and He, J. (2022). Digital economy, technological innovation, and green economic efficiency—empirical evidence from 277 cities in China. *Manag. Decis. Econ.* 43 (3), 616–629. doi:10.1002/mde.3406

Li, T., Yu, L., Ma, Y., Duan, T., Huang, W., Zhou, Y., et al. (2023). Carbon emissions of 5G mobile networks in China. *Nat. Sustain.* 6 (12), 1620–1631. doi:10.1038/s41893-023-01206-5

Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M., and Hao, Y. (2023). Digitalization and sustainable development: how could digital economy development improve green innovation in China? *Bus. Strateg. Environ.* 32 (4), 1847–1871. doi:10.1002/bse.3223

Mi, Z., Zheng, J., Meng, J., Ou, J., Hubacek, K., Liu, Z., et al. (2020). Economic development and converging household carbon footprints in China. *Nat. Sustain.* 3 (7), 529–537. doi:10.1038/s41893-020-0504-y

Müller, L. J., Kätelhön, A., Bringezu, S., McCoy, S., Suh, S., Edwards, R., et al. (2020). The carbon footprint of the carbon feedstock CO2. *Energ. Environ. Sci.* 13 (9), 2979–2992. doi:10.1039/D0EE01530J

Patterson, D., Gonzalez, J., Hölzle, U., Le, Q., Liang, C., Munguia, L. M., et al. (2022). The carbon footprint of machine learning training will plateau, then shrink. *Computer.* 55 (7), 18–28. doi:10.1109/MC.2022.3148714

Ren, S., Li, L., Han, Y., Hao, Y., and Wu, H. (2022). The emerging driving force of inclusive green growth: does digital economy agglomeration work? *Bus. Strateg. Environ.* 31 (4), 1656–1678. doi:10.1002/bse.2975

Saeed, A., Ali, B. A., Javed, M., Atiqur, R., Swapan, T., and Talukdar, S. (2023). Mapping and evaluating sustainable and unsustainable urban areas for ecological management towards achieving low-carbon city: an empirical study of Asir Region, Saudi Arabia. *Environ. Sci. Pollut. R.* 30, 65916–65932. doi:10.1007/s11356-023-27129-4

Shahbaz, M., Wang, J., Dong, K., and Zhao, J. (2022). The impact of digital economy on energy transition across the globe: the mediating role of government governance. *Renew. Sust. Energ. Rev.* 166, 112620. article 112620. doi:10.1016/j.rser.2022.112620

Shang, M., and Luo, J. (2021). The tapio decoupling principle and key strategies for changing factors of Chinese urban carbon footprint based on cloud computing. *Int. J. Env. Res. Pub. He.* 18 (4), 2101. article 2101. doi:10.3390/ijerph18042101

Sharma, M., Kumar, A., Luthra, S., Joshi, S., and Upadhyay, A. (2022). The impact of environmental dynamism on low-carbon practices and digital supply chain networks to enhance sustainable performance: an empirical analysis. *Bus. Strateg. Environ.* 31 (4), 1776–1788. doi:10.1002/bse.2983

Tan, L., Yang, Z., Irfan, M., Ding, C. J., Hu, M., and Hu, J. (2024). Toward low-carbon sustainable development: exploring the impact of digital economy development and industrial restructuring. *Bus. Strateg. Environ.* 33 (3), 2159–2172. doi:10.1002/bse.3584

Valls-Val, K., and Bovea, M. D. (2021). Carbon footprint in Higher Education Institutions: a literature review and prospects for future research. *Clean. Technol. Envir.* 23 (9), 2523–2542. doi:10.1007/s10098-021-02180-2

Wang, L., Chen, L., and Li, Y. (2022). Digital economy and urban low-carbon sustainable development: the role of innovation factor mobility in China. *Environ. Sci. Pollut. R.* 29 (32), 48539–48557. doi:10.1007/s11356-022-19182-2

Wang, X., and Zhong, M. (2023). Can digital economy reduce carbon emission intensity? Empirical evidence from China's smart city pilot policies. *Environ. Sci. Pollut. R.* 30 (18), 51749–51769. doi:10.1007/s11356-023-26038-w

Wang, Z., Teng, Y. P., Wu, S., and Chen, H. (2023). Does green finance expand China's green development space? Evidence from the ecological environment improvement perspective. *Systems* 11 (7), 369. doi:10.3390/systems11070369

Wood, R., Neuhoff, K., Moran, D., Simas, M., Grubb, M., and Stadler, K. (2020). The structure, drivers and policy implications of the European carbon footprint. *Clim. Policy.* 20 (Suppl. 1), S39–S57. doi:10.1080/14693062.2019.1639489

Wu, T., Peng, Z., Yi, Y., and Chen, J. (2023). The synergistic effect of digital economy and manufacturing structure upgrading on carbon emissions reduction: evidence from China. *Environ. Sci. Pollut. R.* 30 (37), 87981–87997. doi:10.1007/s11356-023-28484-y

Xu, A., Song, M., Wu, Y., Luo, Y., Zhu, Y., and Qiu, K. (2024a). Effects of new urbanization on China's carbon emissions: a quasi-natural experiment based on the improved PSM-DID model. *Technol. Forecast Soc.* 200, 123164. doi:10.1016/j.techfore.2023.123164

Xu, C., Zhao, W., Li, X., Cheng, B., and Zhang, M. (2024b). Quality of life and carbon emissions reduction: does digital economy play an influential role? *Clim. Policy.* 24 (3), 346–361. doi:10.1080/14693062.2023.2197862

Xuan, D., Ma, X., and Shang, Y. (2020). Can China's policy of carbon emission trading promote carbon emission reduction? *J. Clean. Prod.* 270, 122383. doi:10.1016/j.jclepro.2020.122383

Yu, H., and Zhu, Q. (2023). Impact and mechanism of digital economy on China's carbon emissions: from the perspective of spatial heterogeneity. *Environ. Sci. Pollut. R.* 30 (4), 9642–9657. doi:10.1007/s11356-022-22552-5

Yu, Z., Liu, S., and Zhu, Z. (2022). Has the digital economy reduced carbon emissions? analysis based on panel data of 278 cities in China. *Int. J. Env. Res. Pub. He.* 19 (18), 11814. doi:10.3390/ijerph191811814

Zhao, S., Zhang, L., An, H., Peng, L., Zhou, H., and Hu, F. (2023). Has China's low-carbon strategy pushed forward the digital transformation of manufacturing enterprises? Evidence from the low-carbon city pilot policy. *Environ. Impact Asses.* 102, 107184. doi:10.1016/j.eiar.2023.107184

Zhong, R., He, Q., and Qi, Y. (2022). Digital economy, agricultural technological progress, and agricultural carbon intensity: evidence from China. *Int. J. Env. Res. Pub. He.* 19 (11), 6488. doi:10.3390/ijerph19116488

Zhu, Z., Liu, B., Yu, Z., and Cao, J. (2022). Effects of the digital economy on carbon emissions: evidence from China. *Int. J. Env. Res. Pub. He.* 19 (15), 9450. doi:10.3390/ijerph19159450

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 20 March 2025
DOI 10.3389/fenvs.2025.1564418

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Lin Zhao,
Qufu Normal University, China
Shenghao Bi,
Beijing Normal University, China

*CORRESPONDENCE
Jianfeng Jiang,
9320040135@gnust.edu.cn
Bingnan Guo,
200600002509@just.edu.cn
Feng Hu,
hufengsuibe@hotmail.com

RECEIVED 21 January 2025
ACCEPTED 05 March 2025
PUBLISHED 20 March 2025

CITATION
Qian Y, Jiang J, Guo B and Hu F (2025) The impact of "zero-waste city" pilot policy on corporate green transformation: a causal inference based on double machine learning. *Front. Environ. Sci.* 13:1564418. doi: 10.3389/fenvs.2025.1564418

COPYRIGHT
© 2025 Qian, Jiang, Guo and Hu. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The impact of "zero-waste city" pilot policy on corporate green transformation: a causal inference based on double machine learning

Yuren Qian[1], Jianfeng Jiang[2]*, Bingnan Guo[1]* and Feng Hu[3]*

[1]School of Humanities and Social Sciences, Jiangsu University of Science and Technology, Zhenjiang, China, [2]School of Economics and Management, Gannan University of Science and Technology, Ganzhou, China, [3]Institute of Digital Economy and Financial Powerhouse Building, Guangdong University of Finance, Guangzhou, China

Introduction: Against the backdrop of China's ambitious "dual carbon" objectives and ongoing economic transformation, this study investigates the efficacy of solid waste management reform through the "Zero-Waste City" pilot program.

Methods: Utilizing a comprehensive dataset of listed companies from pilot regions spanning 2016-2023, we employ sophisticated double machine learning models to empirically evaluate the program's impact on corporate green transformation.

Results: Our findings demonstrate that the pilot policy implementation significantly accelerates the green transformation trajectory of enterprises within designated regions. Through rigorous mechanism analysis, we identify three primary channels through which the policy operates: enhanced green technological innovation, heightened government environmental oversight, and increased investor environmental awareness. Heterogeneity analysis reveals differential policy impacts across ownership structures and industry characteristics, with more pronounced effects observed in non-state-owned enterprises, non-heavily polluting industries, and traditional (non-high-tech) sectors.

Discussion: These nuanced findings provide valuable empirical evidence and policy implications for the strategic expansion of the "Zero-Waste City" initiative during China's 14th Five-Year Plan period, contributing to the broader literature on environmental policy effectiveness and corporate sustainability transitions.

KEYWORDS

"zero-waste city" pilot policy, corporate green transformation, double machine learning, solid waste management, text analysis

1 Introduction

Global climate change has emerged as one of the major challenges facing humanity in the 21st century. To address this challenge, the international community has committed to controlling global greenhouse gas emissions through a series of global climate agreements such as the Paris Agreement (Nordhaus, 2019). As the world's largest carbon emitter, China made a "dual carbon" commitment to the international community in September 2020: to

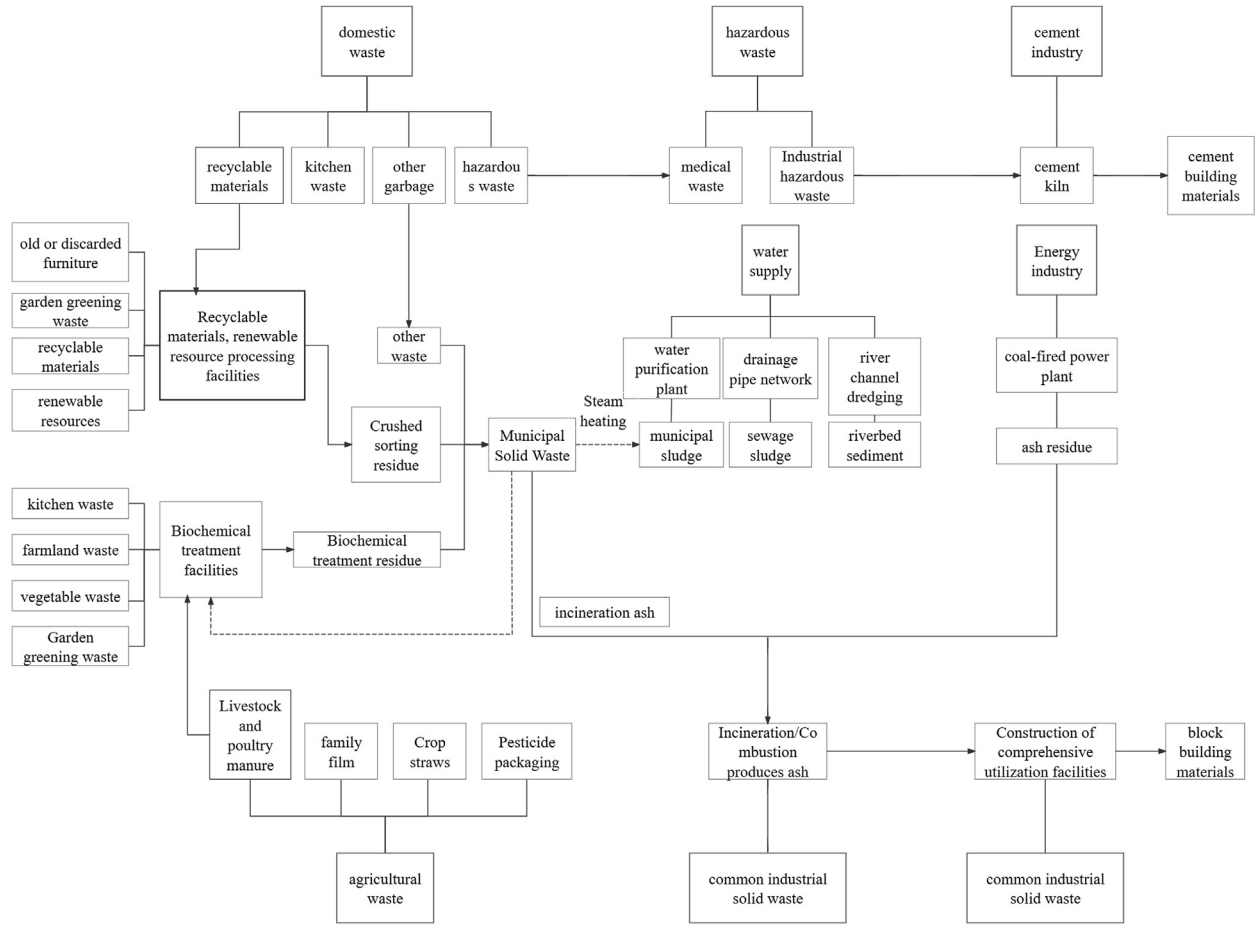


FIGURE 1
Collaborative processing and resource recovery of solid waste.

peak carbon emissions by 2030 and achieve carbon neutrality by 2060. This commitment not only demonstrates China's responsibility as a major global power but also injects new momentum into global climate governance (Zhang et al., 2022). The "2023 State Council Government Work Report" further emphasizes the need to balance energy security and stable supply with green and low-carbon development, advancing carbon peaking and carbon neutrality in a scientific and orderly manner (Wang et al., 2022).

However, during the rapid advancement of industrialization, the extensive resource development and utilization model has led to a continuous increase in solid waste generation, becoming a major constraint in China's pursuit of its "dual carbon" goals (Yu et al., 2022). Data shows that China's annual industrial solid waste generation has exceeded 3 billion tons, with cumulative stockpiles exceeding 60 billion tons, presenting substantial disposal facility deficits. Solid waste not only occupies vast land resources but also causes environmental pollution, affecting ecological system balance (Padilla-Rivera et al., 2020).

To address solid waste management challenges and promote ecological civilization construction, in December 2018, the General Office of the State Council issued the "Pilot Program for Zero-Waste City Construction," proposing an urban development model that continuously advances solid waste source reduction and resource utilization, minimizes landfill volumes, and reduces the environmental impact of solid waste to the lowest level through promoting green development methods and lifestyles. In April 2019, the Ministry of Ecology and Environment announced "11 + 5" Zero-Waste City construction pilots, officially launching China's zero-waste city initiative. In December 2021, the Ministry of Ecology and Environment and other departments issued the "14th Five-Year Plan for Zero-Waste City Construction," clearly proposing that by 2025, the intensity of solid waste generation should decline rapidly and comprehensive utilization levels should improve significantly.

Zero-waste city construction serves as a powerful tool for deepening comprehensive solid waste management reform and promoting the development of a waste-free society at the urban level (Bi et al., 2024a). As the backbone of social modernization, enterprises can play a crucial role in building zero-waste cities under government guidance. Through incentive policies and tax relief measures, enterprises are encouraged to participate in waste sorting and treatment technology development, forming a complete industrial chain and transforming waste treatment into a quality industry. Taking the collaborative and resourceful treatment process of solid waste as an example, through horizontal integration of various solid waste treatments, we

achieve coordinated governance of solid waste management. This approach can significantly enhance the utilization efficiency of various environmental sanitation facilities, while reducing overall transportation costs and lowering total carbon emissions, as shown in Figure 1.

The "Zero-Waste City" pilot policy has profoundly impacted corporate green transformation in several ways: First, it requires enterprises to transform their role from passive participants to active bearers of social responsibility, taking responsibility for the entire product lifecycle and constructing a complete system from source innovation to product recycling. Second, through reward policies and tax incentives, the government encourages enterprises to participate in waste sorting and treatment technology development, guiding them to build a complete waste treatment industrial chain. Third, the policy promotes enterprise green production transformation, implementing cleaner production and green design, constructing resource and energy recycling systems across industrial, agricultural, and domestic sectors. Fourth, by participating in zero-waste city construction, enterprises can transform waste treatment into a quality industry, creating new economic growth points. Fifth, enterprises need to cooperate in building intelligent solid waste monitoring systems to achieve whole-process smart closed-loop supervision (Bi et al., 2024b).

Existing literature has extensively discussed the relationship between environmental regulation and corporate green transformation, forming several research streams: First, research on how environmental regulation affects corporate green transformation. Porter and Linde (1995) first proposed that appropriate environmental regulation could incentivize corporate technological innovation, achieving an "innovation compensation" effect. Subsequently, scholars have verified and extended this theory from different perspectives. Chang et al. (2021) found that policy continuity and stability are key factors in promoting enterprise environmental protection technology investment. Zhai and An (2020) pointed out that environmental technology standards promote manufacturing green transformation through technological reformation pathways (Niazi et al., 2023). proposed that corporate green transformation requires managing relationships between enterprises and nature, society, and internal corporate systems to achieve "dual health" of the planet and humans. Ali et al. (2017), examining the impact of mandatory CSR disclosure on corporate green transformation, found that CSR disclosure drives corporate green transformation by strengthening enterprises' regulatory and normative legitimacy. Krass et al. (2013), based on empirical evidence from China's A-share industrial listed companies during 2008–2016, verified that environmental taxes have a significant forcing effect on corporate green transformation. Second, empirical research on pilot policy effects. Existing studies show that environmental policy pilots have played a positive role in promoting regional green development, although policy effects vary significantly across regions (Zhang et al., 2021). El-Kassar and Singh (2019) pointed out that national big data comprehensive pilot zones have played a significant role in promoting data resource concentration, sharing, circulation, and utilization, catalyzing the enabling effect of data elements and thus playing a key role in promoting corporate green transformation and sustainable development. Third, research on how policy design influences implementation effects. Qiu et al. (2021) found that policy goal clarity and implementation tool operability significantly impact policy implementation effects based on low-carbon city pilot policy research. Feroz et al. (2021) further pointed out that digital empowerment can enhance environmental policy implementation efficiency.

However, existing research still has the following limitations: First, although scholars have deeply explored the relationship between environmental regulation and corporate green transformation, research on the "Zero-Waste City" pilot policy as a novel environmental regulation tool is relatively insufficient. In particular, there is a lack of systematic theoretical analysis and empirical testing regarding how the policy influences corporate decision-making (Lu, 2019). Second, existing studies mainly focus on the macro-level effects of the pilot policy, with limited exploration of its mechanisms and transmission paths at the micro-level of enterprises. Gangi et al. (2020) pointed out that understanding corporate-level policy responses is crucial for improving environmental governance. Third, in terms of research methods, traditional econometric methods may suffer from endogeneity and omitted variable issues, affecting the reliability of causal inference (Andrews et al., 2019).

Based on these considerations, this study selects listed companies from China's "Zero-Waste City" pilot areas during 2016–2023 as research samples, employing double machine learning models to systematically examine the impact of the pilot policy on corporate green transformation. Compared to existing research, this paper's marginal contributions are reflected in three aspects: First, it systematically explores the effects, mechanisms, and heterogeneity characteristics of the "Zero-Waste City" pilot policy on corporate green transformation, enriching theories related to environmental policy and corporate behavior. By constructing a theoretical analysis framework, it reveals multiple pathways through which policy influences corporate green transformation, providing new perspectives for understanding the micro-level mechanisms of environmental regulation. Second, methodologically, this paper introduces double machine learning models for empirical analysis, effectively controlling for covariate effects and significantly improving the accuracy and reliability of causal inference. Third, regarding research data, this paper constructs a corporate green transformation evaluation system based on multi-source textual data using machine learning techniques. Through keyword extraction and analysis, it provides new analytical frameworks and empirical tools for quantitative assessment of corporate green transformation, expanding existing measurement methods in corporate green transformation research.

2 Institutional background and theoretical hypotheses

2.1 Background of ZWCP (zero-waste city pilot policy)

The concept of a "zero waste" society emerged as a global environmental paradigm in the early 21st century, aligned with broader sustainable development objectives (Assi et al., 2020). Nations worldwide have institutionalized this vision through comprehensive legislative and policy frameworks. Japan pioneered

this movement by enacting the "Basic Law for Establishing a Sound Material-Cycle Society" in 2000, subsequently reinforcing its commitment through the "Fourth Basic Plan" in 2019, which delineated seven national initiatives with quantifiable targets for 2025. The European Union demonstrated its dedication to this cause by introducing two landmark policies in 2014: "Towards a Circular Economy: A Zero Waste Programme for Europe" and the "Circular Economy Package," establishing a comprehensive framework for waste reduction and resource efficiency. Similarly, Singapore articulated its ambitious vision of becoming a "zero-waste" nation in the "Sustainable Singapore Blueprint 2015," integrating waste minimization into its national development strategy. This environmental paradigm shift has gained particular traction at the municipal level, where cities serve as laboratories for innovative waste management approaches (Kurniawan et al., 2020). Metropolitan centers such as San Francisco, Vancouver, and Stockholm have emerged as pioneers, developing sophisticated zero-waste urban planning frameworks (Zaman and Lehmann, 2013). The C40 Cities Climate Leadership Group, a network of the world's megacities committed to addressing climate change, has achieved remarkable progress in advancing zero-waste initiatives, demonstrating the effectiveness of city-level action in driving environmental transformation (Sancino et al., 2021). Against this backdrop of global zero-waste initiatives and municipal innovations, China has emerged as a significant player in advancing environmental governance concepts. Prior to the zero-waste city initiative, China had already accumulated valuable experience in environmental policy pilots, having successively designated three batches of low-carbon pilot cities in 2010, 2012, and 2017. Existing research on these "dual carbon" policy pilots has demonstrated their effectiveness in driving green innovation among listed companies in pilot regions, partially supporting the "Porter Hypothesis" that appropriate environmental regulations can stimulate corporate technological innovation (Guo et al., 2025). Building upon this successful experience with low-carbon pilots, China has developed its own comprehensive zero-waste city framework, tailored to its unique urban challenges and developmental context.

China's zero-waste city initiative was inaugurated in early 2018, embodying a comprehensive approach to urban solid waste management that emphasizes minimization of waste generation, maximization of resource utilization, and optimization of disposal safety (Li et al., 2022). This initiative gained significant political momentum when the CPC Central Committee and State Council explicitly incorporated zero-waste city pilots into their broader environmental governance framework through the "Opinions on Comprehensively Strengthening Ecological Environmental Protection and Resolutely Fighting the Battle Against Pollution" (Zhang and Teng, 2023). The policy framework was further solidified in December 2018 when the General Office of the State Council issued the "Zero-Waste City Construction Pilot Work Plan," establishing guidelines for selecting approximately ten pilot cities. The program's implementation phase commenced in April 2019 with the designation of "11 + 5" pilot cities and regions, with Shenzhen and Baotou serving as flagship municipalities in this transformative initiative (Lv and Guo, 2025). The regulatory framework was subsequently enhanced in November 2021 through the collaborative effort of the Ministry of Ecology and Environment and seventeen other governmental departments, resulting in the "Several Opinions on Further Promoting Waste Sorting Work." This was followed by a crucial policy development in December 2021: the release of the "14th Five-Year Plan for Promoting Zero-Waste City Construction Work." This comprehensive plan strategically positions zero-waste city development as a fundamental component of China's carbon peaking and neutrality objectives, introducing sophisticated indicator systems that operate across urban spatial and temporal dimensions (Meng et al., 2021).

2.2 Theoretical analysis and research hypotheses

Guided by the new development concept, zero-waste city construction aims to organically combine solid waste management with economic and social development. Through optimizing urban spatial layout, adjusting industrial structure, innovating production methods, and transforming lifestyles, it achieves resource conservation and environmental protection objectives. From the characteristics and core concepts of zero-waste city construction and green transformation, this policy is expected to promote corporate green transformation. Although initially, zero-waste city construction may increase corporate burdens through mandatory standards and tasks, as the policy progresses, it will gradually demonstrate "compensation effects" and "growth effects" (Qin et al., 2022). The policy's continuity and stability will incentivize enterprises to invest in solid waste recycling and utilization technologies and adjust production modes, thereby offsetting environmental protection costs (Su, 2020). Based on this, this paper proposes Hypothesis 1.

Hypothesis 1: ZWCP accelerates green and low-carbon transformation in pilot areas.

The Zero-Waste City Pilot Policy (ZWCP), as a new exogenous mandatory environmental regulation measure, ultimately aims to foster waste-free enterprises and industries, thereby achieving a green and low-carbon urban development model. This policy influences corporate green transformation through multiple mechanisms. From the perspective of green technological innovation, policy continuity and stability will drive enterprises to invest in various solid waste recycling and utilization technologies and transform their production methods (Peng et al., 2022). The policy increases innovation pressure on enterprises, reducing innovation uncertainty through increased research investment and financial support, ensuring enhanced enterprise innovation capabilities. Through technological innovation, enterprises are promoted to transition from traditional production modes characterized by high input, high output, high energy consumption, and high pollution to material-saving, energy-saving, and low-carbon production modes, thus achieving green transformation and upgrading (Tang et al., 2023). From the perspective of government environmental attention, various levels of government departments have significantly enhanced their environmental focus on ZWCP pilot areas and implemented green manufacturing system construction. Almost all pilot cities have established ZWCP construction working groups led by municipal party secretaries and mayors as dual group leaders, incorporating ZWCP construction effectiveness into the

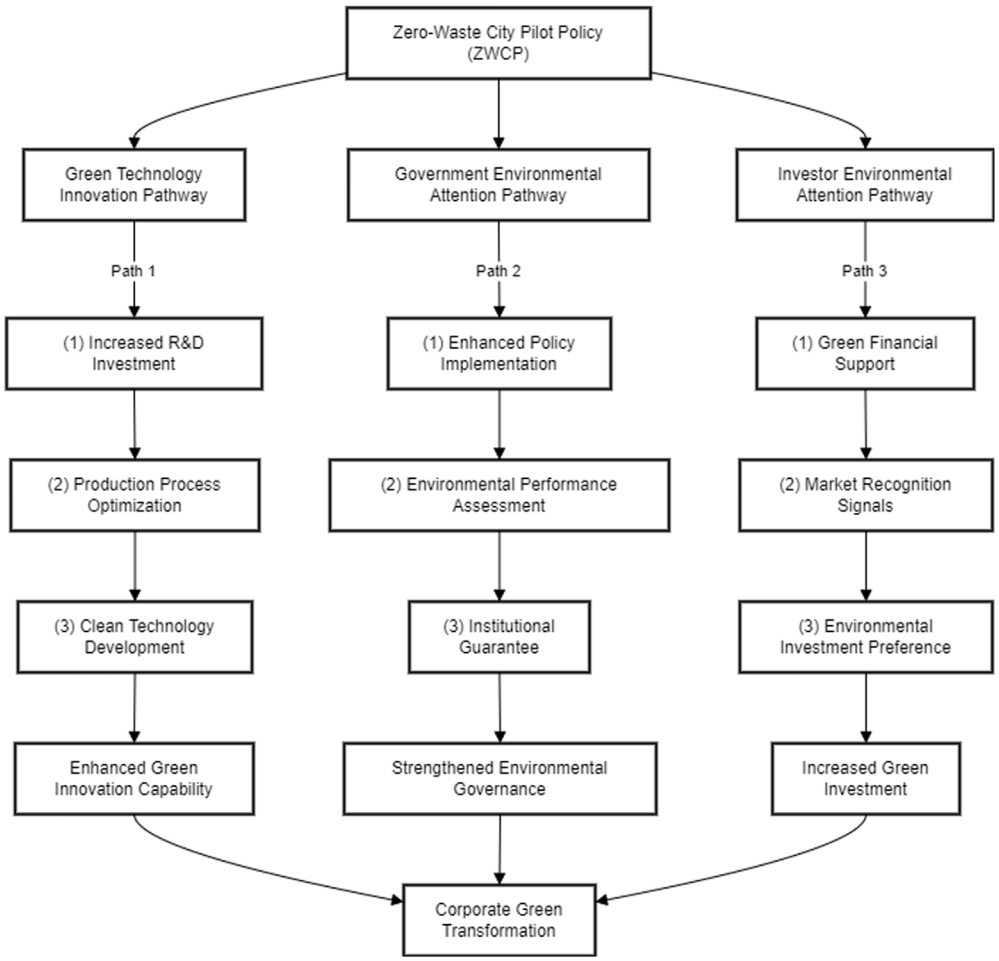


FIGURE 2
Transmission mechanism.

performance evaluation criteria of pilot regions. This top-down environmental attention mechanism provides strong institutional guarantees and policy support for corporate green transformation. From the perspective of investor environmental attention, the policy emphasizes increasing financial support for pilot areas, providing enterprises with greater profit potential. Through green finance and other means, it provides financing support for energy-saving and environmental protection industries, encouraging innovation in financial instruments such as green credit and green bonds, which can induce corporate green innovation (Xie et al., 2024). Investors' environmental attention not only provides financial support for corporate green transformation but also conveys market recognition signals for environmentally friendly enterprises, further promoting corporate development toward green and low-carbon directions. The transmission mechanism of this paper is shown in Figure 2. Based on these considerations, this paper proposes Hypothesis 2.

Hypothesis 2: ZWCP promotes corporate green transformation by enhancing green technological innovation levels, government environmental attention, and investor environmental attention. Specifically:

(a) Green technological innovation serves as a mediating factor between the pilot policy and corporate green transformation;
(b) Government environmental attention serves as a mediating factor between the pilot policy and corporate green transformation;
(c) Investor environmental attention serves as a mediating factor between the pilot policy and corporate green transformation.

3 Research design

3.1 Model specification

This study employs the Double Machine Learning (DML) framework to investigate the causal effect of zero-waste city pilot policy on corporate green transformation. This methodological choice is particularly motivated by the need to address the "curse of dimensionality" and potential functional form misspecification risks in the presence of high-dimensional control variables.

The theoretical framework begins with a partially linear model specification (Chernozhukov et al., 2018). We express the relationship between corporate green transformation ($Green_i$)

and the zero-waste city pilot policy ($Event_i$) through the following equations:

$$Green_i = \alpha_0 Event_i + g(X_i) + U_i \quad (1)$$

$$Event_i = m(X_i) + V_i \quad (2)$$

where α_0 represents our parameter of interest - the policy effect, X_i denotes the high-dimensional control variables, and $g(\cdot)$ and $m(\cdot)$ are unknown nuisance functions.

To ensure robust inference of the main parameter α_0,we implement Neyman orthogonalization. This approach constructs moment conditions that are robust to estimation errors in the nuisance components:

$$\psi(\alpha, g, m) = (Event_i - m(X_i))[Green_i - g(X_i) - \alpha(Event_i - m(X_i))] \quad (3)$$

The estimation procedure incorporates cross-fitting to mitigate potential overfitting concerns and ensure valid inference. This involves randomly partitioning the sample into S folds, training machine learning models on complement sets, computing residuals on each fold, and averaging estimates across folds. This approach effectively separates the sample used for nuisance function estimation from that used for parameter estimation.

The DML framework offers several advantageous properties for our analysis. First, it accommodates non-linear relationships in high-dimensional settings. Second, it allows for the integration of various machine learning algorithms in the estimation of nuisance functions. Third, the resulting estimator exhibits asymptotic normality and achieves $\sqrt{N}$-convergence rates under suitable regularity conditions. Finally, it enables valid statistical inference and the construction of confidence intervals for the treatment effect.

This methodological approach provides a robust foundation for examining the causal relationship between zero-waste city pilot policy and corporate green transformation, while addressing the complexities inherent in high-dimensional economic data analysis.

3.2 Variable definitions and data sources

3.2.1 Dependent variable

Corporate Green Transformation (*Green*)[(1)]: Following existing literature (Wu and Li, 2022), we employ text analysis methods to construct a corporate green transformation indicator. Specifically, we systematically collected multi-source textual data from A-share listed companies between 2016-2023, including annual reports, corporate social responsibility reports, sustainability reports, environmental reports, and ESG reports. Natural Language Processing (NLP) techniques were applied to quantify information related to corporate green transformation. The indicator construction process involves the following steps:

In the text preprocessing stage, we utilized Python's jieba word segmentation tool to process 36,705 text samples. Given the technical nature of corporate reports, we supplemented the standard dictionary with specialized green transformation vocabulary and implemented stop-word filtering for text cleaning to improve segmentation accuracy. To ensure quality, we employed stratified sampling for manual verification and correction of the word segmentation results, guaranteeing accuracy and reliability.

For text vectorization, we adopted a combined approach using the Bag of Words model and TF-IDF (Term Frequency-Inverse Document Frequency) weighting method. Specifically, we first converted the text into word frequency matrices using the Bag of Words model, then applied TF-IDF weighting to the frequencies. The TF-IDF method considers both the frequency of terms within individual documents (TF) and introduces inverse document frequency (IDF) to reduce the weight of common words, thereby highlighting distinctive keywords. This approach enables more precise capture of key information reflecting corporate green transformation. To eliminate the impact of varying report lengths, we applied logarithmic transformation to the final word frequencies.

The green transformation indicator developed in this study offers three significant advantages over traditional environmental disclosure indices: 1) Information Completeness: Integration of multi-source textual data provides more comprehensive information coverage. 2) Objectivity: Machine learning-based text analysis effectively reduces subjective scoring bias. 3) Accuracy: The incorporation of TF-IDF weighting enhances the precision of key information identification. These advantages enable our constructed indicator to more accurately reflect the level of corporate green transformation.

3.2.2 Explanatory variable

Zero-Waste City Pilot Program (*Event*): A significant environmental governance initiative was launched in January 2019 when the General Office of the State Council promulgated the "Zero-Waste City Construction Pilot Work Plan (Liu et al., 2024)." This comprehensive policy framework was collaboratively implemented by 18 central government departments, with the Ministry of Ecology and Environment assuming a leading role. We leverage this policy intervention as a quasi-natural experiment, employing the Double Machine Learning (DML) methodology to rigorously evaluate its causal effects. Drawing upon the official "Zero-Waste City Construction Pilot List" issued by the Ministry of Ecology and Environment in 2019, we construct a binary treatment indicator that assigns a value of 1 to cities designated as pilot zones following the policy's implementation, while maintaining a value of 0 for non-pilot cities and pre-implementation periods. This identification strategy enables us to isolate the policy's impact through a carefully structured difference-in-differences framework within the DML context.

3.2.3 Control variables

The Double Machine Learning methodology employs an automated variable selection process from a comprehensive candidate pool, optimizing predictive accuracy while mitigating concerns of variable redundancy. To ensure robust policy evaluation, following the empirical frameworks established by Wan et al. (2021) and Fang et al. (2024a), we incorporate a carefully curated set of control variables that potentially influence corporate green transformation: Firm Size (*Size*): Operationalized as the natural logarithm of total assets, this metric accounts for heterogeneity in organizational resource endowments. Leverage Ratio (*Lev*): Defined as the ratio of total liabilities to total assets, this indicator captures the firm's financial structure and risk profile. Revenue Growth Rate (*Growth*): Measured through year-over-year

changes in operating revenue, this variable reflects the firm's growth trajectory and market expansion capabilities. Cash Flow Ratio (*Cashflow*): Computed as net operating cash flow scaled by total assets, this measure assesses the firm's operational efficiency in generating cash resources. CEO Duality (*Dual*): A binary indicator taking the value of 1 when the positions of chairman and CEO are consolidated under single leadership, and 0 otherwise, controlling for governance structure variations. Herfindahl-Hirschman Index (*HHI*): Incorporated to quantify industry concentration and competitive dynamics, providing insights into market structure characteristics. Firm Age (*Age*): Calculated as the temporal span between firm establishment and the observation year, this variable accounts for organizational maturity and lifecycle effects.

Drawing upon the methodological innovations of Zhang and Li (2023), we enhance our Double Machine Learning framework by incorporating quadratic specifications for all continuous variables to capture potential complex nonlinear relationships within our model. To optimize the high-dimensional covariate selection, we implement a LASSO regularization framework with a three-tier multicollinearity governance mechanism. First, we determine the optimal LASSO penalty coefficient λ through five-fold cross-validation, minimizing prediction mean squared error across validation sets. The optimization process employs a grid search strategy over λ∈[1e-4, 1e4] on a logarithmic scale, accelerated by Bayesian optimization algorithms. Second, we conduct Bootstrap resampling (1,000 iterations) to assess feature selection stability, retaining only covariates with selection probability exceeding 80%. Third, we verify model identifiability by monitoring the condition number κ(X) of the design matrix XˆT X, maintaining κ < 10ˆ3 as the threshold criterion. This sophisticated econometric approach offers dual advantages: it efficiently manages high-dimensional control variables while employing an automated selection mechanism to identify the most pertinent predictors, thereby substantially enhancing the precision of our parameter estimates. Furthermore, to address potential endogeneity concerns arising from unobservable heterogeneity, we augment our specification with a comprehensive set of fixed effects at both the temporal (year) and entity (firm) levels, ensuring robust identification of our key parameters of interest.

3.2.4 Mediating variables

Green Technology Innovation (*GTI*): Building upon the methodological foundations established by Calel and Dechezleprêtre (2016) and Xu et al. (2021), we operationalize green technology innovation through the natural logarithm of green patent applications (lnpatent). Our deliberate selection of patent applications over granted patents is methodologically motivated by the considerable temporal gap inherent in the patent granting process. This time lag could potentially mask the contemporaneous relationship between green innovation initiatives and corporate environmental transformation. Patent application data offers a more contemporaneous indicator of firms' innovative endeavors, thereby enabling us to capture the dynamic evolution of corporate innovation behavior in response to policy interventions with greater precision. This measurement approach provides a more sensitive instrument for detecting the immediate strategic adjustments in firms' innovative activities following environmental policy implementation.

Government Environmental Attention (*GEA*)[(2)]: As a city-level exogenous environmental governance initiative, the Zero-Waste City pilot program affects corporate green transformation primarily through its influence on local governments' environmental management priorities. The program serves as an institutional catalyst that heightens environmental awareness among local authorities, who subsequently drive corporate green transformation through a combination of policy instruments and regulatory oversight. Drawing on the methodological framework developed by Shen et al. (2020), we systematically analyze Government Work Reports collected from prefecture-level city official portals. Through careful content analysis, we identify and track 53 environment-related key terms. To quantify local government environmental attention, we construct a composite indicator by computing the natural logarithm of these keywords' occurrence frequency. This measurement approach yields a continuous scale where higher values correspond to stronger governmental focus on environmental issues, allowing us to capture variations in policy emphasis across different administrative regions.

Investor Environmental Attention (*IEA*)[(3)]: The implementation of the Zero-Waste City Pilot Program may catalyze corporate green transformation through its influence on investor attention to environmental stewardship initiatives. To empirically capture this transmission mechanism, we adopt a sophisticated textual analysis approach developed by Xiong et al. (2023), leveraging comprehensive investor-company interaction transcripts as our primary data source. Our methodological framework involves systematic content analysis of investor inquiries during company interactions. Specifically, we employ a binary classification system: questions containing environmental protection-related terminology are coded as 1, signifying heightened investor awareness and prioritization of corporate environmental initiatives, while other inquiries are coded as 0. To construct our final measure, we aggregate the frequency of environment-focused questions for each listed company on an annual basis and apply logarithmic transformation to address potential scaling issues and enhance distributional properties. This refined indicator provides a quantitative measure of investor environmental attention that captures both the intensity and evolution of market participants' environmental focus.

This investigation utilizes comprehensive economic data from Chinese A-share listed companies over an 8-year period (2016–2023). To ensure data quality and analytical robustness, we implemented a systematic sample selection protocol with the following exclusion criteria: 1) financial sector enterprises, due to their distinct regulatory environment and accounting practices; 2) companies designated as ST, *ST, or those delisted during the study period, to avoid potential distortions from financially distressed firms; and 3) entities exhibiting substantial missing data, to maintain analytical integrity. The resulting dataset encompasses 25,645 firm-year observations, providing a robust foundation for empirical analysis. The study draws from multiple authoritative databases to ensure comprehensive and reliable data coverage. Corporate financial information was extracted from the CSMAR (China Stock Market and Accounting Research) database, while patent-

TABLE 1 Descriptive statistics.

Var	(1)	(2)	(3)	(4)	(5)
	Obs	Mean	SD	Min	Max
Green	25645	3.5625	0.9492	0.0000	7.7832
Event	25645	0.3403	0.4738	0.0000	1.0000
Size	25645	22.3048	1.3011	19.7343	26.4523
Lev	25645	0.4096	0.2036	0.0487	0.9343
Growth	25645	0.3326	0.8392	−0.9258	8.0791
Cashflow	25645	0.0481	0.0676	−0.1948	0.2656
Dual	25645	0.3288	0.4698	0.0000	1.0000
HHI	25645	0.1888	0.1657	0.0412	1.0000
Age	25645	3.0222	0.3063	1.3863	4.2905
GTI	25645	1.0134	1.3086	0.0000	7.4390
GEA	25645	8.7401	0.4482	0.6931	9.6709
IEA	25645	1.3863	1.1308	0.0000	6.8711

related data was obtained from the CNRDS (China Research Data Services) platform. Corporate disclosures and reports were sourced from the Juchao Information Network, China's designated repository for listed company information. Regional macroeconomic indicators were compiled from respective provincial statistical yearbooks to control for geographical economic variations.

Table 1 presents the descriptive statistics for all variables under investigation.

4 Empirical analysis

4.1 Baseline regression

To eliminate the correlation between residual terms and estimation errors (i.e., to avoid endogeneity problems caused by sample overlap), this paper employs the cross-fitting approach proposed by Chernozhukov et al. (2018) for double machine learning empirical analysis. In the experimental design, we adopt a 1:4 sample splitting ratio and use the LASSO regression algorithm for cross-fitting estimation of main and auxiliary regressions, with results shown in Table 2. The empirical analysis consists of three levels: First, in the baseline model controlling only for firm and year fixed effects (Column (1)), the estimated coefficient of the core explanatory variable is 0.1154, significant at the 5% level, preliminarily verifying that the Zero-Waste City Pilot Program (ZWCP) has a significant promoting effect on corporate green transformation. Second, to mitigate potential omitted variable problems, we gradually introduce first-order terms (Column (2)) and second-order terms (Column (3)) of control variables based on the baseline model. The results show that under all model specifications, the estimated coefficients of the core explanatory variable Event maintain robust positive effects at the 5% significance level, strongly confirming that the ZWCP can significantly enhance the level of corporate green transformation in pilot areas, thereby validating Hypothesis 1 of this study.

TABLE 2 Baseline regression.

Var	(1)	(2)	(3)
	Green	*Green*	*Green*
Event	0.114***	0.037***	0.036***
	(0.012)	(0.012)	(0.012)
_cons	−0.000	0.001	0.001
	(0.006)	(0.004)	(0.004)
Control (single term)	YES	YES	YES
Control (quadratic term)	NO	NO	YES
Year FE	NO	YES	YES
Firm FE	NO	YES	YES
Obs	25645	25645	25645

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

TABLE 3 Robustness checks I.

Var	(1)	(2)	(3)	(4)
	Green	*Green*	*Green*	*Green*
Event	0.037***	0.041***	0.036***	0.036***
	(0.012)	(0.012)	(0.012)	(0.012)
_cons	0.002	0.002	0.001	0.001
	(0.004)	(0.003)	(0.004)	(0.004)
Control (single term)	YES	YES	YES	YES
Control (quadratic term)	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Obs	25645	25645	25645	25645

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

4.2 Robustness checks

To ensure the validity of our findings, we conduct a comprehensive series of robustness tests examining the impact of the Zero-Waste City Pilot Program (ZWCP) on corporate green transformation.

4.2.1 Alternative sample splitting ratios

Building upon the methodology of Zhang and Li (2023), we assess the robustness of our empirical results by implementing alternative sample splitting strategies in our double machine learning framework. We modify the baseline 1:4 sample splitting ratio to 1:3 and 1:5, respectively, and conduct new estimations.

TABLE 4 Robustness checks II.

Var	(1)	(2)	(3)	(4)
	Green	*Green*	*Green*	*Green*
Event	0.072***	0.037***	0.045***	0.047***
	(0.014)	(0.012)	(0.015)	(0.013)
_cons	0.002	0.001	15.296	0.002
	(0.005)	(0.004)	(3.481)	(0.004)
Control (single term)	YES	YES	YES	YES
Control (quadratic term)	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Obs	25645	25645	25645	24999

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

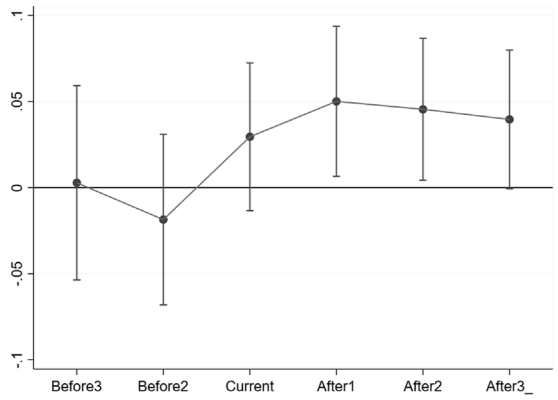


FIGURE 3
Parallel trends test.

Table 3 presents these results. Notably, across different sample splitting specifications (1:3 in Column (1) and 1:5 in Column (2)), the estimated coefficients of our key explanatory variable Event remain not only statistically significant but also consistently positive, with magnitudes closely aligned with our baseline estimates. This consistency across different specifications strongly reinforces the robustness of our baseline findings and lends additional credibility to our empirical results.

4.2.2 Winsorization analysis

To address concerns about the potential influence of outliers on our estimates, we implement a winsorization procedure at both the 1st and 5th percentiles for all control variables. The estimation results under these alternative specifications are reported in Columns (3) and (4) of Table 3, respectively. Our empirical analysis reveals that even after accounting for extreme observations, the estimated coefficients of Event retain their statistical significance and positive direction, with magnitudes remaining remarkably stable relative to our baseline estimates. This consistency demonstrates that our findings are robust to the treatment of outliers, providing compelling evidence that the documented positive effect of the ZWCP on corporate green transformation is not driven by extreme observations.

4.2.3 Alternative machine learning specifications

To further substantiate the robustness of our findings, we extend our analysis by implementing diverse machine learning methodologies. Specifically, we augment our baseline LASSO regression framework by employing two alternative state-of-the-art machine learning algorithms: Elastic Net, which combines L1 and L2 regularization, and Gradient Boosting, an ensemble learning approach. The estimation results from these alternative specifications are reported in Columns (1) and (2) of Table 4, respectively. The empirical investigation reveals that across these different machine learning architectures, the estimated coefficients of our key explanatory variable Event maintain their statistical significance and positive directionality with remarkable consistency. The magnitude and significance of these effects remain stable across specifications, lending strong support to our main findings. This methodological consistency across different algorithmic approaches provides compelling evidence that our documented positive relationship between the ZWCP and corporate green transformation is robust to model specification and is not an artifact of any particular machine learning algorithm.

4.2.4 Difference-in-differences analysis

To further address potential concerns regarding omitted variable bias, we employ the traditional difference-in-differences (DID) approach as an additional robustness check. This methodology effectively mitigates endogeneity concerns arising from omitted variables by controlling for time-invariant individual fixed effects and common temporal trends. Column (3) of Table 4 reports the estimation results from the DID model. The coefficient of our key explanatory variable Event remains positive and statistically significant, indicating that our main finding—that the ZWCP promotes corporate green transformation—remains robust under alternative econometric specifications, providing further support for our baseline results. Notably, the validity of the DID approach hinges on the parallel trends assumption. To verify this crucial identifying assumption, we conduct a parallel trends test using 2018 (the year before policy implementation) as the base period. As illustrated in Figure 3, the test results support the presence of similar trends between the treatment and control groups prior to policy implementation, satisfying the key identification assumption of the DID methodology.

4.2.5 Propensity score matching analysis

The inherent design of our key explanatory variable—the Zero-Waste City Pilot Program—exhibits substantial exogeneity in its implementation, providing a strong theoretical foundation to mitigate concerns regarding reverse causality in our regression framework. Nevertheless, we acknowledge that pilot and non-pilot cities may exhibit systematic heterogeneity across multiple dimensions, particularly in terms of economic development trajectories and environmental policy frameworks. Such underlying differences could potentially introduce sample selection bias, necessitating methodological refinements to ensure

TABLE 5 Mechanism analysis.

Var	(1)	(2)	(3)
	Green	*Green*	*Green*
Event	0.027*	0.033***	0.048***
	(0.016)	(0.008)	(0.018)
_cons	0.002	0.001	0.001
	(0.005)	(0.003)	(0.005)
Control (single term)	YES	YES	YES
Control (quadratic term)	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Obs	25645	25645	25645

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

the validity of our policy effect estimates. To rigorously address these identification challenges, we implement a propensity score matching (PSM) methodology to construct a more balanced and comparable analytical sample. Specifically, we employ a one-to-one nearest neighbor matching algorithm with a stringent caliper to optimize the covariate balance between treatment and control observations. Subsequently, we apply our double machine learning framework to this matched sample to re-estimate the treatment effects. The results, presented in Column (4) of Table 4, reveal that the estimated coefficients demonstrate a modest uptick in magnitude while preserving their statistical significance at conventional levels. This consistency in results across different methodological approaches provides compelling evidence for the robustness of our baseline estimates and strengthens the causal interpretation of our findings.

4.3 Mechanism analysis

Given the ongoing academic discourse concerning endogeneity issues in mediation effect models Jiang (2022), we adopt the methodological framework to investigate the transmission mechanisms through which the Zero-Waste City pilot policy affects corporate green transformation. This approach focuses on identifying the causal relationships between core explanatory variables and mechanism variables. The three mechanism variables identified in this study have been confirmed by existing literature to influence green transformation: green technology innovation (Liu et al., 2024), government environmental attention (Chen et al., 2024), and investor environmental attention (Xiong et al., 2023). The corresponding proxy indicators have been presented in the previous sections. The proxy indicators for these variables have been elaborated in previous sections. The empirical results of our mechanism analysis are presented in Table 5. The estimation results in Column (1) reveal that the coefficient of Event is 0.249, which is statistically significant at the 10% level. This finding provides empirical evidence that the Zero-Waste City pilot policy substantially enhances corporate green transformation through the promotion of enterprises' green innovation capabilities. More specifically, enterprises under the policy framework demonstrate increased commitment to green technology research and development initiatives. These innovative practices yield dual benefits: the optimization of production processes and the advancement of cleaner production technologies alongside improved circular resource utilization. Consequently, this facilitates a fundamental transition from conventional production paradigms to environmentally sustainable development models. Columns (2) and (3) report the empirical findings with environmental attention measures as dependent variables. The Event coefficients exhibit statistically significant positive values for both governmental and investor environmental attention metrics. These results strongly suggest that the Zero-Waste City pilot policy generates a dual effect: it enhances policy effectiveness and resource allocation efficiency while simultaneously influencing investors' financing strategies. This dual mechanism strengthens enterprises' commitment to green transformation and catalyzes their progression toward enhanced environmental performance. These empirical findings provide robust support for Hypothesis 2.

4.4 Heterogeneity analysis

4.4.1 Technology level

We investigate the heterogeneous effects of policy interventions across enterprises with varying technological capabilities. Following the methodological framework of (Yao and Wang, 2020), we stratify our sample into high-tech and non-high-tech industries to examine how technological heterogeneity moderates the impact of the Zero-Waste City policy. The empirical results presented in Table 6 reveal an interesting pattern: while the Event coefficient in Column (1) lacks statistical significance, it exhibits strong positive significance in Column (2), suggesting that the policy's efficacy is particularly pronounced in non-high-tech enterprises' innovation activities and green transformation initiatives. This asymmetric effect can be attributed to the inherent characteristics of non-high-tech industries, particularly their substantial resource dependence in manufacturing and traditional service sectors. These industries, characterized by more visible waste generation and pollution intensity in their production processes, demonstrate greater responsiveness to the Zero-Waste City policy's resource management and waste treatment protocols. Furthermore, within non-high-tech industries, green transformation emerges as a strategic differentiator for competitive advantage. The policy framework enables these enterprises to establish environmental leadership positions, consequently enhancing their market positioning and brand equity (Chen et al., 2025). Conversely, high-tech industries, already equipped with advanced innovation capabilities and established environmental protocols, exhibit diminishing marginal returns to additional policy interventions due to their pre-existing technological sophistication in waste management.

4.4.2 Pollution level

To further explore the policy's heterogeneous effects, we examine the moderating role of pollution intensity, categorizing enterprises into heavily polluting and non-heavily polluting entities,

TABLE 6 Heterogeneity analysis.

Var	(1)	(2)	(3)	(4)	(5)	(6)
	Green	*Green*	*Green*	*Green*	*Green*	*Green*
Event	0.001	0.060***	0.006	0.049***	0.062**	0.043***
	(0.023)	(0.014)	(0.044)	(0.013)	(0.026)	(0.014)
_cons	0.006	0.000	−0.002	0.002	0.003	0.001
	(0.006)	(0.004)	(0.012)	(0.004)	(0.007)	(0.004)
Control (single term)	YES	YES	YES	YES	YES	YES
Control (quadratic term)	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Obs	7,057	18588	2,367	23278	7,640	17555

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

following Guo et al. (2019). The empirical evidence from Table 6 demonstrates a distinct pattern: while the Event coefficient lacks significance in Column (3), it exhibits robust positive significance in Column (4), indicating enhanced policy responsiveness among non-heavily polluting enterprises. This differential impact can be attributed to several factors. First, the pilot policy's clear regulatory framework and support mechanisms facilitate more efficient adaptation of production processes and management systems among non-heavily polluting enterprises. Second, these enterprises typically possess greater operational flexibility in technological innovation implementation. Conversely, heavily polluting enterprises, subject to long-standing stringent environmental regulations, may exhibit "policy fatigue" toward additional environmental initiatives. The Zero-Waste City framework's specific focus on "industries such as coking, non-ferrous metals, gold, metallurgy, and chemicals" for green mining implementation acknowledges the pre-existing regulatory burden on these heavily polluting sectors.

4.4.3 Ownership structure

Given that the effectiveness of policy interventions may differ across ownership structures, we incorporate state ownership (SOE) as a categorical variable to investigate how ownership heterogeneity moderates the impact of zero-waste city policy implementation. Table 6 presents compelling evidence through event coefficients demonstrating positive significance across both Columns (5) and (6), with notably stronger effects in Column (6), providing robust support for Hypothesis 4c regarding the policy's enhanced impact on non-SOEs. This differential effect can be primarily attributed to the institutional advantages derived from China's mixed-ownership reforms, as recent empirical evidence suggests that private enterprises with state-owned shareholders demonstrate enhanced environmental governance capabilities through dual mechanisms: optimized supervision structures and reduced policy constraints (Guo et al., 2023). Several institutional and organizational factors contribute to this enhanced responsiveness: First, non-SOEs typically demonstrate heightened sensitivity to brand reputation and corporate social responsibility considerations, leveraging policy compliance to enhance stakeholder trust and market positioning. Second, their superior operational agility enables more rapid adaptation of production processes and management systems to meet policy requirements, in contrast to SOEs which often face operational constraints due to multiple policy objectives and rigid budgetary systems (Guo et al., 2025). Third, the streamlined governance structures characteristic of non-SOEs facilitate the swift implementation of circular production models mandated by the Zero-Waste City framework, while their market-oriented positioning provides strong incentives for strategic environmental investments. Moreover, their enhanced responsiveness to market signals and stronger innovation incentives under the policy framework, as emphasized in regulatory documents focusing on "nurturing environmental governance and ecological protection market entities," further enables them to capitalize on environmental cost advantages more effectively.

5 Conclusion and policy recommendations

5.1 Conclusion

China is currently at a crucial stage of economic development. While environmental governance and economic benefits were once viewed as opposing objectives, their synergistic effects actually form the foundation and driving force for sustainable economic development. This study combines the Zero-Waste City pilot policy, implemented in December 2018, with corporate green transformation, employing double machine learning methods to empirically examine their relationship. The findings reveal that the Zero-Waste City pilot policy has significantly promoted green transformation among enterprises in pilot regions. Mechanism tests indicate that this policy encourages corporate green transformation by enhancing enterprises' green innovation levels and increasing environmental attention from both government and investors. Heterogeneity tests further demonstrate that the pilot policy has particularly significant effects on improving green

transformation levels in non-high-tech industries, non-heavily polluting enterprises, and non-state-owned enterprises. However, this study has certain limitations. Due to the relatively short implementation period, the 2019–2023 evaluation window primarily captures initial policy responses while potentially missing long-term adaptation dynamics, as observed in Germany's Zero-Waste City transition case. Moreover, the generalizability of our findings may be limited by China's unique institutional context, as international waste management paradigms demonstrate significant variations in policy mechanisms, such as the European Union's Extended Producer Responsibility (EPR) framework emphasizing market-driven approaches and San Francisco's "Pay-As-You-Throw" system achieving 80% waste diversion through economic incentives. This suggests the need for future research to employ extended time series data and cross-national comparative analyses to further validate policy effectiveness.

5.2 Policy recommendations

First, incentivize enterprises to actively participate in Zero-Waste City construction and promote corporate green transformation. Regarding fiscal and tax support policies, environmental protection tax exemptions should be granted to enterprises that legally conduct comprehensive solid waste utilization and meet national and local environmental protection standards. In agricultural support and protection subsidies, increase subsidies for comprehensive utilization of livestock manure and straw for organic fertilizer production while simultaneously reducing chemical fertilizer subsidies and expanding government green procurement of recycled products. In terms of financial support, actively promote green financial instruments such as green credit and green bonds, explore green financial support pilots for livestock waste disposal and harmless treatment, support solid waste utilization and disposal industry development, and establish diversified financing channels. In government-invested public works, prioritize the use of comprehensive utilization products made from bulk industrial solid waste. Meanwhile, accelerate the establishment of incentive and constraint mechanisms promoting solid waste reduction, resource utilization, and harmless treatment, with clear specifications for usage scope and proportion requirements.

Second, green transformation of heavily polluting industries is crucial for future Zero-Waste City achievement, requiring more specific environmental governance plans. The regulatory system for heavily polluting industries should be improved by establishing a city-wide smart supervision information platform for solid waste, achieving comprehensive GPS and video coverage for intelligent monitoring. Empirical evidence from pilot cities has demonstrated the effectiveness of such platforms. For instance, Shenzhen's construction waste smart supervision platform, operated through a "state-owned capital holding + market-oriented operation" mixed-ownership reform model, has achieved remarkable results through three innovative modules: 1) an intelligent sensing layer deploying millimeter-wave radar and weight sensor networks with an error rate below 2.5% for real-time site emission measurement; 2) a blockchain evidence layer based on the Hyperledger Fabric framework, reducing transportation trajectory tampering risks by 92%; and 3) a decision optimization layer using deep Q-learning algorithms for dynamic route planning, reducing average daily mileage by 18.7 km per vehicle (Wang et al., 2024). Another successful case is demonstrated by Hangzhou's "Zero-Waste Cell" IoT system implemented during the Asian Games venue construction, which achieved a 98.4% closed-loop utilization rate for 2,000 tons of event waste through RFID tracking technology. The system's success validates the adaptability of intelligent supervision platforms in time-compressed scenarios through distributed edge computing nodes and digital twin technology for waste diversion path optimization (Fang et al., 2024b). Law enforcement personnel can conduct real-time online inspections of enterprises' solid waste management records and storage standardization through synchronized video, enabling immediate correction of identified issues and forming closed-loop regulatory supervision. Establish a list of key environmental monitoring units for hazardous waste, promote comprehensive intelligent supervision of hazardous waste, and enhance risk prevention capabilities. Improve the environmental credit evaluation system and strengthen joint penalties for dishonest enterprises and practitioners. Fully utilize information technologies such as IoT and GPS to achieve information visualization of solid waste collection, transfer, and disposal, improving supervision efficiency. Establish a multi-level environmental emergency system connecting "enterprise-street-district-city" levels.

Third, solid waste management effectiveness in state-owned enterprises is key to Zero-Waste City construction. Improve assessment mechanisms for state-owned enterprises by incorporating solid waste reduction and resource utilization targets into evaluation systems and establishing comprehensive solid waste management systems. Encourage state-owned capital to increase investment in ecological protection and restoration, supporting technological innovation in solid waste treatment. Actively cultivate third-party markets, encourage specialized third-party institutions to engage in solid waste resource utilization, environmental pollution treatment, and consulting services, fostering leading enterprises in solid waste resource utilization. With government as the responsible entity, promote solid waste collection, utilization, and disposal project implementation and facility operation. While avoiding local government debt increase, legally explore third-party governance or Public-Private Partnership (PPP) models to achieve risk and benefit sharing with social capital.

Fourth, construct a systematic solid waste management innovation system. As the Zero-Waste City policy's effect on high-tech enterprises' green transformation remains unclear, establish a comprehensive technical innovation ecosystem for solid waste management integrating "industry integration, urban-industrial integration, and functional integration" through national and local government funding support. Increase support from green low-carbon development funds and environmental protection special funds, ensuring strong scientific and technological service support. Improve talent recruitment incentive policies in solid waste technical and management fields, promoting high-level scientific and technological innovation talent team building. Develop online trading platforms enabling precise matching between solid waste generators and processors, integrating information about waste generation units, processing units, transportation units, and detailed waste conditions and treatment requirements. High-tech enterprises should establish solid waste research platforms, creating

technology demonstration and achievement transformation bases. Through setting up research projects (special programs, funds), identifying industry demands, publicizing project information, promoting achievement transformation, and establishing exchange cooperation, promote effective combination and precise investment of talent, information, capital, and technology, strengthening deep integration of industry-university-research collaboration and collaborative innovation, improving the speed and efficiency of scientific research achievement transformation. Meanwhile, solid waste research platforms can also carry public services, enhancing public participation and achieving collaborative governance.

6 Notes

(1) Keywords for green transformation include: green, low-carbon, green innovation, green transformation, green upgrading, green mountains and clear waters, carbon reduction, carbon verification, ecological restoration, environmental protection management measures, environmental management systems, environmental management procedures, carbon asset management, energy management, three simultaneities, environmental protection investment, refined management, environmental governance, process control, end-of-pipe treatment, carbon management, carbon emission management, lean management, energy efficiency management, accountability system, performance assessment, environmental impact assessment, environmental responsibility, environmental protection officials, environmental supervision, land reclamation, soil and water conservation, efficiency, energy saving, environmental protection, electricity saving, water conservation, sustainable development, development trends, market prospects, environmental optimization, resource regeneration, new energy development, recycling, circular regeneration, green finance, climate change, alternative technologies, carbon footprint, carbon trading, etc.

(2) Keywords for government environmental protection attention mainly include: haze, environmental protection, resources, recycling, global warming, acid rain, greenhouse effect, water conservation, afforestation, greening, dust, smoke, exhaust, atmosphere, clear waters, blue sky, sewage, treatment rate, river chief, green space, beautiful, water source, water consumption, particles, joint prevention, joint control, air quality, environmental protection, pollution, energy consumption, emission reduction, sewage discharge, ecology, green, low-carbon, air, sulfur dioxide, carbon dioxide, sustainable, clean energy, fossil fuels, coal, petroleum, natural gas, solar energy, nuclear energy, recycling, etc.

(3) Keywords for investor environmental protection attention mainly include: environmental protection, pollution, energy conservation and emission reduction, wastewater treatment, etc.

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

YQ: Data curation, Methodology, Writing–original draft. JJ: Supervision, Validation, Writing–review and editing. BG: Investigation, Writing–review and editing. FH: Conceptualization, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was supported by the National Natural Science Foundation of China (Grant No. 72373135); the Humanities and Social Sciences Research Project of the Ministry of Education (Grant No: 24YJAZH081).

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 author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Ali, W., Frynas, J. G., and Mahmood, Z. (2017). Determinants of corporate social responsibility (csr) disclosure in developed and developing countries: a literature review. *Corp. Soc. Responsib. Environ. Manag.* 24 (4), 273–294. doi:10.1002/csr.1410

Andrews, I., Stock, J. H., and Sun, L. (2019). Weak instruments in instrumental variables regression: theory and practice. *Annu. Rev. Econ.* 11 (1), 727–753. doi:10.1146/annurev-economics-080218-025643

Assi, A., Bilo, F., Zanoletti, A., Ponti, J., Valsesia, A., La Spina, R., et al. (2020). Zero-waste approach in municipal solid waste incineration: reuse of bottom ash to stabilize fly ash. *J. Clean. Prod.* 245, 118779. doi:10.1016/j.jclepro.2019.118779

Bi, S., Du, J., Yan, Z., and Appolloni, A. (2024b). Can " zero waste city" policy promote green technology? evidence from econometrics and machine learning. *J. Environ. Manag.* 370, 122895. doi:10.1016/j.jenvman.2024.122895

Bi, S., Kang, C., Bai, T., and Yi, X. (2024a). The effect of green fiscal policy on green technological innovation: evidence from energy saving and emission reduction fiscal policy. *Environ. Sci. Pollut. Res. Int.* 31 (7), 10483–10500. doi:10.1007/s11356-023-31798-6

Calel, R., and Dechezleprêtre, A. (2016). Environmental policy and directed technological change: evidence from the european carbon market. *Rev. Econ. Statistics* 98 (1), 173–191. doi:10.1162/rest_a_00470

Chang, K.-C., Wang, D., Lu, Y., Chang, W., Ren, G., Liu, L., et al. (2021). Environmental regulation, promotion pressure of officials, and enterprise environmental protection investment. *Front. Public Health* 9, 724351. doi:10.3389/fpubh.2021.724351

Chen, X., Jiang, S., and He, L. (2024). The impact of pilot policies of "Zero-Waste city" on enterprise green innovation. *East China Econ. Manag.* 38 (02), 42–52. doi:10.19629/j.cnki.34-1014/f.221104018

Chen, Y., Zhong, B., and Guo, B. (2025). Does energy-consuming right trading policy achieve a low-carbon transition of the energy structure? a quasi-natural experiment from China. *Front. Environ. Sci.* 12. doi:10.3389/fenvs.2024.1502860

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., et al. (2018). Double/debiased machine learning for treatment and structural parameters. *Econ. J.* 21 (1), C1–C68. doi:10.1111/ectj.12097

El-Kassar, A.-N., and Singh, S. K. (2019). Green innovation and organizational performance: the influence of big data and the moderating role of management commitment and hr practices. *Technol. Forecast. Soc. Change* 144, 483–498. doi:10.1016/j.techfore.2017.12.016

Fang, H., Jie, H., and Zhao, Q. (2024a). Establishment of big data comprehensive pilot Area,Data element enabling effect and green transformation of enterprises. *World Econ. Stud.* 11, 93–107+137. doi:10.13516/j.cnki.wes.2024.11.002

Fang, W., Guo, B., and Yu, Y. (2024b). The impact of green finance reform on industrial water pollution: evidence from innovation pilot zones in China. *Water Econ. Policy*. doi:10.1142/s2382624x24400101

Feroz, A. K., Zo, H., and Chiravuri, A. (2021). Digital transformation and environmental sustainability: a review and research agenda. *Sustainability* 13 (3), 1530. doi:10.3390/su13031530

Gangi, F., Daniele, L. M., and Varrone, N. (2020). How do corporate environmental policy and corporate reputation affect risk-adjusted financial performance? *Bus. Strategy Environ.* 29 (5), 1975–1991. doi:10.1002/bse.2482

Guo, B., Feng, W., and Lin, J. (2025). The impact of green finance on labor income share: evidence from green finance reform and innovation pilot zone. *Econ. Analysis Policy* 84, 1347–1358. doi:10.1016/j.eap.2024.10.014

Guo, B., Feng, Y., and Wang, X. (2023). The effect of environmental information disclosure on carbon emission. *Pol. J. Environ. Stud*. doi:10.15244/pjoes/173106

Guo, B., Hu, J., and Guo, X. (2025). Can the industrial transformation and upgrading demonstration zones policy improve urban green technology innovation? an empirical test based on old industrial cities and resource-based cities in China. *Front. Environ. Sci.* 12. doi:10.3389/fenvs.2024.1505177

Guo, Y., Su, C., and Zhang, Y. (2019). Does corporate social responsibility disclosure improve the company's market performance? *Syst. Engineering-Theory and Pract.* 39 (04), 881–892. doi:10.12011/1000-6788-2018-2074-12

Jiang, T. (2022). Mediating effects and moderating effects in causal inference. *China Ind. Econ.* 05, 100–120. doi:10.19581/j.cnki.ciejournal.2022.05.005

Krass, D., Nedorezov, T., and Ovchinnikov, A. (2013). Environmental taxes and the choice of green technology. *Prod. Operations Manag.* 22 (5), 1035–1055. doi:10.1111/poms.12023

Kurniawan, T. A., Avtar, R., Singh, D., Xue, W., Dzarfan Othman, M. H., Hwang, G. H., et al. (2020). Reforming mswm in sukunan (yogjakarta, Indonesia): a case-study of applying a zero-waste approach based on circular economy paradigm. *J. Clean. Prod.* 284, 124775. doi:10.1016/j.jclepro.2020.124775

Li, X., Fang, Y., and Luo, F. (2022). A study on the willingness of industrial ecological transformation from China's zero waste cities perspective. *Int. J. Environ. Res. Public Health* 19 (15), 9399. doi:10.3390/ijerph19159399

Liu, M., Chen, L., Sheng, X., Xu, Y., Yuan, X., Wang, Q., et al. (2024). Zero-waste city pilot and urban green and low-carbon transformation: quasi-experimental evidence from China. *Resour. Conservation Recycl.* 206, 107625. doi:10.1016/j.resconrec.2024.107625

Lu, J. G. (2019). Air pollution: a systematic review of its psychological, economic, and social effects. *Curr. Opin. Psychol.* 32, 52–65. doi:10.1016/j.copsyc.2019.06.024

Lv, L., and Guo, B. (2025). Can green finance policy reduce energy consumption: quasi-natural experimental evidence from green finance reform and innovations pilot zone. *Front. Environ. Sci.* 13. doi:10.3389/fenvs.2025.1511837

Meng, M., Wen, Z., Luo, W., and Wang, S. (2021). Approaches and policies to promote zero-waste city construction: China's practices and lessons. *Sustainability* 13 (24), 13537. doi:10.3390/su132413537

Niazi, U. I., Nisar, Q. A., Nasir, N., Naz, S., Haider, S., and Khan, W. (2023). Green hrm, green innovation and environmental performance: the role of green transformational leadership and green corporate social responsibility. *Environ. Sci. Pollut. Res. Int.* 30 (15), 45353–45368. doi:10.1007/s11356-023-25442-6

Nordhaus, W. (2019). Climate change: the ultimate challenge for economics. *Am. Econ. Rev.* 109 (6), 1991–2014. doi:10.1257/aer.109.6.1991

Padilla-Rivera, A., Russo-Garrido, S., and Merveille, N. (2020). Addressing the social aspects of a circular economy: a systematic literature review. *Sustainability* 12 (19), 7912. doi:10.3390/su12197912

Peng, B., Zhao, Y., Elahi, E., and Wan, A. (2022). Investment in environmental protection, green innovation, and solid waste governance capacity: empirical evidence based on panel data from China. *J. Environ. Plan. Manag.* 66 (6), 1229–1252. doi:10.1080/09640568.2021.2017866

Porter, M. E., and Linde, C. van der. (1995). Toward a new conception of the environment-competitiveness relationship. *J. Econ. Perspect.* 9 (4), 97–118. doi:10.1257/jep.9.4.97

Qin, T., She, L., Wang, Z., Chen, L., Xu, W., Jiang, G., et al. (2022). The practical experience of "zero waste city" construction in foshan city condenses the Chinese solution to the sustainable development goals. *Sustainability* 14 (19), 12118. doi:10.3390/su141912118

Qiu, S., Wang, Z., and Liu, S. (2021). The policy outcomes of low-carbon city construction on urban green development: evidence from a quasi-natural experiment conducted in China. *Sustain. Cities Soc.* 66, 102699. doi:10.1016/j.scs.2020.102699

Sancino, A., Stafford, M., Braga, A., and Budd, L. (2021). What can city leaders do for climate change? insights from the c40 cities climate leadership group network. *Reg. Stud.* 56 (7), 1224–1233. doi:10.1080/00343404.2021.2005244

Shen, W., Chai, Z., and Zhang, H. (2020). Heterogeneous ecological environmental attention and environmental governance performance. *Soft Sci.* 34 (09), 65–71. doi:10.13956/j.ss.1001-8409.2020

Su, Y. (2020). Multi-agent evolutionary game in the recycling utilization of construction waste. *Sci. Total Environ.* 738, 139826. doi:10.1016/j.scitotenv.2020.139826

Tang, L., Jiang, H., Hou, S., Zheng, J., and Miao, L. (2023). The effect of enterprise digital transformation on green technology innovation: a quantitative study on Chinese listed companies. *Sustainability* 15 (13), 10036. doi:10.3390/su151310036

Wan, P., Yang, M., and Chen, L. (2021). How do environmental technology standards affect the green transition of China's manufacturing industry——a perspective from technological transformation. *China Ind. Econ.* 09, 118–136. doi:10.19581/j.cnki.ciejournal.2021.09.006

Wang, G., Li, S., and Yang, L. (2022). Research on the pathway of green financial system to implement the realization of China's carbon neutrality target. *Int. J. Environ. Res. Public Health* 19 (4), 2451. doi:10.3390/ijerph19042451

Wang, M., Wang, Y., Yang, Z., and Guo, B. (2024). Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? a quasi-natural experiment from China. *Front. Environ. Sci.* 12. doi:10.3389/fenvs.2024.1430031

Wu, F., and Li, W. (2022). Tax incentives and corporate green transformation—empirical evidence based on text recognition of listed Companies'Annual reports. *Public Finance Res.* 04, 100–118. doi:10.19477/j.cnki.11-1077/f.2022.04.006

Xie, C., Ye, L., Zhong, N., and Wan, W. (2024). Impact of digital finance on corporate green innovation: exploring role of land resource misallocation in China. *Resour. Policy* 91, 104920. doi:10.1016/j.resourpol.2024.104920

Xiong, X., Di, J., and Gao, Y. (2023). The influence of green concerns on the green innovation of listed companies——based on the investor interactive platforms. *Syst. Engineering-Theory and Pract.* 43 (07), 1873–1893. doi:10.12011/SETP2022-1955

Xu, L., Fan, M., Yang, L., and Shao, S. (2021). Heterogeneous green innovations and carbon emission performance: evidence at China's city level. *Energy Econ.* 99, 105269. doi:10.1016/j.eneco.2021.105269

Yao, K., and Wang, Y. (2020). RETURNED executives and internationalization of enterprises——empirical study on China's listed high-tech companies. *Econ. Theory Bus. Manag.* 11, 55–71. Available online at: http://jjll.ruc.edu.cn/EN/Y2020/V40/I11/55.

Yu, Z., Liu, S., and Zhu, Z. (2022). Has the digital economy reduced carbon emissions? analysis based on panel data of 278 cities in China. *Int. J. Environ. Res. Public Health* 19 (18), 11814. doi:10.3390/ijerph191811814

Zaman, A. U., and Lehmann, S. (2013). The zero waste index: a performance measurement tool for waste management systems in a 'zero waste city. *J. Clean. Prod.* 50, 123–132. doi:10.1016/j.jclepro.2012.11.041

Zhai, X., and An, Y. (2020). Analyzing influencing factors of green transformation in China's manufacturing industry under environmental regulation: a structural equation model. *J. Clean. Prod.* 251, 119760. doi:10.1016/j.jclepro.2019.119760

Zhang, S., Wang, Y., Hao, Y., and Liu, Z. (2021). Shooting two hawks with one arrow: could China's emission trading scheme promote green development efficiency and regional carbon equality? *Energy Econ.* 101, 105412. doi:10.1016/j.eneco.2021.105412

Zhang, S., Yang, Y., Wen, Z., Peng, M., Zhou, Y., and Hao, J. (2022). Sustainable development trial undertaking: experience from China's innovation demonstration zones. *J. Environ. Manag.* 318, 115370. doi:10.1016/j.jenvman.2022.115370

Zhang, T., and Li, J. (2023). Network Infrastructure,Inclusive green growth, and regional inequality: from causal inference based on double machine learning. *J. Quantitative and Tech. Econ.* 40 (04), 113–135. doi:10.13653/j.cnki.jqte.20230310.005

Zhang, Z., and Teng, J. (2023). Role of government in the construction of zero-waste cities: a case study of China's pearl river delta city cluster. *Sustainability* 15 (2), 1258. doi:10.3390/su15021258

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 26 March 2025
DOI 10.3389/fenvs.2025.1543211

Check for updates

OPEN ACCESS

EDITED BY
Martin Siegert,
University of Exeter, United Kingdom

REVIEWED BY
Irina Georgescu,
Bucharest Academy of Economic Studies, Romania
Yayan Lu,
Henan Normal University, China

*CORRESPONDENCE
Hainan Liu,
liuhainan@sdjzu.edu.cn

RECEIVED 11 December 2024
ACCEPTED 28 February 2025
PUBLISHED 26 March 2025

CITATION
Lin Z, Liu H, Shi L and Cui D (2025) Seeing green high-quality development: how the digital economy affects carbon emissions in the yellow river basin and yangtze river economic belt. *Front. Environ. Sci.* 13:1543211. doi: 10.3389/fenvs.2025.1543211

COPYRIGHT
© 2025 Lin, Liu, Shi and Cui. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Seeing green high-quality development: how the digital economy affects carbon emissions in the yellow river basin and yangtze river economic belt

Zhijian Lin[1], Hainan Liu[1]*, Lei Shi[2] and Dongxu Cui[2]

[1]School of business, Shandong Jianzhu University, Jinan, China, [2]School of Architecture and Urban Planning, Shandong Jianzhu University, Jinan, China

The digital economy (DE) is an essential transmitter of CO_2 within the economic system, significantly impacting carbon emissions and high-quality development. The Yellow River Basin (YRB) and the Yangtze River Economic Belt (YREB), China's two most important economic regions, are critical strategically for achieving the dual carbon target. This paper uses panel data from the YRB and YREB in China from 2011 to 2021 and adopts fixed and mediating effects to explore the internal impact mechanisms and spatial heterogeneity of the DE and carbon emission intensity (CEI) in the context of new quality productivity (NQP). The research results indicate that (1) the DE can significantly reduce CEI. A 1% increase in the DE reduces CEI by 0.1536% in the YRB and 0.0643% in the YREB, respectively. (2) The DE can affect CEI in the YRB and the YREB through mechanisms such as the economic development level, industrial structure advancement and rationalization, energy structure, and level of technological progress, with industrial structure advancement having the highest impact. (3) The YRB has a lower level of DE development and a higher overall CEI than the YREB. (4) A 1% increase in the DE leads to regional CEI variations: in the upstream of the YRB and YREB, CEI decreases by 0.1424% and 0.1956%, respectively, whereas in the midstream of the YRB, it decreases by 0.1298%, and in the downstream of the YREB, it increases by 0.0707%. We propose accelerating the development of the DE and constructing a green and modernized industrial system to achieve carbon reduction and emission mitigation goals.

KEYWORDS

digital economy, carbon emissions, comparative study, yellow river basin, yangtze river economic belt

1 Introduction

Excessive CO_2 emissions profoundly affect climate change (Jiang et al., 2024), directly and indirectly influencing achieving the Sustainable Development Goals (Hermwille et al., 2023). China is the world's largest economy and, thus, is crucial in mitigating global climate change (Liu L. et al., 2023; Yu et al., 2023). At the 75th session of the United Nations General Assembly in 2020, the Chinese government proposed ambitious targets to achieve peak carbon emissions by 2030 and carbon neutrality by 2060, demonstrating its commitment to addressing climate change (Li L. et al., 2022; Gao et al., 2017). China has proposed reducing carbon emissions through a dual drive of digital empowerment and green development under NQP framework to achieve sustainable development.

The DE is a significant transmitter of CO_2 in the economic system (Wang et al., 2023). According to the "Global Digital Economy White Paper (2024)" released by the China Academy of Information and Communications Technology, the estimated added value of China's core DE industries in 2023 exceeded 12 trillion yuan, accounting for approximately 10% of GDP. The DE's rapid development has improved resource utilization efficiency and reduced pollution and carbon emissions. The prospects of this fast-growing sector for lowering carbon emissions are promising. Therefore, an in-depth study of the relationship between DE and carbon emissions is important theoretically for achieving the dual carbon goals. Current research on the impact of the DE on carbon emissions mainly focuses on four aspects: first, the analysis of how the DE affects carbon emissions, such as industrial structure (Lin and Zhou, 2021), technological progress (Yi et al., 2022), energy intensity (Zhang W. et al., 2022), and human capital (Wang et al., 2022b); second, the analysis of regional heterogeneity of this impact is often conducted at different scales, such as the provincial (Chen et al., 2023), the city (Cheng et al., 2023), and the county scales (Ma and Zhang, 2025); third, the impact of various aspects of DE development on carbon emissions involves perspectives of digital city construction (Yang et al., 2022), digital infrastructure development (Zhang et al., 2023), and digital taxation (Zeng and Yang, 2023); and fourth, the impact on different dimensions of carbon emissions, such as the effect of digital finance on carbon productivity (Sun et al., 2023) and the influence of digitalization and industrialization on total factor carbon emission performance (Ma R. et al., 2023). However, these studies typically employed singular and unsystematic indicators of the DE. Moreover, they focused on broad regions, lacking detailed investigations into specific areas and comparative analyses. The impact of the DE on carbon emissions requires further exploration, especially in the context of NQP. As China entered this higher-level form of productivity, there was an urgent need to break away from traditional economic development models and productivity paths, significantly enhancing total factor productivity and, thus, indirectly affecting carbon emissions. Therefore, in the era of NQP, it is important to explore the impact and improvement potential of traditional and NQP paths on carbon emissions under different structures according to the innovative forms of the volatile DE industry, to promote the high-quality green development of carbon emissions and the economy.

To further highlight the differences between the DE and carbon emissions under traditional and new-quality paths, this study compares the YRB and the YREB. The YRB is a crucial base for China's energy, chemical, and basic industries, traditionally supported by agriculture, energy, and heavy industry. In recent years, it has gradually shifted toward manufacturing and high-tech industries. The YREB represents half of the country's population and total economic output, with manufacturing, high-tech industries, and modern services serving as key pillars of the economy, possessing broad developmental depth. This research centers on single-region carbon emission evolution (Rong et al., 2023), carbon emission efficiency (Wang and Shao, 2024), CEI (Chen et al., 2022), and driving factors (Wang and Xue, 2023). Despite the research on the DE and carbon emissions in both the YRB and the YREB (Dong and Zhou, 2023; Xu and Ci, 2023), comparative research between these regions under traditional production modes and NQP is lacking. Especially in the context of NQP, developing DE in the YRB and the YREB will have different driving models owing to the regional heterogeneity of carbon emissions, leading to time lags and differences in mechanisms and spatial–temporal distributions. Therefore, studying the DE and carbon emissions in the YRB and the YREB in the context of NQP will help stakeholders and governments formulate differentiated regional development strategies, learning from one another, complementing one another's strengths, and promoting the high-quality development of the basin economy.

Based on the above, we use panel data from 58 prefecture-level cities in the YRB and 104 in the YREB from 2011 to 2021. We analyze the impact of the DE on CEI in the YRB and YREB by employing fixed and mediating effects, focusing on the intrinsic mechanisms and spatial heterogeneity between the two regions with NQP as a key driving force. This study makes the following marginal contributions: (1) It innovatively constructed an index system of the DE comprising five key dimensions: element configuration, elemental support, innovative performance, digital industrialization, and industry digitalization. This comprehensive framework enabled a scientific measurement of the DE's development, allowing policymakers and stakeholders to formulate precise development strategies, optimize resource allocation, and foster innovation-driven growth. (2) This study also compared the impact of the DE on CEI under NQP paradigm in the YRB and the YREB. This regional comparison provided valuable empirical insights and practical references for leveraging the DE to drive high-quality development. (3) By integrating Grossman's theory and the Environmental Kuznets Curve (EKC) hypothesis, the study innovatively explored how the DE empowered NQP to influence carbon emissions. This introduced a novel theoretical framework for relevant research and offered concrete policy pathways to help China achieve its 2030 carbon peak and 2060 carbon neutrality goals. (4) The study revealed the differentiated effects of the DE on CEI under spatial heterogeneity across river basins. The study incorporated economic development, development models, and technological foundations, conducting a detailed assessment of the impact of the DE on carbon emissions across the upper, middle, and lower reaches of the YRB and the YREB. These findings support local governments in formulating region-specific strategies for the DE and carbon reduction policies.

The rest of this paper is organized as follows: Section 3 presents the theoretical framework and research hypotheses. Section 4 outlines the methodology, variables, and data sources. Section 5 presents the empirical results. Sections 6, 7 provide the comparative mechanism analysis and heterogeneity analysis. Finally, Section 8 concludes and provides policy implications. Section 9 discusses the study's limitations and suggests future research. The technology roadmap is shown in Figure 1.

2 Theoretical analysis and research hypotheses

2.1 Direct effects of DE on carbon emissions

The direct impact of the DE on carbon emissions manifested primarily in three ways. First, as a foundational element of the DE,

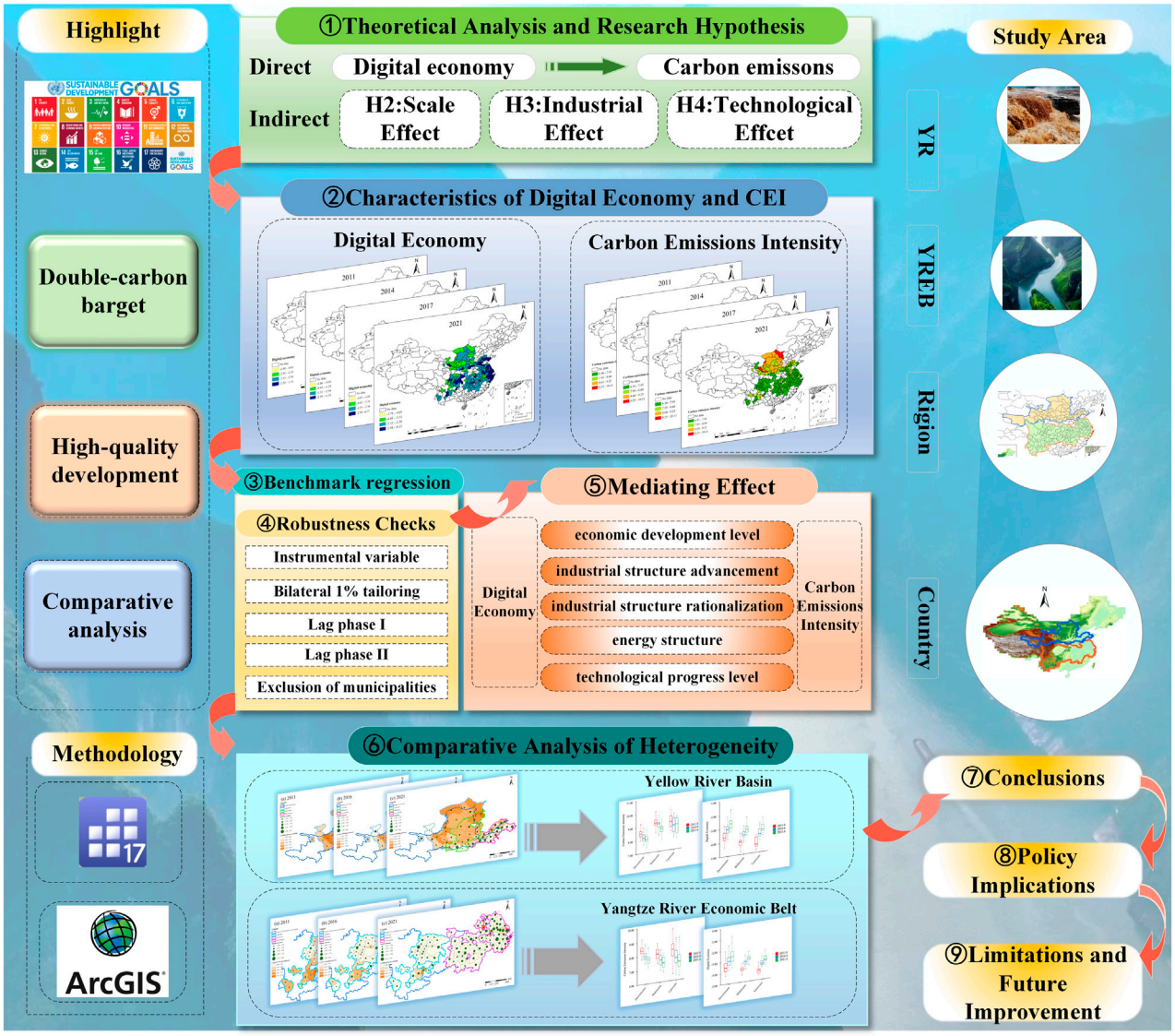


FIGURE 1
Technology roadmap.

digital infrastructure reduced the resource dependency of economic development, significantly lowering CEI (Zhang et al., 2023). Second, the DE broke through the regional barriers of data elements and digital technologies through spatial spillover effects. Enhancing resource mobility altered the geographical distribution of data elements, optimized resource allocation, positively influenced the energy-saving and emission-reduction efficiency of neighboring regions, and reduced CEI (Wu et al., 2021; Yi et al., 2022; Bai et al., 2023; Cheng et al., 2023). Third, developing digital technologies increases the input levels of data elements and the output levels of digital innovation, advancing the flow of innovative resources and the integration of industrial resources, enhancing economic operational efficiency and innovation capacity, reducing energy consumption, and decreasing carbon emissions (Zhang W. et al., 2022; Lin and Zhou, 2021). Based on these studies, we proposed Hypothesis 1.

Hypothesis 1. Developing DE positively contributes to decreasing carbon emissions.

2.2 Mediating effects on DE and carbon emissions relationship

NQP refers to the productivity of leading technological innovation and achieving critical disruptive technological breakthroughs. It comprises three key dimensions: the "new economy," "new industrial forms" and "new technologies" (Zhou and Xu, 2023). As an inherently green type of productivity, it facilitates carbon reduction and emission mitigation. A significant driving force for developing NQP (Zhang and Wen, 2024), the DE directly influenced carbon reduction and sustainable development by transforming NQP and production relations. Grossman and

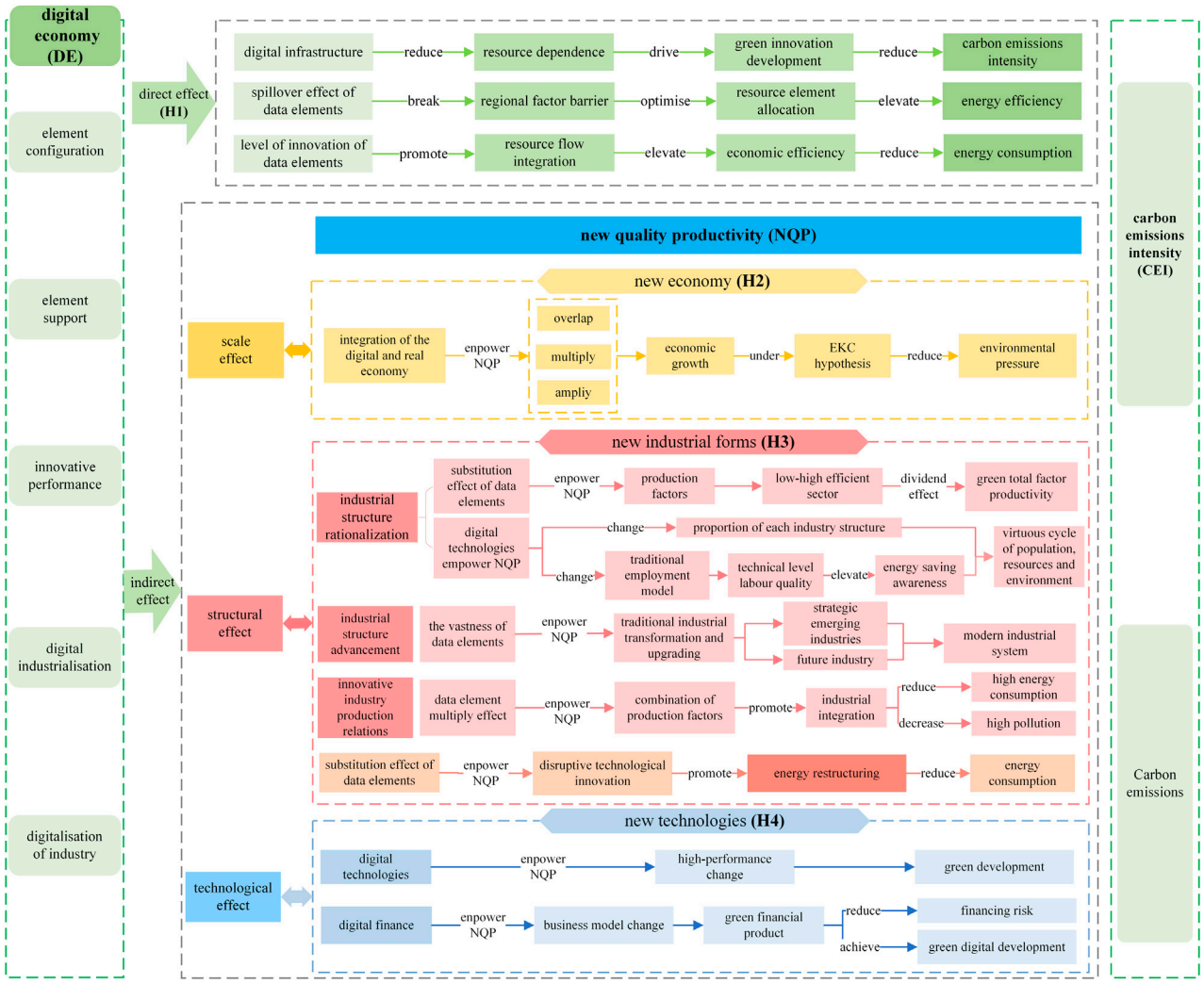


FIGURE 2
The mechanism between DE, NQP and CEI.

Krueger (Grossman and Krueger, 1991) utilized the LMDI index to decompose the driving factors of carbon emissions into scale, structural, and technological effects, which logically correspond to the three dimensions of NQP, i.e., new economy, industrial forms, and technologies. By integrating Grossman's theory with the theoretical framework of NQP, we innovatively propose a new theoretical pathway among the DE, NQP, and carbon emissions, as indicated in Figure 2.

2.2.1 Scale effect

The EKC hypothesis posits an inverted U-shaped relationship between economic growth and environmental pressure, as shown in Figure 3. Environmental pressure increased with economic growth in the initial stages of economic development. However, once economic growth reached a certain level, policymakers and stakeholders recognized that excessive economic development was causing significant ecological damage. Consequently, there was a need to emphasize the dual benefits of environmental and economic sustainability. After implementing protective measures, environmental pressure decreased and the ecological environment improved (Grossman and Krueger, 1995; Yang et al., 2022; Chang et al., 2023).

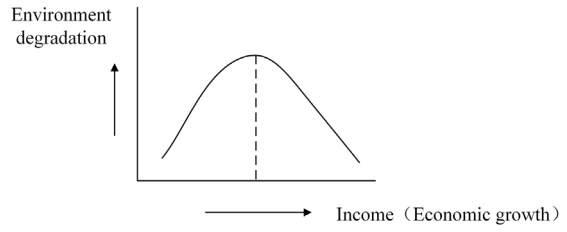


FIGURE 3
The Environmental Kuznets Curve (EKC) hypothesis.

The DE, driven by technological and institutional innovations, represents a new economic type integrated with the real economy. Through aspects such as digital infrastructure, industrial

digitization, and digital industrialization, it empowered the development of NQP in the "new economy," with amplifying, overlapping, and multiplicative effects on economic growth (Chang et al., 2023; Zhang and Wen, 2024). According to the EKC hypothesis, carbon emissions are anticipated to decline once the DE attains a certain level of development and the government begins to prioritize the dual benefits of environmental and economic sustainability. Based on these studies, we proposed Hypothesis 2.

Hypothesis 2. The DE empowers the "new economy" dimension of NQP, reducing carbon emissions through the scale effect.

2.2.2 Structural effect

Industry is a fundamental driver of NQP and a key dimension of "new industrial forms," with structural shifts significantly impacting carbon emissions (Cheng et al., 2023). Within the framework of NQP, the DE influenced carbon emissions through the industrial structure in three main ways. First, the DE empowered NQP by rationalizing industrial structures. On the one hand, data elements exerted a substitution effect, shifting traditional production factors such as land and labor toward innovative configurations involving data and technology (Lu et al., 2024). This shift permitted effective production factors to flow from low-to high-efficiency sectors, leveraging the dividend effect of the DE to upgrade industrial structures, improving green total factor productivity (Lee et al., 2023). On the other hand, carbon emissions were reduced by expanding the economic scale of the tertiary industry and decreasing the proportion of coal consumption (Wang et al., 2022a). Additionally, as the DE transformed traditional industrial structures, employment models in traditional enterprises were also altered, imposing higher requirements on the workforce's technical skills and professional qualities. The increase in high-tech personnel has increased energy-saving awareness (Edziah et al., 2021), influencing carbon emissions and achieving a virtuous cycle among the population, resources, and the environment. Second, the DE empowered NQP by advancing industrial upgrading. Leveraging its extensive factor coverage, the DE transformed traditional industries toward strategic emerging industries such as high-end equipment manufacturing and low-altitude economy industries. This transition contributed to establishing a modern industrial system, achieving new industrialization, and promoting carbon reduction. Third, the DE fostered the innovative upgrading of industrial production relations in NQP, transitioning industries from segregation to integration. The data elements' multiplier effect advanced their integration with various production factors, fostering innovative upgrades in industrial production relations, reducing high energy consumption and pollution, and lowering CEI (Wang et al., 2022a; Wang et al., 2022c; Chang et al., 2023; Lan et al., 2023; Lee et al., 2023).

Meanwhile, energy served as a critical pillar for developing NQP and represented an essential dimension of transforming and upgrading "new industrial forms." Its structural changes profoundly affected carbon emissions. The DE, by leveraging the substitution effect of data elements, empowered NQP, driving disruptive technological innovations that facilitated the transition of the energy structure toward low-carbon and cleaner alternatives. This transformation enhanced energy conservation and emission reduction efficiency (Wu et al., 2021; Zhang W. et al., 2022), effectively lowering CEI and contributing to developing a green industrial system. Based on these studies, we proposed Hypothesis 3.

Hypothesis 3. The DE empowers the "new industrial forms" of NQP, reducing carbon emissions through structural effects.

2.2.3 Technological effect

The rapid advancement of information technology reduced the costs of information transmission and processing (Moore, 1965; Brenner, 1997), contributing to the swift growth of the DE. "New technologies," a critical dimension of NQP development, involved significant disruptive technological breakthroughs (Zhou and Xu, 2023). The DE, through digital technologies and data elements, empowered NQP to achieve these breakthroughs by enhancing the efficiency and quality of economic operations, optimizing the coordination between economic development and ecological protection, and influencing carbon emissions through three pathways. First, the DE boosted innovation momentum in NQP through digital technologies, achieved high-efficiency innovation transformations, reduced transaction costs for factors such as land and capital, improved transaction efficiency, and lowered energy consumption in economic operations, all of which advanced green, low-carbon development (Lin and Zhou, 2021). Second, the DE utilized the data substitution effect of data elements to empower NQP and drove disruptive technological innovations to improve traditional production methods, facilitated energy structure adjustments, reduced energy consumption, and lowered CEI (Huang, 2023; Zeng and Yang, 2023; Yu et al., 2024). Third, developing digital finance propelled NQP through disruptive technological innovations, spurred the market to create new production methods and business models, generated more green financial products, reduced investment and financing risks, and achieved green digital development, thus affecting carbon emissions (Liu Q. et al., 2023). Based on these findings, we proposed Hypothesis 4.

Hypothesis 4. The DE empowers NQP's "new technologies," reducing carbon emissions through technological effects.

3 Methodology, variables, and data

3.1 Study area

The major cities within the YRB and the YREB are selected as the study area, as shown in Figure 4. Situated between longitudes 96°–119° E and latitudes 32°–42° N, the YRB covers approximately 795,000 km^2, including 42,000 km^2 of inland river areas. The YRB's population constitutes nearly 30% of the national total, with economic development primarily concentrated in the middle and lower reaches—especially in Shandong and Henan provinces, which account for the majority share. The YREB encompasses about 2,052,000 km^2, representing 21.4% of China's total area. As of 2021, its population and regional GDP constitutes 42.9% and 46.4% of the national totals, respectively. Due to their unique geographical areas, populations, and economies, changes in carbon emissions within the YRB and the YREB profoundly affect the entire country. Moreover, under the pathway of NQP, these

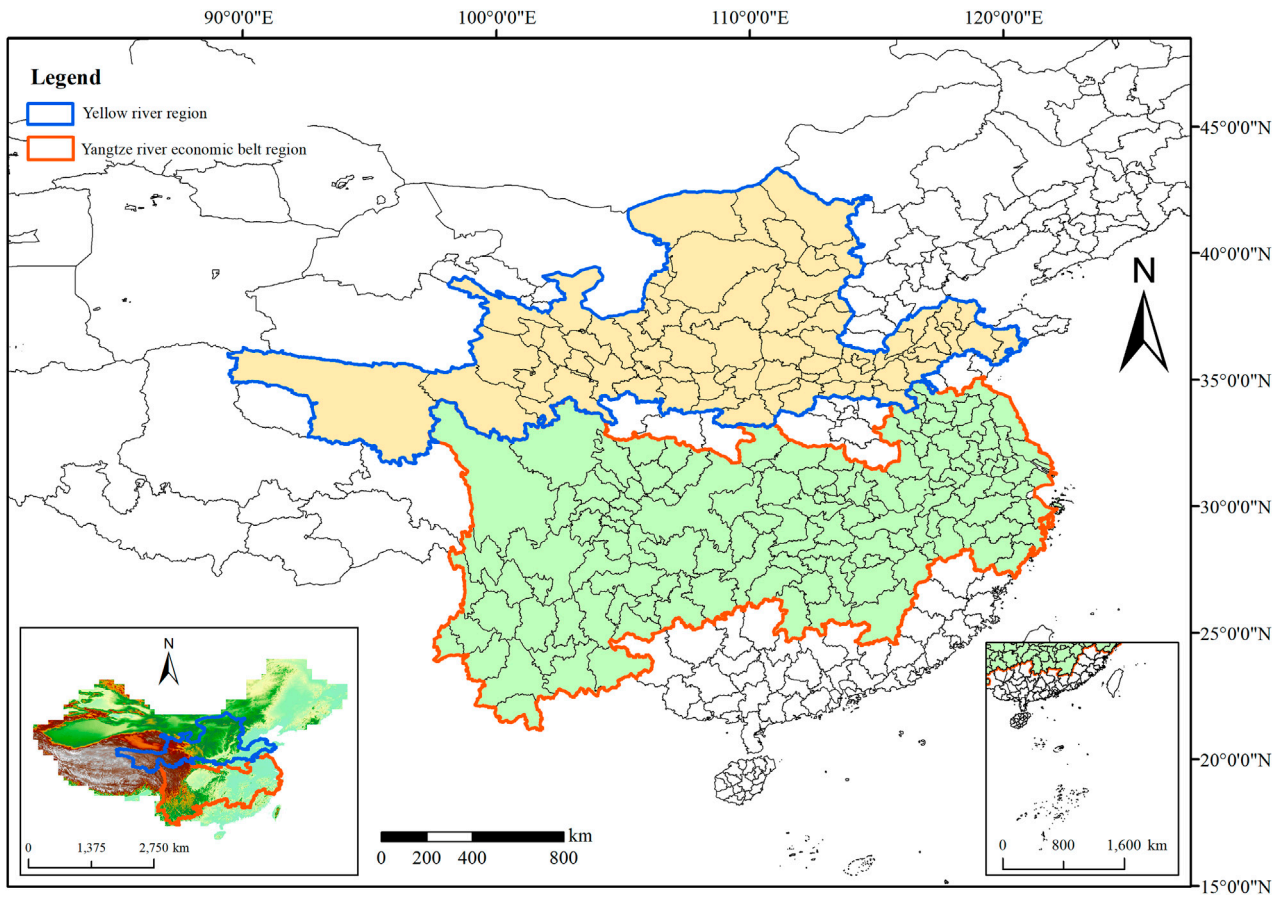


FIGURE 4
The geographical locations of the YRB and YREB within the study area.

regions exert different impacts. The study area's boundaries are delineated by the administrative divisions of prefecture-level cities. Additionally, based on geographical characteristics, the upper, middle, and lower reaches are distinguished to facilitate a comparative analysis of the DE and carbon emissions among the basins.

3.2 Methodology

3.2.1 Entropy method

The entropy method was utilized to reflect the utility value of the information entropy of indicators (Chen et al., 2023). We objectively evaluated the comprehensive DE indicator system, constructed using 18 subindicators and referencing previous studies (Lin and Zhou, 2021; Yang et al., 2022), by applying the entropy method for measuring the DE development levels of 58 prefecture-level cities in the YRB and 104 prefecture-level cities in the YREB from 2011 to 2021.

Initially, the data were standardized as follows:

$$Y_{ij} = \frac{X_{ij} - min(X_{1j}, \cdots, X_{nj})}{max(X_{1j}, \cdots, X_{nj}) - min(X_{1j}, \cdots, X_{nj})} \quad (1)$$

where X_{ij} denotes the value of subindex j for city i, and Y_{ij} denotes the standardized value of subindex j for city i in Equation 1. Therefore, the ratio of the subindex j value for city i to the standardized values of subindex j across all cities is given by Equation 2:

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}} \quad (2)$$

Furthermore, the entropy value of the subindex was calculated as shown in Equation 3:

$$e_j = -k\sum_{i=1}^{m} P_{ij} \ln (P_{ij}) \quad (3)$$

Where $k > 0$ and $e_j \geq 0$. Subsequently, the redundancy of the information entropy was calculated as $d_j = 1 - e_j$. Therefore, the weight of subindex j was evaluated using Equation 4:

$$w_j = \frac{d_j}{\sum_{i=1}^{n} d_j} \quad (4)$$

Finally, the weights of the comprehensive DE indicator system were calculated by Equation 5 (as shown in Table 1):

$$DE_i = \sum_{i=1}^{n} w_j P_{ij} \ (j = 1, 2, 3....) \quad (5)$$

TABLE 1 Index system of DE.

Target level	First-level Index	Second-level Index	Indicators	Unit	References	Weight
DE	Element configuration	Hardware	Number of internet access ports	10,000	Zhang et al. (2022a)	0.0375
			Number of domain names	10,000	Wang et al. (2022b), Wang et al. (2022a)	0.0698
		Software	Number of mobile phone users	10,000	Sun et al. (2024)	0.0320
			number of broadband Internet subscribers	10,000	Yi et al. (2022)	0.0408
	Element support	Policy element	DE policy level	%	Tang et al. (2021)	0.0218
		Market element	Marketability index	%	Zhang et al. (2022a)	0.0032
		Labour element	Number of people employed in the information transmission, computer services and software industry	10,000		0.1160
	Innovative performance	Level of innovation input	Science and technology expenditure/local public general budget expenditure ratio	%	Wang et al. (2022a)	0.0319
			Number of patent applications in the DE	piece	Ma and Zhu (2022)	0.1168
		Level of innovative output	Number of patent authorizations in the DE	piece	—	0.1124
			Number of startups	per 100 people	—	0.0193
	Digital industrialisation	Communications industry	Total telecommunications business/GDP ratio	%	Ma and Zhu (2022)	0.0270
		Electronic information manufacturing industry	Number of AI enterprises	unit	Wang and Li (2023)	0.1330
		Software and information technology services industry	Percentage of people employed in software and information technology services	%		0.0225
	Digitalisation of industry	Digitalisation of agriculture	Total agricultural machinery power	10,000 kW	—	0.0208
		Digitalisation of transport and logistics	Total postal business volume	10,000	Wang et al. (2022b), Zhang et al. (2022a)	0.1057
			Number of employees in transport, storage, postal and telecommunications	10,000		0.0801
		Financial digitalisation	Digital financial inclusion index	—	Sun et al. (2024)	0.0092

3.2.2 Benchmark model

The IPAT model (Ehrlich and Holdren, 1971) is typically used to identify the causes of environmental problems resulting from human activities. The model is as follows:

$$I = P \times A \times T \tag{6}$$

where I denotes the environmental impact, P denotes the population factors, A denotes affluence, and T denotes the broad level of technology. However, the model is limited for being singly linearized. Consequently, Dietz and Rosa (Dietz and Rosa, 1994) introduced a stochastic error term, extending the IPAT model to the STIRPAT model, allowing a more extensive analysis of the impact of social and ecological factors on the environment. The specific model is as follows:

$$I = \varphi_0 \times P^{\varphi_1} \times A^{\varphi_2} \times T^{\varphi_3} \times \varphi_4 \tag{7}$$

Referring to the study (Li et al., 2023), to reduce the abnormal volatility of the data, Equation 8 was logarithmically transformed as follows:

$$\ln I = \ln \varphi_0 \times \varphi_1 \ln P \times \varphi_2 \ln A \times \varphi_3 \ln T \times \varphi_4 \tag{8}$$

where φ_0 denotes the constant term; and φ_1, φ_2, and φ_3 denote the coefficients of the variables, i.e., the indicator terms. φ_4 is the stochastic error term.

The impact of the DE on carbon emissions in the YRB and the YREB were compared by constructing the following research model and Hypothesis 1 following previous theoretical models (Wang et al., 2022b; Wang et al., 2022a; Chen et al., 2023; Ma R. et al., 2023; Wang and Li, 2023):

$$\begin{aligned} \ln CEI_{it} = {} & \alpha_0 + \alpha_1 \ln DE_{it} + \alpha_2 \times \ln Erg_{it} + +\alpha_3 \times \ln Ppd_{it} \\ & + \alpha_4 \times \ln Lopn_{it} + \alpha_5 \times \ln Lgs_{it} + \alpha_6 \times \ln Urb_{it} \\ & + \alpha_7 \times \ln Lug_{it} + \varepsilon_{it} \end{aligned} \tag{9}$$

where CEI_{it} denotes CEI of city i in year t, corresponding to I in Equation 8, i.e., environmental impact, serving as the dependent variable; DE_{it} denotes the DE of city i in year t, corresponding to A in Equation 8, i.e., affluence, serving as the independent variable. Additionally, several control variables were included: Ppd_{it} denotes the population density of city i in year t, corresponding to P in Equation 8, i.e., population factors, measured in people per square kilometer; Erg_{it} denotes the environmental regulation of city i in year t, corresponding to T in Equation 8, i.e., the broad level of technology, measured in percentage (%); $LOPN_{it}$ denotes the level of openness of city i in year t, measured in percentage (%); Lgs_{it} denotes the level of government support of city i in year t, measured in percentage (%); Urb_{it} denotes the urbanization level of city i in year t, measured in percentage (%); and Lug_{it} denotes the urban greening level of city i in year t, measured in square meters (m^2). α_0 is the constant term, i denotes the time fixed effects, t denotes the individual fixed effects, and ε_{it} denotes the stochastic error term. All variables were logarithmically transformed. Moreover, based on Hypothesis 1, it was assumed that $\alpha_1 > 0$.

Furthermore, this study investigated the intrinsic mechanisms between DE and carbon emissions by referencing relevant theoretical models (Baron and Kenny, 1986; MacKinnon et al., 2000). The following mechanism model was constructed by introducing the interaction term between the mediating variable and DE_{it} of the explanatory variable in the benchmark regression:

$$\boldsymbol{ln\, MEA_{it} = \partial_0 + \partial_1 ln\, DE_{it} + \sum_{k=2}^{7} \partial_k\, ln\, C_{it} + \varepsilon_{it}} \tag{10}$$

$$\boldsymbol{ln\, CEI_{it} = \delta_0 + \delta_1 ln\, DE_{it} + \delta_2 ln\, DE_{it} \times ln\, MEA_{it} + \delta_3 ln\, MEA_{it}}$$

$$\boldsymbol{+\sum_{k=4}^{9} \delta_k\, ln\, C_{it} + \varepsilon_{it}} \tag{11}$$

The mediating variable, MEA_{it} encompassed economic development level ($pgdp_{it}$), industrial structure (Isr_{it}; Isa_{it}), energy structure (Ens_{it}), and level of technological progress (Ltp_{it}). The control variables in Equation 9 were represented by $ln\, C_{it}$. The estimated coefficients are denoted as $\partial_0 \cdots \partial_7$ and $\delta_1 \cdots \delta_9$, where ∂_0 and δ_0 represent the constant terms. If the estimated coefficients ∂_1 and δ_2 were both significant, the mediating variable mediates between the DE and carbon emissions, verifying Hypothesis 2–4.

3.3 Variable selection and data

3.3.1 Dependent variable

CEI was selected as the dependent variable from an equity perspective, quantifying the relative variation in carbon emissions within the study region. Referring to the study by (Wang and Li, 2023), CEI was estimated as carbon emissions per unit of GDP, specifically the ratio of carbon emissions to GDP for each prefecture-level city.

3.3.2 Independent variable

The DE development index was chosen as the explanatory variable. The World Economic Forum and the G20 defined the DE as "a broad range of economic activities that use digital information and knowledge as key production factors, modern information networks as important activity spaces, and information and communication technologies to drive productivity growth." Based on theoretical foundations and practical needs, we created an index that accurately reflects the essence of the DE and its impact on economic development. Simultaneously, we thoroughly considered the multidimensional characteristics of DE development to construct a hierarchical index system with strong practical applicability and scalability. Additionally, considering data reliability, availability, consistency, and temporal continuity, we developed a DE index system comprising five key dimensions: element configuration, elemental support, innovative performance, digital industrialization, and digitalization of industry. This framework effectively captures the DE's growth potential and development trends. We selected 18 specific indicators to measure the DE development index and utilized the entropy weight method to synthesize the indicator system. The specific weights and indicator systems are presented in Table 1.

3.3.3 Mediating variables

The mediating variables were primarily based on Grossman's "scale–structure–technology" principle and the hypothesis analysis presented in Section 2.2. The mediating variables are as follows.

(1) Economic development level, Pgdp: This variable originates from the scale effect and the "new economy" dimension. The DE empowered NQP through digital technologies, advancing the deep integration of the digital and real economies, facilitating economic growth (Liu et al., 2024) and subsequently affecting CEI. Per capita GDP directly reflected the level of economic development (Chang et al., 2023). Therefore, we used each prefecture-level city's *per capita* GDP to represent the economic development level.

(2) Industrial structure: This variable is derived from the structure effect and the "new industrial forms" dimension. The industrial structure is formed through market selection under constraints such as technology and the stage of economic development. Its optimization and upgrading can generate a "structural dividend" effect, thereby reducing carbon emissions (Wang et al., 2019). The DE promoted the collaborative development of digital and industrial digitalization through digital technologies, facilitating the innovative flow of production factors (Zhou and Xu, 2023). This empowered NQP to build a modern industrial system. Additionally, data factors had a multiplier effect, allowing for the combination of production factors and fostering industrial integration, which influences the industrial structure and indirectly impacts carbon emissions. Consequently, we selected the advancement and rationalization of the industrial structure to illustrate its mechanistic effects.

Industrial structure advancement, Isa. Data factors possessed broad applicability, empowering NQP to drive the transformation and upgrading of traditional industries to advanced industries. This expanded the proportion of emerging and future industries, achieving green and low-carbon development and reducing

carbon emissions. Referring to the relevant study by (Fu, 2010), we employed the cosine method to measure the advancement of the industrial structure. First, spatial vectors were constructed based on the proportions of the primary, secondary, and tertiary industries' added value to GDP, forming a three-dimensional industrial structure spatial vector $P_0 = (P_{10}, P_{20}, P_{30})$, where P_0 represents the proportion of the ath industry to GDP ($a = 1$、2、3). Subsequently, the angles r_b ($b = 1, 2, 3$) between P_0 and the vectors representing different industries, $P_1 = (1, 0, 0)$, $P_2 = (0, 1, 0)$, and $P_3 = (0, 0, 1)$, were calculated as follows:

$$r_b = arccos\left[\frac{\sum_{a=1}^{3}(P_{ab} \times P_{a0})}{\sqrt{\sum_{a=1}^{3}(P_{ab}^2) \times \sum_{a=1}^{3}(P_{a0}^2)}}\right]$$
$$b = 1、2、3$$

Subsequently, the industrial advancement value G was calculated using the following formula:

$$G = \sum_{a=1}^{3}\sum_{b=1}^{a} r_b$$

where P_{ab} represents the coordinate values of the three-dimensional vectors P_1, P_2, and P_3.

Industrial structure rationalization, Isr. Rationalizing the industrial structure refers to the quality of industry aggregation, reflecting the degree of input–output coupling and the effective utilization of resources between industries. Typically, structural deviation is used to measure this; however, this approach neglects the importance of each industry to the economy; additionally, using absolute values complicates the analysis. Therefore, to assist in the study, Gan et al. (Gan et al., 2011) introduced the Theil index (Theil, 1967), which measures the structural deviations in output and employment among different industries and assesses the superior characteristics of each industry in the economy (Yuan and Zhu, 2018). Thus, the Theil index was utilized to calculate the rationalization of the industrial structure using the following formula:

$$R_{i,t} = \sum_{n=1}^{3} Y_{i,n,t}\, ln\left(\frac{Y_{i,n,t}}{L_{i,n,t}}\right)$$

Where $i = 1, 2, 3$ represents the primary, secondary, and tertiary industries, respectively. $Y_{i,n,t}$ denotes the proportion of the ith industry's gross regional product in region n during period t, and $L_{i,n,t}$ indicates the proportion of employment in the ith industry relative to total employment in region n during period t. When the economy is in equilibrium, $R_{i,t} = 0$. The smaller the value of $R_{i,t}$, the more rational the industrial structure.

(3) Energy structure, Ens: The energy structure was derived from the technology effect and the "new technologies" dimension. Digital technologies fostered NQP development by driving the extensive integration of data elements and disruptive technological innovations. This transformation increased the share of green and low-carbon industries while reducing reliance on high-energy-consuming and high-carbon-emitting sectors, such as coal, accelerating the energy structure's transition and upgrading (Yang et al., 2022; Huang et al., 2023). It also enhanced carbon emission efficiency, reduced energy consumption, and promoted a sustainable balance among the population, resources, and the environment. Because coal has remained China's primary energy source, its consumption trends effectively reflected adjustments in the energy structure. Therefore, the energy structure was measured by the proportion of coal consumption to total energy consumption in each prefecture-level city (Wang et al., 2022a). Owing to data acquisition considerations, total energy consumption was calculated using natural gas, liquefied petroleum gas, social electricity consumption, and urban heating (including steam heating and thermal power plant heating), converted using standard coal coefficients. The specific formula is as follows:

$$\text{Coal Proportion} = (\text{Urban Heating} + \text{Total Social Electricity Consumption})/(\text{Natural Gas} + \text{Liquefied Petroleum Gas} + \text{Urban Heating} + \text{Total Social Electricity Consumption}).$$

(4) Level of technological progress, Ltp: The level of technological progress was derived from the technology effect and the "new technologies" dimension. Digital technologies empowered NQP, fostering disruptive technological innovations and achieving efficient transformations that enhanced total factor productivity and improved carbon emission efficiency. Additionally, digital finance drove the innovation of production relations, altered production and consumption patterns, enhanced the technological momentum of industrial forms toward decarbonization, fostered green and low-carbon financial products, reduced carbon emissions, and realized green digital development (Liu Q. et al., 2023; Sun et al., 2023; Tian et al., 2024). Consequently, technological progress was proxied by the number of green patents issued (Bottazzi and Peri, 2007; Wang et al., 2022a).

3.3.4 Control variables

To mitigate the omitted variable bias, control variables potentially influencing the CEP were selected based on the aforementioned STIRPAT theoretical framework, in conjunction with frequency statistical methods and data availability. These variables were subsequently log-transformed:

(1) Level of Opening (Lopn): The level of openness affects energy-saving and emission reduction efficiency through internet-related channels (Wu et al., 2021). Therefore, the opening level was measured by the total import and export trade ratio to GDP (Han et al., 2021). (2) Broad Level of Science and Technology (Erg): Government environmental regulations influence the development of environmental technologies, under which the internet economy impacts total factor carbon emissions to some extent (Kou and Xu, 2022). Consequently, the broad level of science and technology was quantified using the ratio of environmental keywords to the total number of words in government work reports. (3) Population Density (Pop): An increase in population typically stimulates greater consumption demand, leading to elevated industrial and household carbon emissions (Hua et al., 2018). Thus, population density was assessed by the ratio of the permanent population to the administrative area of each region. (4) Level of Government Support: Low government subsidies, such as fossil fuel subsidies,

TABLE 2 Descriptive statistics of the variables (after logarithm).

Variable	Obs		Mean		Std. Dev		Min		Max	
Region	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB
lnCEI	638	1144	8.658	7.795	0.574	0.582	7.432	6.09	10.111	10.096
lnDE	638	1144	−3.426	−3.179	0.597	0.693	−4.804	−4.727	−1.181	−0.324
lnErg	638	1144	−1.082	−1.163	0.395	0.433	−2.817	−3.525	0.004	0.214
lnPop	638	1144	5.5	6.028	1.017	0.624	0.683	4.026	7.273	7.747
lnLopn	638	1144	1.393	2.161	1.489	1.399	−2.697	−2.404	4.404	5.449
lnLgs	638	1144	2.954	2.892	0.496	0.377	1.905	2.028	4.517	4.212
lnUrb	638	1144	3.977	3.979	0.264	0.249	2.973	2.899	4.563	4.495
lnLug	638	1144	2.632	2.555	0.37	0.291	1.112	0.307	3.722	3.445

negatively impact economic growth and carbon dioxide emissions (Lin and Ouyang, 2014). Therefore, government support was measured by the ratio of local general public budget expenditure to GDP (Ma R. et al., 2023). (5) Level of Urbanization (URB): The level of urbanization affects the energy efficiency (Han et al., 2021) and consumption per unit of time and space, thereby influencing carbon emissions per unit of space. Accordingly, urbanization was measured by the proportion of the urban population to the total population (Wang et al., 2022a). (6) Level of Urban Greening: Larger *per capita* areas of urban parks corresponded to greater fixed amounts of carbon dioxide, t positively contributing to local carbon emission control (Chen and Lee, 2020; Wang and Li, 2023). Consequently, the *per capita* park green space area (Zhang W. et al., 2022; Wang and Li, 2023) determined the level of urban greening.

3.4 Data resources and statistical description

Per data availability and watershed administrative divisions, we used panel data from 58 cities in the YRB and 104 cities in the YREB from 2011 to 2021 to explore the impact of the DE on carbon emissions. CEO was the dependent variable, with the total carbon emission data obtained from the Emissions Database for Global Atmospheric Research. The independent variable, DE, was measured using data sourced from the National Bureau of Statistics, the China Statistical Yearbook, the China Urban Statistical Yearbook, provincial statistical yearbooks, the China Academy of Information and Communications Technology, CINIC, the CNRDS database, local business registration records, prefecture-level city statistical bulletins, local government websites, the China Regional Statistical Yearbook, and the Peking University Inclusive Finance Index. Mediating variables included industrial structure, with data derived from provincial statistical yearbooks; energy structure, with data obtained from the China Urban Statistical Yearbook, provincial statistical yearbooks, and prefecture-level city bulletins; and green technology level, with data sourced from CNRDS. The control variables were measured using data from the National Bureau of Statistics, the China Urban Statistical Yearbook, provincial statistical bulletins, government work reports, and the China Urban Construction Yearbook. Additionally, we applied interpolation to supplement and estimate missing data for certain years in the indicators. Table 2 presents the descriptive statistics of the variables, all of which were log-transformed.

4 Results and discussion

4.1 DE and CEI characteristics

Figure 5 illustrates the DE and CEI spatial distribution across the YRB and the YREB. The DE's overall development gradually increased, which was mainly attributed to the promotional effects of national policies such as "Broadband China" "Internet +" and "Big Data Action" (State Council, 2013; State Council, 2015b; State Council, 2015a). The overall development of the DE in the YREB was significantly higher than in the YRB. One possible reason could be that Hangzhou, as the birthplace of China's DE, generated economic agglomeration effects due to its geographic closeness to neighboring cities, thus promoting economic growth along the Yangtze River.

Overall CEI also gradually decreased, which was closely related to policy guidance emphasizing climate change and constructing an environmentally friendly society, as outlined in the "China's Policies and Actions for Addressing Climate Change (2011)" white paper and the 12th Five-Year Plan, 13th Five-Year Plan, and 14th Five-Year Plans (Ministry of Ecological Environment, 2011; State Council, 2011; State Council, 2016a; State Council, 2021b). As economic development levels improve, cleaning technology is constantly innovated, reducing the potential energy intensity (Li et al., 2017)and reducing CEI. However, CEI in the YRB continued to be significantly higher than in the YREB, possibly because the YRB served as an essential energy and chemical industrial base in China, characterized by higher industrial pollutant emissions and low-quality, inefficient industrial development with insufficient high-quality progress.

4.2 Benchmark regression results

In the benchmark model, we primarily assessed the direct impact of DE on CEI. In the third row of columns (1) and (2) of

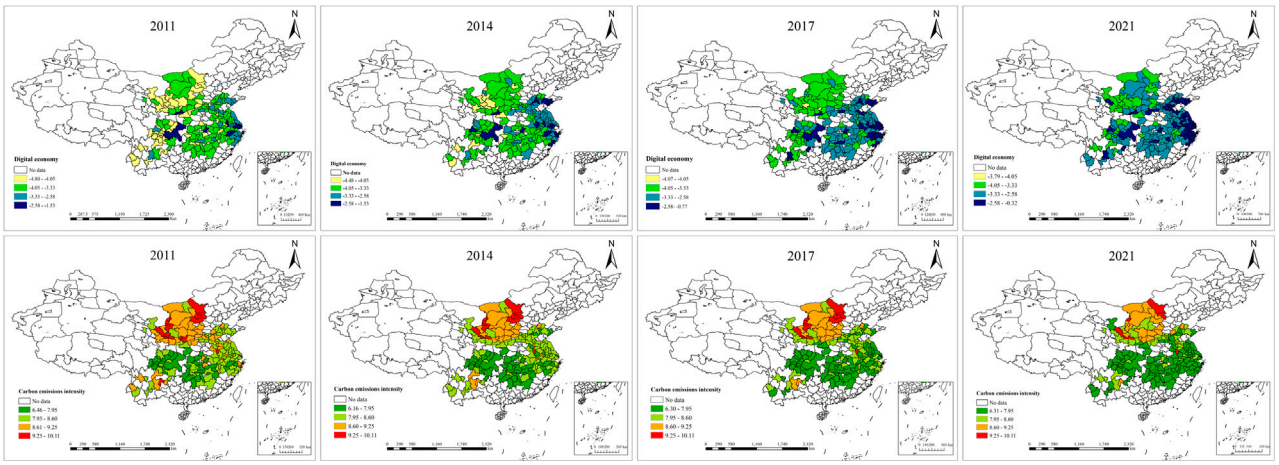


FIGURE 5
Spatial distribution of CEI and DE in the YRB and YREB for selected years.

TABLE 3 Estimation results for the benchmark model.

Denpendent variable: lnCEI	(1)	(2)
Region	YRB	YREB
lnDE	−0.1536***	−0.0643***
	(0.0333)	(0.0236)
lnErg	0.0152*	−0.0034
	(0.0089)	(0.0059)
lnPop	−0.0271*	−0.0427
	(0.0149)	(0.0443)
lnLopn	0.0216**	0.0324***
	(0.0097)	(0.0067)
lnLgs	0.7096***	0.3385***
	(0.0416)	(0.0386)
lnUrb	−0.0432	−0.1122***
	(0.0584)	(0.0411)
lnLug	−0.0461***	−0.0137
	(0.0173)	(0.0154)
Constant	6.4638***	7.2768***
	(0.2752)	(0.3874)
Observations	638	1,144
R^2	0.9813	0.9882

Notes: (1) Robust standard errors in parentheses. (2) ***p < 0.01, **p < 0.05, *p < 0.

Table 3, the coefficients of lnDE for both the YRB and the YREB were negative at the 1% significance level, indicating that DE development significantly reduced CEI. Specifically, each 1% increase in the level of DE development reduced CEI by 0.1536% in the YRB and 0.0643% in the YREB. First, under the "Broadband China" strategy, improving and developing digital infrastructure reduced CEI (Yang et al., 2022). Second, due to the efficient, integrated, and green nature of digital technologies such as big data and artificial intelligence, they enhanced energy efficiency and advanced green technological innovation, reducing carbon emissions (Wang and Li, 2023). Additionally, digital innovation facilitated digital industrialization and industrial digitization, positioning data as a new factor of production, transforming the structure of production factors, and reducing carbon emissions generated in social production. Therefore, Hypothesis 1 was confirmed.

The first column of Table 3 reflected the key influencing factors of CEI: (1) lnErg positively impacted CEI in the YRB, indicating that the strengthening of environmental regulations in this region increased CEI. (2) lnPop hurt CEI in the YRB. Population agglomeration reduced the scope of pollution diffusion, improving the quality and efficiency of carbon emission purification within the region, thereby reducing CEI. (3) lnLopn positively impacted CEI in both the YRB and the YREB at the 10% significance level, indicating that greater openness was associated with higher CEI. (4) lnLgs positively impacted CEI in the YRB and the YREB at the 1% significance level. Higher government subsidies, such as fossil fuel subsidies, led to greater consumption, which was not conducive to reducing CEI. (5) lnUrb significantly negatively impacted CEI in the YREB. The high level of urbanization in this region promoted improvements in energy efficiency, thereby reducing CEI. (6) lnLug significantly negatively impacted CEI in the YRB. A larger *per capita* area of urban parks indicated a more substantial carbon sink capacity, which was beneficial for controlling carbon emissions.

4.3 Robustness checks

We employed the instrumental variable method (IV) to address the endogeneity issues arising from omitted variables, reverse causality, or measurement errors. Lagged variables are generally not influenced by the current regression error term, satisfying the exogeneity condition, and are highly correlated with the level of DE

TABLE 4 Estimation results for the robustness checks.

Denpendent variable: lnCEI										
	IV		Bilateral 1% tailoring		Lag phase I		Lag phase II		Exclusion of municipalities	
Region	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnDE	−0.5620***	−0.4593***	−0.1410***	−0.0764***	−0.1425***	−0.0556***	−0.1681***	−0.0487*	−0.1536***	−0.0702***
	(0.0502)	(0.0488)	(0.0343)	(0.0229)	(0.0373)	(0.0236)	(0.0427)	(0.0274)	(0.0333)	(0.0239)
Underidentification test test	123.03	215.996								
P-value	0.000	0.000								
C-D Wald F statistic	1565.812	4095.684								
Kleibergen-Paap rk Wald F statistic	434.516	2164.975								
Constant	3.2815***	3.3000***	6.5612***	7.2256***	7.6621***	7.7654***	8.4120***	7.6421***	6.4638***	7.2323***
	(0.7232)	(1.1185)	(0.2863)	(0.4073)	(0.3178)	(0.4783)	(0.3915)	(0.5962)	(0.2752)	(0.3884)
Observations	580	1,040	638	1,144	580	1,040	522	936	638	1,122
R^2	0.4501	0.1470	0.9806	0.9875	0.9858	0.9860	0.9734	0.9843	0.9813	0.9882

Notes: (1) Robust standard errors in parentheses. (2) ***p < 0.01, **p < 0.05, *p < 0.

development. The lagged value of the DE level, calculated through the principal component analysis, was used as an instrument for the DE level. First, the Hausman test was used to verify endogeneity; it found that the p-values for both the YRB and the YREB were below 0.1, confirming the endogeneity between the DE and CEI. Next, we conducted underidentification and weak instrumental variable tests on the selected instrumental variable. As shown in Table 4, the p-values for the underidentification test in columns (1) and (2) for the YRB and the YREB were both below 0.1, passing the underidentification test (Kleibergen and Paap, 2006). Additionally, the C-D Wald F statistic and the Kleibergen–Paap r Wald F statistic in both regions exceeded the critical values, confirming the weak instrumental variable test. These tests confirmed the robustness of the instrumental variable results.

Moreover, we conducted three types of robustness checks (as shown in Table 4). (1) Bilateral 1% tailoring: all variables were subjected to 1% two-sided winsorization prior to regression analysis to mitigate the potential adverse effects of outliers on the baseline regression results. The estimation results are presented in columns (3) and (4) of Table 4, where the coefficients of lnDE in both the YRB and the YREB remained significantly negative, ratifying the robustness of the baseline regression. (2) Lag Effects: Following the relevant study by (Chen et al., 2023), all variables except CEI were lagged by one to two periods to examine the impact of lagged effects on the relationship between the DE and CEI. The regression results with a one-period lag are shown in columns (5) and (6) of Table 4, where the coefficients of the DE in the YRB and the YREB were 0.1425 and 0.0556, respectively, both significant at the 1% level. The regression results with a two-period lag are displayed in columns (7) and (8) of Table 4, with coefficients of 0.1681 and 0.0487 for the DE in the YRB and the YREB, respectively (significant at the 1% and 10% levels, respectively). These findings confirmed the robustness of the baseline regression. (3) Excluding Municipalities: Considering that the economic scale of municipalities far exceeds that of other cities, and following (Wang and Li, 2023), we excluded Shanghai and Chongqing from the sample for the regression analysis. The estimated results in column (10) of Table 4 indicate that developing DE inhibited CEI within the YREB, satisfying the 1% significance level. These tests confirmed the robustness of the baseline regression results.

5 Mediating effect on the nexus of theDE and CEI

Based on Hypotheses two to four and Grossman's theory, we proposed that within the YRB and the YREB, the DE influenced CEI through scale, structural, and technological effects through four potential pathways—economic development, industrial structure, energy structure, and technological progress—as shown in Table 5 and Figure 6.

5.1 Mediating effect analysis of scale effect

With reference to studies by (Jaccard, 2001; Brambor et al., 2006), we examined the mediating role of the level of economic development in DE's effect on CEI using an interaction term between the levels of DE development and economic development in Equations 10, 11. Considering the multicollinearity and model fit, we centered all interaction terms in this paper. The results in columns (1) to (4) of Table 5 indicate that c.lnDE#c.lnpgdp significantly impacted CEI

TABLE 5 Results of the mediating effects.

Variables	lnPgdp				lnIsa				lnIsr				lnEns				lnLtp			
	lnDE		lnCEI		lnDE		lnCEI		lnDE		lnCEI		lnDE		lnCEI		lnDE		lnCEI	
	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB	YRB	YREB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
lnDE			0.6328***	0.2188***			1.1689***	0.9619***			−0.1613***	−0.0677***			−0.6356***	0.5891***			−0.1833***	−0.0549**
			(0.1075)	(0.0812)			(0.3161)	(0.1804)			(0.0373)	(0.0238)			(0.2043)	(0.1022)			(0.0324)	(0.0228)
lnpgdp	0.3700***	0.3111***	−0.9683***	−0.5040***																
	(0.0107)	(0.0088)	(0.0519)	(0.0510)																
c.lnDE#c.lnpgdp	0.0906***	0.0839***	−0.0703***	−0.0257***																
	(0.0013)	(0.0008)	(0.0103)	(0.0074)																
lnIsa					1.9033***	1.7552***	−3.1611***	−2.2898***												
					(0.0376)	(0.0388)	(0.6557)	(0.3324)												
c.lnDE#c.lnIsa					0.5237***	0.5077***	−0.6967***	−0.5336***												
					(0.0046)	(0.0035)	(0.1710)	(0.0943)												
lnIsr									−0.3595***	−0.0076	−0.1965***	0.0047								
									(0.0987)	(0.0351)	(0.0322)	(0.0118)								
c.lnDE#c.lnIsr									−0.1043***	−0.0119	−0.0711***	−0.0018								
									(0.0276)	(0.0106)	(0.0103)	(0.0054)								
lnEns													0.8428***	0.7966***	0.3980**	−0.4995***				
													(0.0130)	(0.0136)	(0.1774)	(0.0857)				
c.lnDE#c.lnEns													0.2267***	0.2216***	0.1115**	−0.1492***				
													(0.0019)	(0.0016)	(0.0464)	(0.0240)				
lnLtp																	−0.1547***	0.0983***	−0.0739***	−0.0491***
																	(0.0527)	(0.0285)	(0.0258)	(0.0149)
c.lnDE#c.lnLtp																	−0.0382***	0.0157**	−0.0224***	−0.0111***
																	(0.0127)	(0.0071)	(0.0059)	(0.0035)
Constant	−4.4180***	−3.7295***	17.7459***	13.2562***	−3.8192***	−3.1872***	12.6651***	11.5199***	−3.9900***	−3.3246***	7.0216***	7.4722***	−3.5661***	−3.1550***	4.8121***	9.1316***	−2.5898***	−3.5234***	6.5049***	7.2404***
	(0.1179)	(0.1546)	(0.6236)	(0.6960)	(0.0807)	(0.0983)	(1.3163)	(0.6560)	(0.3859)	(0.3963)	(0.2802)	(0.3742)	(0.0816)	(0.0981)	(0.7807)	(0.4584)	(0.3131)	(0.4647)	(0.2786)	(0.3857)
Observations	638	1,144	638	1,144	638	1,144	638	1,144	638	1,144	638	1,144	638	1,144	638	1,144	638	1,144	638	1,144
R^2	0.9989	0.9990	0.9946	0.9918	0.9997	0.9997	0.9822	0.9889	0.9740	0.9830	0.9812	0.9882	0.9993	0.9993	0.9815	0.9887	0.9687	0.9801	0.9821	0.9884

Notes: (1) Robust standard errors in parentheses. (2) ***p < 0.01, **p < 0.05, *p < 0.

10.3389/fenvs.2025.1543211

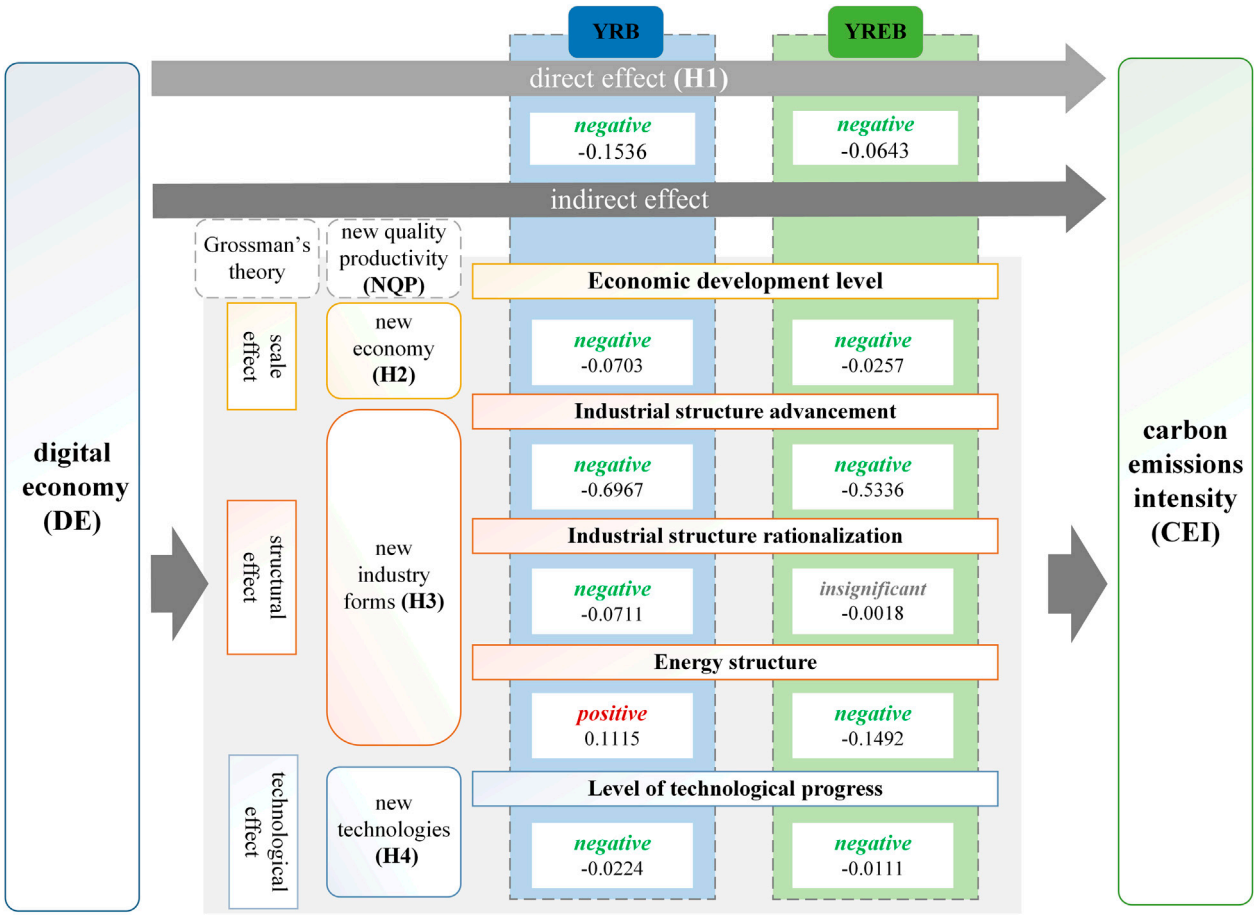


FIGURE 6
Results of the mediating effects in the YRB and YREB.

negatively in both the YRB and the YREB. Specifically, a 1% increase in the DE reduced CEI of the YRB and YREB by 0.0703% and 0.0257%, respectively, through improved economic development, with more pronounced results observed in the YRB. This finding aligns with the EKC hypothesis. In the YRB, where the development of DE remains relatively underdeveloped and the traditional economy continues to be dominant, digitalization has a more pronounced enabling effect. A leading driver of economic growth, developing DE enhances resource allocation efficiency and induces structural shifts in production methods and development models. This transformation accelerates the transition toward a technology-intensive and low-carbon economy, potentially facilitating an earlier arrival at the EKC turning point, resulting in a more rapid decline in CEI and fostering sustainable low-carbon development. Therefore, Hypothesis 2 was confirmed.

5.2 Mediating effect analysis of the structural effect

5.2.1 Mediating effect analysis of the Industrial Structure

To comprehensively assess the mediating effect of the industrial structure, it was divided into two pathways: industrial structure advancement and rationalization. The interaction term between the DE development level and industrial structure advancement was used in the estimation Equations 10, 11 to test the mediating role of industrial structure advancement in the impact of the DE on CEI. Columns (5)–(8) of Table 5 indicate that c.lnDE#c.lnIsa negatively affected CEI in both the YRB and the YREB, with industrial structure advancement the most influential pathway among all effects. Specifically, a 1% increase in the DE reduced CEI by 0.6967% and 0.5336% in the YRB and the YREB, respectively, through industrial structure advancement. The study by (Wang et al., 2022c) found that, overall, production structure factors related to the digital industry significantly negatively affected China's embodied carbon emissions from 2002 to 2017, which aligned with our conclusion on the development of industries toward digitalization and advancement. Both regions thoroughly understood supply-side structural reform, continuously advancing the transformation of industrial structures toward technology-, knowledge-, and innovation-intensive types, such as vigorously advancing strategic emerging industries driven by cutting-edge technologies. However, the pace of traditional industry renewal and development in the YRB was slower than in the YREB. Therefore, utilizing the DE to support the digital and green transformation of traditional industries in the YRB had a more substantial dividend effect, advancing industry reductions of CEI.

The interaction term between the level of DE development and industrial structure rationalization was then used in the estimation Equations 10, 11 to test the mediating role of industrial rationalization. Columns (9)–(12) of Table 5 indicate that c.lnDE#c.lnIsr negatively affected CEI in the YRB. Specifically, a 1% increase in the DE reduced CEI by 0.0711% through industrial rationalization. However, this effect was not significant in the YREB, possibly because the YREB's industrial rationalization level from 2011 to 2017 was above the national average; thus, the impact of using the DE to achieve green innovation through industrial rationalization was less significant than in the YRB. According to the analysis in Section 4.1, the overall development level of the DE in the YREB was higher than in the YRB. Consequently, we concluded that significant reforms in industrial rationalization were likely less effective at reducing CEI than other beneficial adjustments, such as advancements in the industrial structure.

5.2.2 Mediating effect analysis of the energy structure

The interaction term between the DE development level and the energy structure was utilized in estimation Equations 10, 11 to examine the mediating role of the energy structure. Columns (13)–(16) of Table 5 present the regression results, indicating that c.lnDE#c.lnEns was significant in both YREB and YRB, but had opposite effects. Specifically, a 1% increase in DE results in a 0.1492% reduction in CEI in YREB, while it increases CEI by 0.1115% in YRB. A possible explanation is that, in recent years, the YREB has leveraged digital technologies like artificial intelligence to improve the intelligence and greening of the energy system, continually increasing the proportion of clean and green energy consumption and thus reducing CEI. In contrast, the situation in YRB can be explained from two perspectives. First, the YRB still heavily depends on traditional energy sources like coal, and the lack of diversification in its energy structure has led to increased CEI as DE grows. Second, the energy transition in YRB has been relatively slow; the development of DE has not effectively harnessed the substitution effect of clean and green energy, resulting in concentrated energy consumption and a further rise in CEI. Therefore, while fostering the development of DE, it is essential to accelerate the green transformation of the energy structure to achieve coordinated and sustainable economic and environmental development.

In summary, although some effects were not significant, this did not hinder verifying the structural effect's mediating role in the impact of the DE on CEI. Therefore, Hypothesis 3 was confirmed.

5.3 Mediating effect analysis of the technological effect

Finally, columns (17)–(20) of Table 5 estimated Equations 10, 11 to test the mediating role of the interaction term between the level of DE development and technological progress on CEI. Columns (19) and (20) showed that c.lnDE#c.lnLtp was significant, with a 1% increase in the DE reducing CEI by 0.0224% and 0.0111% in the YRB and the YREB, respectively, by improving the green technology level. The effect was more significant in the YRB. The findings in the YREB aligned with those of Ma L. et al. (2023). Wang et al. (2022d) demonstrated that ICT agglomeration reduced carbon emissions through technological innovation, particularly when the level of technological innovation surpassed a critical threshold. Our conclusions were logically consistent with this finding. A possible explanation for the more significant mediating effects in the YRB was that the region's industrial structure was mainly composed of energy and chemical industries, and the level of carbon emission reduction through digital technology was not as advanced as in the YREB. Digital technology plays a crucial role in promoting carbon emission reduction. For the YRB, strengthening the depth of technological development might have amplified the impact of the technical effect. Therefore, Hypothesis 4 was confirmed.

6 Heterogeneity comparative analysis

To explore the differences in the impact of the DE on CEI in the YRB and the YREB, we divided each basin into upper, middle, and lower reaches according to their geographic characteristics. We conducted separate estimations for subsamples in each region (Table 6).

First, in the sample regression for each basin, the DE coefficients in the upper and middle reaches of the YRB were significantly negative. Specifically, a 1% increase in DE resulted in a decrease of CEI by 0.1424% and 0.1298% in the upper and middle reaches, respectively. However, developing DE in the downstream reaches did not meaningfully contribute to reducing CEI. From a spatial perspective, the average level of DE development in the upper and middle reaches was lower than in the downstream regions, while the average CEI was higher. Possible explanations for the results in the upper and middle reaches of the YRB include the following: first, the provinces in these areas had relatively low levels of economic development and engaged in significant industrial transfers from downstream areas, leading to a high proportion of traditional and heavy industries. Simultaneously, the development of digital technologies and supporting infrastructure was insufficient, hindering both digitalization and industrial digitalization. The industrial structure was inefficient, with significant carbon emissions. Second, energy consumption intensity was high, while clean energy technologies, such as carbon capture and storage, trailed behind those in downstream regions. An explanation for the situation in the downstream region may lie in its industrial structure, primarily composed of light industries and agriculture, resulting in low CEI and limiting the potential of DE to reduce emissions. Investing in digital technologies, optimizing industrial structures, enhancing regulations on traditional energy sectors, supporting renewable energy industries like wind and solar, and advancing green innovation technologies could help to lower carbon emissions in the upper and middle reaches (Tian et al., 2024).

In the sample regression of the YREB, the DE coefficients were −0.1956 ($P < 0.01$) and 0.0707 ($P < 0.05$) in the upper and lower reaches, respectively. This indicated that a 1% increase in DE decreased CEI by 0.1956% in the upstream regions, with an increase of 0.0707% in the downstream regions. However, in the middle reaches, developing DE did not significantly reduce CEI. Figure 7(3), 7 (4) display the quantile distributions of DE and CEI in the YREB, showing that the average levels in some downstream regions were higher than in the upper and middle reaches. These results can be interpreted as follows: in the downstream provinces of the YREB, digital information technology was highly advanced, with industries

TABLE 6 Estimation results for different watersheds.

Dependent variable: lnCEI						
Watershed	Upstream		Midstream		Downstream	
Region	YRB	YREB	YRB	YREB	YRB	YREB
lnDE	−0.1424**	−0.1956***	−0.1298**	−0.0435	−0.0637	0.0707**
	(0.0593)	(0.0513)	(0.0588)	(0.0308)	(0.0486)	(0.0357)
lnErg	−0.0306	−0.0072	−0.0083	−0.0101	0.0124	0.0116
	(0.0212)	(0.0127)	(0.0184)	(0.0087)	(0.0133)	(0.0084)
lnPop	0.0202	−0.2197***	−0.2146***	−0.0175	0.0272	0.2564**
	(0.0216)	(0.0612)	(0.0703)	(0.0594)	(0.0294)	(0.1019)
lnLopn	0.0176	0.0391***	0.0394***	0.0162**	0.0178	0.0948***
	(0.0108)	(0.0138)	(0.0126)	(0.0082)	(0.0325)	(0.0131)
lnLgs	0.6142***	0.4201***	0.6529***	0.2741***	0.7477***	0.2921***
	(0.0553)	(0.0955)	(0.0716)	(0.0518)	(0.0587)	(0.0290)
lnUrb	−0.6173***	−0.1181	0.1312**	−0.2299***	0.2211***	−0.0297
	(0.1135)	(0.0828)	(0.0558)	(0.0658)	(0.0792)	(0.0698)
lnLug	−0.0248	0.0039	−0.0257	−0.0136	−0.1283***	−0.1364***
	(0.0219)	(0.0231)	(0.0294)	(0.0219)	(0.0355)	(0.0391)
Constant	8.7325***	7.3469***	7.1303***	7.7092***	5.3428***	6.0406***
	(0.5341)	(0.6415)	(0.5285)	(0.4821)	(0.4133)	(0.7444)
Observations	209	330	198	418	231	396
R^2	0.9810	0.9883	0.9867	0.9876	0.9689	0.9909

Notes: (1) Robust standard errors in parentheses. (2) ***p < 0.01, **p < 0.05, *p < 0.

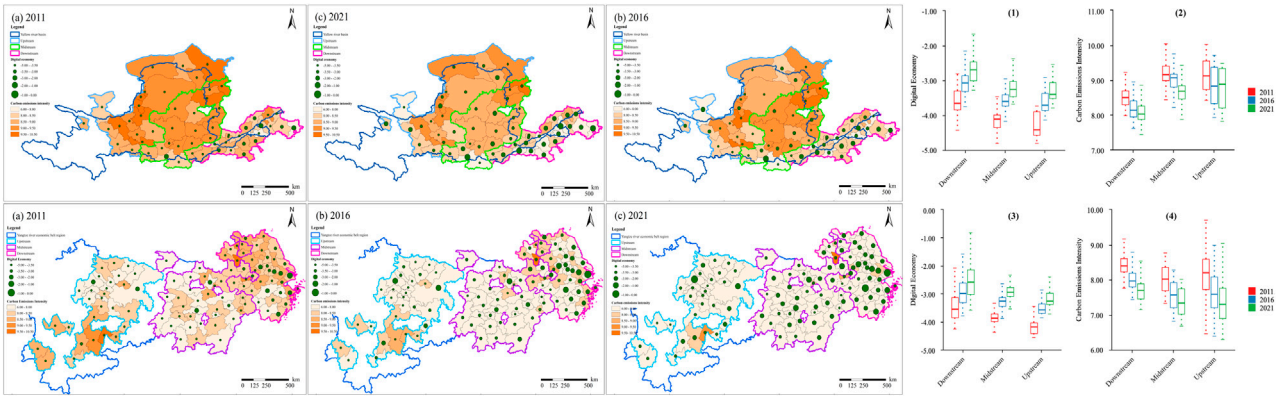


FIGURE 7
Spatial and data distribution of CEI and DE in different watersheds of the YRB and YREB in selected years.

such as telecommunications and electronic information expanding significantly and actively integrating digital elements, leading to an advanced DE. However, this development was accompanied by substantial electricity consumption, with coal-fired power generation and other high-carbon energy sources comprising a large share of the energy supply, resulting in higher CEI. Additionally, the rapid growth of the logistics industry driven by online shopping led to hidden carbon emissions, particularly in manufacturing and transportation. In the upstream regions of the YREB, near Sichuan and Yunnan, natural advantages such as high altitudes and abundant water flow gradients supported the development of clean hydropower, providing energy for DE. At the same time, these regions were dominated by traditional heavy industries and resource-based sectors, contributing to higher CEI. DE

development in these areas assisted in transforming industry, improving energy utilization efficiency, and reducing carbon emissions. In the middle reaches of the YREB, the lack of significant effects on CEI reduction could be explained by the predominance of traditional high-carbon industries and delays in digital transformation, which limited the carbon reduction potential of DE. The insufficient development of digital infrastructure and inadequate application of clean and green technologies further constrained progress toward green transformation and low-carbon development.

Then, in the overall sample regression of the YRB and the YREB, the effect of DE development on reducing CEI was significant in the upstream regions of both basins, with a more pronounced effect in the YREB than in the YRB. In the middle reaches, the effect was significant in the YRB, while the downstream effects were not significant in either basin. A possible explanation for this was that the YREB's upstream area has steep terrain, and hydropower development has taken place. At the same time, the upstream area contains many metal industries, and using hydropower-driven electricity helped convert the development momentum, reduce environmental pollution, achieve digital and green development, and lower CEI. This also reflected the differences between the basins.

In 2016, China introduced the "Internet Plus" initiative, marking a critical turning point in accelerating its DE. Following the 2015 Paris Agreement, China reinforced its low-carbon policies 2016, shaping the carbon emissions trajectory. Additionally, the release of the Yangtze River Economic Belt Development Plan Outline (State Council, 2016b) the same year advanced the region's transition toward high-quality development. Therefore, we selected 2016 as the dividing point, as it was a pivotal year, to provide a more explicit analysis of the development differences in DE and CEI between the YRB and the YREB, as shown in Figure 7. The results indicated that, across the upper, middle, and lower reaches, with few exceptions, the overall level of DE development in the YRB was below that in the YREB, while CEI remained generally higher. A possible explanation was that, since the reform and opening-up, China's economic center has gradually shifted southward, driving th growth of emerging technology enterprises, such as Huawei and Tencent, in southern provinces, which spurred forward industrial transformation, andupgrades in surrounding areas, advancing green development (Li J. et al., 2022; Wang et al., 2022b).

7 Conclusions and policy implications

7.1 Conclusions

Considering the potential relationship between the DE and CEI in the YRB and the YREB, we employed fixed effects and mechanism effects to conduct a thorough study of the impact of the DE on CEI in the context of NQP in the YRB and the YREB from 2011 to 2021. Furthermore, we explored the intrinsic mechanisms and spatial variability of the DE's influence on CEI and investigated how to achieve green, high-quality development. The study reached the following conclusions: (1) Between 2011 and 2021, the DE played a positive role in reducing CEI in both the YRB and the YREB, with a more pronounced impact observed in the YRB; (2) The DE in the YRB and the YREB affects CEI through scale, structural, and technological effects, aligning with the concepts of the new economy, new industrial forms, and innovations in technology under the theory of NQP. The economic development level, the advancement of the industrial structure, the optimization of the industrial framework, the energy structure, and the level of technological progress varied across the regions. Additionally, digital industrialization and the advancement of green technology highlighted vital developmental pathways through which the DE influences CEI; (3) Overall, from 2011 to 2021, the levels of the DE in both the YRB and the YREB consistently improved, while CEI steadily decreased. However, the overall development level of the DE in the YRB was lower than that of the YREB, and its CEI was higher than that of the YREB; (4) The results of the heterogeneity analysis indicated that the impact of the DE on CEI in the YRB was such that the effect in the upstream region was greater than in the middle reaches, with no significant effect observed downstream. In contrast, in the YREB the upstream effect was greater than the downstream effect, with no notable effect in the middle reaches.

7.2 Policy implications

Achieving national climate goals and the corresponding costs depend entirely on regional actions within the country (Yu et al., 2023). Therefore, based on the research analysis, we proposed several policy implications.

First, cities in the YRB and YREB should emphasize the role of the DE in reducing CEI. The YRB should focus on leveraging the DE to mitigate CEI in the upper and middle reaches, promote the creation of a digital twin of the Yellow River, enhance monitoring and sensing capabilities, improve ecological monitoring, and increase efficiency in addressing carbon emission issues. The YREB should highlight the positive impact of the DE on reducing CEI in both upstream and downstream regions, develop green logistics, strengthen supply chain resilience, and promote smart logistics and low-carbon transportation technologies to minimize carbon emissions in the transportation sector. Additionally, cities in both the YRB and YREB should further enhance digital infrastructure, increase financial investments, and fully utilize technologies such as cloud computing and big data to advance the digital transformation of traditional industries, empowering low-carbon and green development by constructing the DE.

Second, cities in the YRB and the YREB should optimize their economic structures and facilitate the deep integration of industrial upgrades and digitalization, systematically establishing a green and low-carbon modern industrial system. The Yellow River Basin Ecological Protection and High-Quality Development Strategy (State Council, 2021a) provides essential guidance for balancing the region's economic growth with ecological sustainability. In light of the research findings, cities in the YRB should consider the following: (1) developing strategic emerging industries that integrate production, supply, and demand through innovative resource aggregation, promoting green, low-carbon, and digital development to achieve new scale effects through the integration of digital and physical economies; (2) leveraging the role of industrial clusters and urban agglomerations as demonstration zones for industrial transfer, enhancing the capacity to undertake industrial transfers both domestically and internationally; (3) establishing comprehensive pilot zones for transforming old and new growth drivers, demonstration zones for industrial transformation and upgrading, and bases for new industrialization. For cities in the YREB: (1) further improve the

collaborative development of industrial, innovation, and supply chains, promoting their deep integration; (2) accelerate the high-end, intelligent, and green upgrading of traditional industries, enhancing the use of digital technologies to empower the digital transformation of competitive manufacturing sectors in the YREB, create competitive digital industry clusters, build an intelligent manufacturing system with low consumption and high output, and effectively implement the requirements for green and high-quality development.

Third, cities in the YRB and the YREB should accelerate developing green technologies and constructing innovation systems to provide vital technical support for building a high-quality development framework. NQP has inherent characteristics that protect the ecological environment and promote the harmonious coexistence of humans and nature, aligning with green and high-quality development. Therefore, the cities of YRB and YREB should thoroughly prioritize applying new technologies. Cities and governments in the YRB should remove barriers to the cross-regional and cross-basin flow of resource factors, promote the efficient flow of technology as a factor of production, improve resource utilization efficiency, and construct a pilot area for ecological protection and high-quality development. Cities and governments in the YREB should increase investment in the research and development of green technology, encourage industry-university-research cooperation, and use digital low-carbon technology to achieve the green transformation of enterprises. For example, big data technology can monitor emissions in real time and reduce pollution.

Moreover, cities within the YREB accelerated optimizing and adjusting their energy structures by promoting the integration of digital technologies with energy transformation. They advanced the deployment of smart grids and distributed energy systems to improve energy efficiency. Simultaneously, efforts were made to reduce reliance on high-carbon energy, expand the use of renewable sources, and work toward building a clean, low-carbon, safe, and efficient modern energy system.

8 Limitations and future improvements

Although this study addresses some research gaps in the relationship between DE and carbon emissions, it also has some limitations and research prospects.

First, geographic factors such as land use and urbanization influence the spatial heterogeneity of carbon emissions in the YRB and the YREB. The extent to which spatial and human factors shape the underlying mechanisms remain underexplored. Future studies could incorporate interdisciplinary driving factor detection to investigate further heterogeneity differences across the upper, middle, and lower reaches.

Second, the proportion of coal consumption in the total energy consumption was a proxy for the energy structure. However, due to data availability constraints, equally important factors such as renewable energy penetration and energy efficiency could not be quantitatively examined. Future research should consider these factors to provide a more comprehensive understanding of how energy structure adjustments influence carbon emissions.

Third, our study primarily focused on CEI while overlooking efficiencies due to data limitations. Future research could compare how the development of DE affects the carbon emission efficiency in the YRB and YREB. A multiperspective, multidimensional approach is needed to explore the strategic differences in how the DE contributes to regional carbon peaking and carbon neutrality.

Fourth, the applicability of this research's findings to other developing countries requires further validation. Economic structures, energy reliance, and policy frameworks likely shaped the effects of DE on carbon reduction. For instance, energy dependencies varied across major river basins, including India's Ganges and Brahmaputra, Brazil's São Francisco and Amazon, and Egypt's Nile. While India and Egypt depend on fossil fuels, Brazil primarily utilizes hydropower. Policy approaches also diverged, with India advancing its digital infrastructure via the India Stack and Brazil prioritizing renewable energy strategies (Empresa de Pesquisa Energética, 2020). Furthermore, data limitations restricted the external validity of the findings. Future research should incorporate multicountry panel data and microlevel analyses to facilitate comparative assessments and inform policy design for sustainable development in emerging economies.

Data availability statement

The datasets presented in this article are not readily available because Data will be made available on request. Requests to access the datasets should be directed to ZL, zhijianlin_work@163.com.

Author contributions

ZL: Conceptualization, Data curation, Formal Analysis, Methodology, Resources, Software, Validation, Visualization, Writing–original draft, Writing–review and editing. HL: Conceptualization, Supervision, Validation, Writing–review and editing. LS: Conceptualization, Resources, Validation, Writing–review and editing. DC: Funding acquisition, Project administration, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by the National Key Research and Development Program of China (grant number 2019YFD1100800) and the Shandong Provincial Social Science Planning Research Project (grant number 19CDNJ21).

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Bai, L., Guo, T., Xu, W., Liu, Y., Kuang, M., and Jiang, L. (2023). Effects of digital economy on carbon emission intensity in Chinese cities: a life-cycle theory and the application of non-linear spatial panel smooth transition threshold model. *Energy Policy* 183, 113792. doi:10.1016/j.enpol.2023.113792

Baron, R. M., and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *J. Pers. Soc. Psychol.* 51, 1173–1182. doi:10.1037/0022-3514.51.6.1173

Bottazzi, L., and Peri, G. (2007). The international dynamics of R&D and innovation in the long run and in the short run. *Econ. J.* 117, 486–511. doi:10.1111/j.1468-0297.2007.02027.x

Brambor, T., Clark, W. R., and Golder, M. (2006). Understanding interaction models: improving empirical analyses. *Polit. Anal.* 14, 63–82. doi:10.1093/pan/mpi014

Brenner, A. E. (1997). Moore's law. *Science* 275, 1401–1404. doi:10.1126/science.275.5306.1401c

Chang, H., Ding, Q., Zhao, W., Hou, N., and Liu, W. (2023). The digital economy, industrial structure upgrading, and carbon emission intensity — empirical evidence from China's provinces. *Energy Strategy Rev.* 50, 101218. doi:10.1016/j.esr.2023.101218

Chen, L., Lu, Y., Meng, Y., and Zhao, W. (2023). Research on the nexus between the digital economy and carbon emissions—evidence at China's province level. *J. Clean. Prod.* 413, 137484. doi:10.1016/j.jclepro.2023.137484

Chen, X., Meng, Q., Shi, J., Liu, Y., Sun, J., and Shen, W. (2022). Regional differences and convergence of carbon emissions intensity in cities along the Yellow River Basin in China. *Land* 11, 1042. doi:10.3390/land11071042

Chen, Y., and Lee, C.-C. (2020). Does technological innovation reduce CO2 emissions?Cross-country evidence. *J. Clean. Prod.* 263, 121550. doi:10.1016/j.jclepro.2020.121550

Cheng, Y., Zhang, Y., Wang, J., and Jiang, J. (2023). The impact of the urban digital economy on China's carbon intensity: spatial spillover and mediating effect. *Resour. Conserv. Recycl.* 189, 106762. doi:10.1016/j.resconrec.2022.106762

Dietz, T., and Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. *Hum. Ecol. Rev.* 1, 277–300.

Dong, R., and Zhou, X. (2023). Analysis of the nonlinear and spatial spillover effects of the digital economy on carbon emissions in the Yellow River Basin. *Sustainability* 15, 5253. doi:10.3390/su15065253

Edziah, B. K., Sun, H., Anyigbah, E., and Li, L. (2021). Human capital and energy efficiency: evidence from developing countries. *Am. J. Ind. Bus. Manag.* 11, 599–610. doi:10.4236/ajibm.2021.116038

Ehrlich, P. R., and Holdren, J. P. (1971). Impact of population growth. *Obstet. Gynecol. Surv.* 26, 769–771. doi:10.1097/00006254-197111000-00014

Empresa de Pesquisa Energética (2020). Plano Nacional de Energia - 2050. EPE, Brasília, Brazil. Available online at: https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/Plano-Nacional-de-Energia-2050 (Accessed December 10, 2024).

Fu, L. (2010). An empirical research on industry structure and economic growth. *Stat. Res.* 27, 79–81. doi:10.19343/j.cnki.11-1302/c.2010.08.011

Gan, C., Zheng, R., and Yu, D. (2011). An empirical study on the effects of industrial structure on economic growth and fluctuations in China. *China Econ. Res.* 46 (4–16), 31.

Gao, Y., Gao, X., and Zhang, X. (2017). The 2 °C global temperature target and the evolution of the long-term goal of addressing climate change—from the united Nations framework convention on climate change to the Paris agreement. *Engineering* 3, 272–278. doi:10.1016/J.ENG.2017.01.022

Grossman, G. M., and Krueger, A. B. (1991). *Environmental impacts of a north american free trade agreement*. Cambridge, Mass: National Bureau of Economic Research.

Grossman, G. M., and Krueger, A. B. (1995). Economic growth and the environment. *Q. J. Econ.* 110, 353–377. doi:10.2307/2118443

Han, J., Miao, J., Shi, Y., and Miao, Z. (2021). Can the semi-urbanization of population promote or inhibit the improvement of energy efficiency in China? *Sustain. Prod. Consum.* 26, 921–932. doi:10.1016/j.spc.2021.01.008

Hermwille, L., Dzebo, A., Iacobuță, G. I., and Obergassel, W. (2023). Global stocktake and the SDG midterm review as opportunities for integration. *Nat. Clim. Change* 13, 1002–1004. doi:10.1038/s41558-023-01813-2

Hua, Y., Xie, R., and Su, Y. (2018). Fiscal spending and air pollution in Chinese cities: identifying composition and technique effects. *China Econ. Rev.* 47, 156–169. doi:10.1016/j.chieco.2017.09.007

Huang, L., Zhang, H., Si, H., and Wang, H. (2023). Can the digital economy promote urban green economic efficiency? Evidence from 273 cities in China. *Ecol. Indic.* 155, 110977. doi:10.1016/j.ecolind.2023.110977

Huang, S. (2023). The comprehensive environmental efficiency analysis based on a new data envelopment analysis: the super slack based measure network three-stage data envelopment analysis approach. *J. Clean. Prod.* 400, 136689. doi:10.1016/j.jclepro.2023.136689

Jaccard, J. (2001). Interaction effects in logistic regression. SAGE Publications, Inc. doi:10.4135/9781412984515

Jiang, T., He, X., Su, B., Havea, P. H., Wei, K., Kundzewicz, Z. W., et al. (2024). COP 28: challenge of coping with climate crisis. *Innovation* 5, 100559. doi:10.1016/j.xinn.2023.100559

Kleibergen, F., and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *J. Econom.* 133, 97–126. doi:10.1016/j.jeconom.2005.02.011

Kou, J., and Xu, X. (2022). Does internet infrastructure improve or reduce carbon emission performance? -A dual perspective based on local government intervention and market segmentation. *J. Clean. Prod.* 379, 134789. doi:10.1016/j.jclepro.2022.134789

Lan, Y., Wei, J., and Duan, X. (2023). The effects of the digital economy on carbon emission: evidence from China. *Emerg. Mark. Finance Trade* 60, 1468–1483. doi:10.1080/1540496X.2023.2256942

Lee, C.-C., He, Z.-W., and Yuan, Z. (2023). A pathway to sustainable development: digitization and green productivity. *Energy Econ.* 124, 106772. doi:10.1016/j.eneco.2023.106772

Li, A., Zhang, A., Zhou, Y., and Yao, X. (2017). Decomposition analysis of factors affecting carbon dioxide emissions across provinces in China. *J. Clean. Prod.* 141, 1428–1444. doi:10.1016/j.jclepro.2016.09.206

Li, J., Chen, L., Chen, Y., and He, J. (2022a). Digital economy, technological innovation, and green economic efficiency—empirical evidence from 277 cities in China. *Manag. Decis. Econ.* 43, 616–629. doi:10.1002/mde.3406

Li, L., Zhang, Y., Zhou, T., Wang, K., Wang, C., Wang, T., et al. (2022b). Mitigation of China's carbon neutrality to global warming. *Nat. Commun.* 13, 5315. doi:10.1038/s41467-022-33047-9

Li, X., Li, S., Li, C., Shi, J., and Wang, N. (2023). The impact of high-quality development on ecological footprint: an empirical research based on STIRPAT model. *Ecol. Indic.* 154, 110881. doi:10.1016/j.ecolind.2023.110881

Lin, B., and Ouyang, X. (2014). A revisit of fossil-fuel subsidies in China: challenges and opportunities for energy price reform. *Energy Convers. Manag.* 82, 124–134. doi:10.1016/j.enconman.2014.03.030

Lin, B., and Zhou, Y. (2021). Does the Internet development affect energy and carbon emission performance? *Sustain. Prod. Consum.* 28, 1–10. doi:10.1016/j.spc.2021.03.016

Liu, L., Yang, Y., Liu, S., Gong, X., Zhao, Y., Jin, R., et al. (2023a). A comparative study of green growth efficiency in Yangtze River Economic Belt and Yellow River Basin between 2010 and 2020. *Ecol. Indic.* 150, 110214. doi:10.1016/j.ecolind.2023.110214

Liu, Q., Wu, W., Song, J., Dai, T., Jiang, H., Xu, J., et al. (2023b). How does digital finance accelerate low-carbon development: evidence from the Yellow River Basin, China. *J. Environ. Plan. Manag.* 68, 386–405. doi:10.1080/09640568.2023.2258449

Liu, Y., Zhang, X., and Shen, Y. (2024). Technology-driven carbon reduction: analyzing the impact of digital technology on China's carbon emission and its mechanism. *Technol. Forecast. Soc.* 200, 123124. doi:10.1016/j.techfore.2023.123124

Lu, J., Guo, Z., and Wang, Y. (2024). Levels of development of new quality productivity, regional differences and paths to enhancement. *J. Chongqing Univ.(Soc. Sci. Ed.)* 30, 1–17. doi:10.11835/j.issn.1008-5831.jg.2024.03.002

Ma, D., and Zhu, Q. (2022). Innovation in emerging economies: research on the digital economy driving high-quality green development. *J. Bus. Res.* 145, 801–813. doi:10.1016/j.jbusres.2022.03.041

Ma, L., Hong, Y., He, S., Luo, H., Liu, G., Zheng, J., et al. (2023a). The influence of digital economy development on urban carbon emission intensity in the Yangtze River Economic Belt: mediating mechanism and spatial effect. *Front. Ecol. Evol.* 11. doi:10.3389/fevo.2023.1148505

Ma, R., Zhang, Z., and Lin, B. (2023b). Evaluating the synergistic effect of digitalization and industrialization on total factor carbon emission performance. *J. Environ. Manag.* 348, 119281. doi:10.1016/j.jenvman.2023.119281

Ma, Z., and Zhang, P. (2025). Myth of the digital economy: can it continually contribute to a low-carbon status and sustainable development? *Environ. Impact Assess. Rev.* 110, 107688. doi:10.1016/j.eiar.2024.107688

MacKinnon, D. P., Krull, J. L., and Lockwood, C. M. (2000). Equivalence of the mediation, confounding and suppression effect. *Prev. Sci.* 1, 173–181. doi:10.1023/A:1026595011371

Ministry of Ecological Environment (2011). White paper on China's policies and actions to address climate change. Available online at: https://www.mee.gov.cn/ywgz/gjjlhz/lydt/201111/t20111123_220431.shtml (Accessed December 10, 2024).

Moore, G. E. (1965). Cramming more components onto integrated circuits. *Electronics* 38.

Rong, T., Zhang, P., Li, G., Wang, Q., Zheng, H., Chang, Y., et al. (2023). Spatial correlation evolution and prediction scenario of land use carbon emissions in the Yellow River Basin. *Ecol. Indic.* 154, 110701. doi:10.1016/j.ecolind.2023.110701

State Council (2011). Outline of the Twelfth five-year plan for national economic and social development of the people's Republic of China. Available online at: https://www.gov.cn/zhuanti/2011-03/16/content_2623428.htm (Accessed December 10, 2024).

State Council (2013). Circular of the state Council on the issuance of the 'broadband China' strategy and implementation programme. Available online at: https://www.gov.cn/zhengce/zhengceku/2013-08/16/content_5060.htm (Accessed December 10, 2024).

State Council (2015a). Circular of the state Council on the issuance of the action programme for promoting the development of big data. Available online at: https://www.gov.cn/gongbao/content/2015/content_2929345.htm (Accessed December 10, 2024).

State Council (2015b). Guiding opinions of the state Council on actively promoting 'internet Plus' actions. Available online at: https://www.gov.cn/zhengce/zhengceku/2015-07/04/content_10002.htm (Accessed December 10, 2024).

State Council (2016a). Official issuance of the outline of the plan for the development of the Yangtze River Economic Belt. Available online at: https://www.gov.cn/xinwen/2016-09/12/content_5107501.htm (Accessed December 10, 2024).

State Council (2016b). Outline of the Thirteenth five-year plan for national economic and social development of the people's Republic of China. Available online at: https://www.gov.cn/xinwen/2016-03/17/content_5054992.htm (Accessed December 10, 2024).

State Council (2021a). The central committee of the communist party of China and the state Council have issued the 'outline of the ecological protection and high-quality development plan for the Yellow River Basin. Available online at: https://www.gov.cn/gongbao/content/2021/content_5647346.htm (Accessed December 10, 2024).

State Council (2021b). Outline of the Fourteenth five-year plan for the national economic and social development of the people's Republic of China and the vision 2035. Available online at: https://www.gov.cn/xinwen/2021-03/13/content_5592681.htm (Accessed December 10, 2024).

Sun, G., Fang, J., Li, J., and Wang, X. (2024). Research on the impact of the integration of digital economy and real economy on enterprise green innovation. *Technol. Forecast. Soc. Change* 200, 123097. doi:10.1016/j.techfore.2023.123097

Sun, H., Chen, T., and Wang, C. N. (2023). Spatial impact of digital finance on carbon productivity. *Geosci. Front.* 15, 101674. doi:10.1016/j.gsf.2023.101674

Tang, L., Lu, B., and Tian, T. (2021). Spatial correlation network and regional differences for the development of digital economy in China. *Entropy* 23, 1575. doi:10.3390/e23121575

Theil, H. (1967). *Economics and information theory*. North-Holland Publishing Company.

Tian, H., Zhao, T., Wu, X., and Wang, P. (2024). The impact of digital economy development on carbon emissions-based on the perspective of carbon trading market. *J. Clean. Prod.* 434, 140126. doi:10.1016/j.jclepro.2023.140126

Wang, J., Dong, K., Dong, X., and Taghizadeh-Hesary, F. (2022a). Assessing the digital economy and its carbon-mitigation effects: the case of China. *Energy Econ.* 113, 106198. doi:10.1016/j.eneco.2022.106198

Wang, J., Dong, K., Sha, Y., and Yan, C. (2022b). Envisaging the carbon emissions efficiency of digitalization: the case of the internet economy for China. *Technol. Forecast. Soc. Change* 184, 121965. doi:10.1016/j.techfore.2022.121965

Wang, J., Dong, X., and Dong, K. (2022c). How digital industries affect China's carbon emissions? Analysis of the direct and indirect structural effects. *Technol. Soc.* 68, 101911. doi:10.1016/j.techsoc.2022.101911

Wang, J., Dong, X., and Dong, K. (2022d). How does ICT agglomeration affect carbon emissions? The case of Yangtze River Delta urban agglomeration in China. *Energy Econ.* 111, 106107. doi:10.1016/j.eneco.2022.106107

Wang, K., Wu, M., Sun, Y., Shi, X., Sun, A., and Zhang, P. (2019). Resource abundance, industrial structure, and regional carbon emissions efficiency in China. *Resour. Policy* 60, 203–214. doi:10.1016/j.resourpol.2019.01.001

Wang, L., and Xue, W. (2023). Analysis of carbon emission drivers and multi-scenario projection of carbon peaks in the Yellow River Basin. *Sci. Rep.* 13, 13684. doi:10.1038/s41598-023-40998-6

Wang, W., He, Y., Lei, Y., Gao, W., Li, Y., Lan, H., et al. (2023). Digital economy sectors are key CO2 transmission centers in the economic system. *J. Clean. Prod.* 407, 136873. doi:10.1016/j.jclepro.2023.136873

Wang, X., and Li, J. (2023). Heterogeneous effect of digital economy on carbon emission reduction. *J. Clean. Prod.* 429, 139560. doi:10.1016/j.jclepro.2023.139560

Wang, Z., and Shao, H. (2024). Spatiotemporal interactions and influencing factors for carbon emission efficiency of cities in the Yangtze River Economic Belt, China. *Sustain. Cities Soc.* 103, 105248. doi:10.1016/j.scs.2024.105248

Wu, H., Xue, Y., Hao, Y., and Ren, S. (2021). How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Econ.* 103, 105577. doi:10.1016/j.eneco.2021.105577

Xu, Z., and Ci, F. (2023). Spatial-temporal characteristics and driving factors of coupling coordination between the digital economy and low-carbon development in the Yellow River Basin. *Sustainability* 15, 2731. doi:10.3390/su15032731

Yang, Z., Gao, W., Han, Q., Qi, L., Cui, Y., and Chen, Y. (2022). Digitalization and carbon emissions: how does digital city construction affect China's carbon emission reduction? *Sustain. Cities Soc.* 87, 104201. doi:10.1016/j.scs.2022.104201

Yi, M., Liu, Y., Sheng, M. S., and Wen, L. (2022). Effects of digital economy on carbon emission reduction: new evidence from China. *Energy Policy* 171, 113271. doi:10.1016/j.enpol.2022.113271

Yu, B., Zhao, Z., Wei, Y.-M., Liu, L., Zhao, Q., Xu, S., et al. (2023). Approaching national climate targets in China considering the challenge of regional inequality. *Nat. Commun.* 14, 8342. doi:10.1038/s41467-023-44122-0

Yu, Z., Liu, Y., Yan, T., and Zhang, M. (2024). Carbon emission efficiency in the age of digital economy: new insights on green technology progress and industrial structure distortion. *Bus. Strategy Environ.* 33, 4039–4057. doi:10.1002/bse.3683

Yuan, H., and Zhu, C. (2018). Do national high-tech zones promote the transformation and upgrading of China's industrial structure. *China ind. Econ.*, 60–77. doi:10.19581/j.cnki.ciejournal.2018.08.004

Zeng, J., and Yang, M. (2023). Digital technology and carbon emissions: evidence from China. *J. Clean. Prod.* 430, 139765. doi:10.1016/j.jclepro.2023.139765

Zhang, J., Lyu, Y., Li, Y., and Geng, Y. (2022a). Digital economy: an innovation driving factor for low-carbon development. *Environ. Impact Assess. Rev.* 96, 106821. doi:10.1016/j.eiar.2022.106821

Zhang, S., and Wen, J. (2024). Digital economy empowers new quality productivity: an analytical framework. *Contemp. Econ. Manag.* 46, 1–9. doi:10.13253/j.cnki.ddjjgl.2024.07.001

Zhang, W., Fan, H., and Zhao, Q. (2023). Seeing green: how does digital infrastructure affect carbon emission intensity? *Energy Econ.* 127, 107085. doi:10.1016/j.eneco.2023.107085

Zhang, W., Liu, X., Wang, D., and Zhou, J. (2022b). Digital economy and carbon emission performance: evidence at China's city level. *Energy Policy* 165, 112927. doi:10.1016/j.enpol.2022.112927

Zhou, W., and Xu, L. (2023). On new quality productivity: connotative characteristics and important focus. *reform*, 1–13.

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 09 April 2025
DOI 10.3389/fenvs.2025.1523850

Check for updates

OPEN ACCESS

EDITED BY
Ji Zheng,
The University of Hong Kong, Hong Kong SAR, China

REVIEWED BY
Ying Zhu,
Xi'an University of Architecture and Technology, China
Yan Sun,
Beijing Forestry University, China

*CORRESPONDENCE
Wenxue Lin,
linwenxue2019@163.com

RECEIVED 06 November 2024
ACCEPTED 24 March 2025
PUBLISHED 09 April 2025

CITATION
Zhu Z and Lin W (2025) Impact of livelihood development on CO_2 emissions: empirical evidence from Yangtze River delta urban agglomeration.
Front. Environ. Sci. 13:1523850.
doi: 10.3389/fenvs.2025.1523850

COPYRIGHT
© 2025 Zhu and Lin. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Impact of livelihood development on CO_2 emissions: empirical evidence from Yangtze River delta urban agglomeration

Zhiming Zhu and Wenxue Lin*

School of Economics and Finance, Hohai University, Nanjing, Jiangsu, China

In the context of the "dual-carbon" goal and the building of a moderately prosperous society, it is of great significance to explore in depth the impact of livelihood development on urban carbon emissions. This paper uses the Human Development Index (HDI) as a proxy for assessing livelihood development. Based on the data of a panel of 41 cities in the Yangtze River Delta urban agglomeration from 2000 to 2021, this study constructs the fixed effect model, mediating effect and moderating effect models to empirically test the impact of livelihood development on CO_2 emissions from energy consumption and its mechanism. The HDI of the Yangtze River Delta urban agglomeration exhibited a steady increase from 0.64 in 2000 to 0.81 in 2021, marking a significant leap from a moderate to a very high level of human development, with an overall increase of 27.41%. The results show that there is a significant inverted U-shaped relationship between livelihood development and urban CO_2 emissions. Innovation inputs play an intermediary role and investment intensity positively moderates the inverted U-shaped relationship between livelihood development and CO_2 emissions. Moreover, the analysis finds that the impact of livelihood development on CO_2 emissions varies significantly among regions with different geographic locations and resource endowments. The inverted U-shaped relationship between livelihood development and CO_2 emissions is more pronounced in central cities and non-resource-based cities. The above research results show that urban carbon emissions can be effectively reduced by optimizing livelihood development, and provide a scientific basis for achieving the target of carbon peak. This study reveals the relationship between livelihood development and CO_2 emissions, provides a new perspective for sustainable urban development, and provides a basis for promoting the simultaneous realization of livelihood development and carbon emission reduction targets in the Yangtze River Delta urban agglomeration.

KEYWORDS

CO2 emissions from energy consumption, human development index, Yangtze River delta urban agglomeration, livelihood development, fixed effect model

1 Introduction

Human society has now entered the "Anthropocene" (Crutzen, 2002), which means that human activities have become a major driver of global environmental change (Will et al., 2007; Tyrrell, 2011; Zalasiewicz et al., 2011). Global warming and sea level rise are altering the earth system, posing a severe threat to the natural environment and human life, and are

mostly driven by human excessive carbon dioxide emissions (Marra et al., 2015; Kijewska and Bluszcz, 2016; Tyagi et al., 2016). China's economic development and social activities have advanced significantly since the country's reform and opening up. Notable advancements have been made in education, national health and medical care, and the pace at which people's livelihoods are developing thanks to economic growth. People's living conditions have improved more swiftly as a result of the east wind of economic progress. However, China's traditional and crude approach to development has resulted in large energy consumption and CO_2 emissions. According to the IEA's *CO_2 Emissions in 2023* report, China's carbon emissions grew to 12.6 billion tons in 2023, with *per capita* emissions 15% higher than those of advanced economies (IEA, 2024). A commitment to emission peak and carbon neutrality has been put forth by China in response to the urgent issue of global warming. Enhancing livelihood development and fostering green and low-carbon development are the clear objectives of the 20th CPC National Congress, which emphasized the significance of people's livelihood and green development. Enhancing people's quality of life can encourage more economic growth, while economic development itself gives the means and conditions for doing so. Therefore, the growth of people's livelihoods should have a carbon emission reduction effect, as it is a crucial sector to support China's social development. Thus, the primary issue that must be addressed as a priority is how to alter the course of development to maximize the improvement of livelihood development at the lowest possible cost to the environment.

Due to the Environmental Kuznets Curve (EKC) hypothesis, CO_2 emissions will have an inverted U-shaped tendency to rise and then decline as the economy grows (Kuznets, 1955; Grossman and Krueger, 1995). Studies have generally taken economic growth as an indicator of development. However, human beings are the core beneficiaries of the development process. Thus, the evaluation of development should not only focus on the inputs, but also emphasize the results that the society obtains from the development (Hussain and Dey, 2021). Therefore, the Human Development Index (HDI) provides a more comprehensive measure of the development (Cracolici et al., 2010; Sen et al., 2010; Cumming and von Cramon-Taubadel, 2018). The HDI was first released by the United Nations Development Program in 1990 (UNDP, 1990), and contains three sub-indicators: health, education, and standard of living. It serves as a tool for comprehensively reflect prosperity in the economy, advancement in society, and balance with the environment. It has since become the most influential indicator of human development worldwide (Morse, 2020). Therefore, this paper selects the HDI to measure the level of livelihood development in the Yangtze River Delta urban agglomeration.

Urban agglomerations are becoming the hub for energy resources due to the rapid expansion of urban areas, and they are also taking on more responsibility for reducing carbon emissions. The Yangtze River Delta, the biggest and most economically significant metropolitan agglomeration in China, is not only a pioneer in creating a "happy circle" for people's livelihood, but also a typical model for energy conservation and emission reduction (He et al., 2021). "14th Five-Year Comprehensive Work Plan for Energy Conservation and Emission Reduction" explicitly proposed to strictly control coal consumption in the Yangtze River Delta Urban Agglomeration. In this context, accurately assessing the carbon emissions from energy consumption and the level of livelihood development in the Yangtze River Delta urban area is highly important. Additionally, it is crucial to empirically evaluate the impact and mechanisms of energy-related carbon emission reductions in livelihood development. These efforts aim to enhance the quality of life for residents and encourage a synchronized peak in carbon emissions.

This paper potentially makes contributions in the following three areas. First, we integrate livelihood development and carbon emissions into a single research framework, offering an innovative approach to enhancing the degree of livelihood development and lowering carbon emissions. Subsequently, we conduct an empirical investigation into the precise pathways by which livelihood development influences carbon emissions, including both innovation inputs and investment intensity. Our goal is to offer recommendations for future initiatives aimed at reducing carbon emissions. Thirdly, to ascertain the varying effects of livelihood development on carbon emissions, we carried out a heterogeneous analysis of urban geographic location and resource reliance.

2 Literature review

These three distinct strands represent the research that is relevant to this particular investigation. The first strand is the research on CO_2 emissions. Research currently conducted indicates that many factors, including population size, urbanization rate, economic development level, and foreign direct investment, have varying degrees of impact on carbon dioxide emissions (Liu et al., 2017; Wang S. et al., 2019; Ma et al., 2022; Wu and Xu, 2023). In terms of research methods of influencing factors, there are mainly IPAT or STIRPAT models, Kaya constant equation and LMDI method (Shao et al., 2016; Chen et al., 2018; Guan et al., 2018; Yang et al., 2022). The STIRPAT model is traditionally defined as the Stochastic (ST) estimation of environmental impacts (I) by regression (R) on population (P), affluence (A), and technology (T) (Wei, 2011).

The second strand focuses on the measurement of livelihood development. Some scholars have constructed different indicator systems for measurement through the understanding of the connotation of livelihood development. For instance, (Chen et al., 2020) selected indicators from the five dimensions of economic progress, quality of life, societal advancement, environmental stewardship, and scientific and technological innovation as an assessment system for the city's livelihood based on the entropy value method (Chen et al., 2020). Ye et al. (2018) constructed the indicators of the sense of livelihood acquisition and livelihood satisfaction and carried out the questionnaire measurements and empirical analyses. Wang et al. (2022) constructed China's livelihood development indicator system from the four dimensions of economic prosperity, quality of life, societal progress, and environmental conservation. While some scholars have utilized objective indicators such as Better Life Index, Human Development Index and Genuine Progress Index to measure the level of human wellbeing (Wang et al., 2018; Michalos and Hatch, 2020; Pala, 2024).

The third strand is dedicated to examining the impact of urban development on the reduction of energy-related carbon emissions within the context of livelihood improvement. According to some research, nations with more developed livelihoods typically have greater *per capita* carbon dioxide emissions and a higher prevalence of environmental issues (Kvon et al., 2019). However, Van Tran's study shows that environmental quality can be improved by livelihood development (Van Tran et al., 2019). Research on the connection between human development and the decrease of carbon emissions is scarce at the moment. For the most part, it looks at how the HDI affects carbon emissions, but the relationship has not been thoroughly established. The influence of the level of human development on CO_2 emissions is found to be industry-specific (Mohmmed et al., 2019). Specifically, the human development index (HDI) has a negative regression coefficient in the agricultural sector. This suggests that human activities can help reduce carbon emissions in this sector. Researchers also found that humans can reduce agricultural carbon emissions through improved farming practices (Aminetzah et al., 2020). For example, Brazil and the United States currently use low- and no-tillage practices on about 40% of hectares, reducing fuel use and denitrification, thereby reducing greenhouse gas emissions. Conversely, in the transportation and bunker sectors, the HDI shows a positive regression coefficient. This implies that human activities have led to increased carbon emissions in these areas. According to the IEA, passenger and freight activity rebounded after the coronavirus (COVID-19) pandemic in 2022, leading to a 3% increase in CO_2 emissions from transportation over the previous year (IEA, 2023). Ocean shipping, heavily dependent on bunker fuels, is projected to see ship-source greenhouse gas emissions increase by up to 250% by 2050 from 2012 levels due to rising global freight volumes (Wan et al., 2018). The energy, industry, and manufacturing sectors did not exhibit any significant effects. Using quantile regression based on panel data of emerging economies, Banday and Kocoglu (2023) found that HDI had a significant carbon abatement effect in all quartiles. (Maji, 2019) verified the carbon abatement effect of HDI by employing a systematic GMM approach to assess data from 42 sub-Saharan nations (Maji, 2019). Additionally, (Yumashev et al., 2020) included the HDI's quadratic term into the model and verified the inverted "U" nonlinear relationship between livelihood development and CO_2 emissions (Yumashev et al., 2020). Subsequently, other researchers like (Hussain and Dey, 2021) also used the HDI as an indicator of development and found the existence of environmental Kuznets curves in 30 countries from 1990 to 2016 (Hussain and Dey, 2021). Through a comparison of the model's GDP and HDI performance, Majewska and Gierałtowska (2022) determined that the model which uses the HDI as a measure of affluence fits better than GDP, based on data from 2000 to 2019 for Central and Eastern European nations.

In general, prior studies have not resulted in a consistent criterion for measuring the level of livelihood development. Furthermore, there is no agreement on how to understand the carbon emission reduction effects of livelihood development. There has been little quantitative investigation of the impact mechanism in the correlation between livelihood development and carbon emissions, and even less on the heterogeneity of these driving relationships. Based on this, the study attempts to investigate through theoretical and empirical analyses the extent to which livelihood development affects urban CO_2 emissions, whether or not it shares features with other studies, and what the processes and outcomes of this function are. To be more precise, this paper uses 41 prefecture-level cities in the Yangtze River Delta urban agglomeration from 2000 to 2021 as research samples. Estimates are made first for carbon emissions and the degree of livelihood development. The impact of livelihood development on reducing carbon emissions is then empirically tested using the STIRPAT model. Also, a controlling variable called investment intensity is presented. Subsequently, the geographical and typological diversity of the correlation between the two are examined with the goal of acting as a guide for developing livelihood development plans that complement low-emission development.

3 Theoretical framework and research hypothesis

In the early development stages, industrialization was gaining momentum due to a spike in energy use, particularly from fossil fuels, and significant CO_2 emissions from human activity. People's standard of living was comparatively underdeveloped, and their knowledge of and capacity for environmental protection was constrained. The mid-development phase has witnessed structural changes because of the rise of the service and high-tech sectors, which have slowed down the growth of carbon emissions, reduced reliance on heavy and energy-intensive industries, and raised public awareness of environmental issues. When people's livelihoods have advanced to a high degree, governments and corporations start to place more emphasis on environmental preservation and sustainable development. People also recognize the necessity to employ "clean energy" and reduce pollution. Society starts to transition to a more sustainable development model with a decrease in carbon emissions when governments start to take action, such as making investments in clean energy and enforcing environmental rules (Yumashev et al., 2020). Consequently, the following hypothesis is put forth:

Hypothesis 1: The livelihood development has a carbon emission reduction effect. And there is an inverted U-shaped relationship between livelihood development and CO_2 emissions.

The livelihood development can reduce CO_2 emissions by increasing investment in science and technology innovation. The insatiable demand for human's own development serves as a catalyst for scientific and technical advancement, which in turn serves as a major impetus for energy conservation and emission reduction (Zou et al., 2022). Through legislative support and investment in science and technology education, livelihood development may offer a strong foundation and sustained momentum for scientific and technology innovation. Firstly, livelihood development creates an atmosphere that is conducive to creativity. The livelihood development can influence the introduction of policies by the government in this area. Examples of such policies include those that encourage businesses and research institutions to invest more in

innovation by offering R&D funds, tax breaks, intellectual property protection, and other incentives. Secondly, livelihood development offers a consistent flow of skilled individuals who foster innovation. More investment in STEM education, higher spending on education and science and technology, and reasonable modifications to national public budget expenditures based on human development needs will all contribute to the creation of more innovative individuals and offer a human resource base for innovation. Investment in innovation significantly reduces CO_2 emissions. More financing for innovation will, on the one hand, lead to decreased CO_2 emissions through the development of energy-efficient buildings, the iterative improvement of technology, research and development into renewable energy sources, integration of energy systems, etc. On the other hand, funding for innovation can be used to raise public knowledge of the significance of reducing carbon emissions and to motivate more individuals to live low-carbon lives through public awareness and education, thus lowering CO_2 emissions.

Hypothesis 2: Innovation inputs play a mediating effect in the impact of livelihood development on CO_2 emissions.

One of the "troika" forces behind economic growth is thought to be investment, and fixed asset investment, which makes up a large portion of investment, has grown to be crucial for fostering economic development and enhancing people's quality of life (Bond et al., 2010). A moderating effect on the route of livelihood development that influences CO_2 emissions could be expected from investment intensity. On the one hand, higher investment intensity might guarantee that the improvement of livelihoods has a favorable effect on cutting carbon emissions. The development of environmentally friendly infrastructure, including green buildings and low-carbon transportation systems, is aided by fixed asset investment. This influences the degree to which the development of livelihood improves the environmental quality. Adjusting investment intensity, on the other hand, increases the desire of enterprises to implement green projects. The need for green development and the need to update the economic development paradigm are being emphasized by the government more and more. It also tends to allocate fixed asset investment to sectors of the economy that are dedicated to developing low-carbon technology and increasing carbon efficiency, which encourages businesses to adopt low-carbon practices and advances the reduction of carbon emissions.

Hypothesis 3: Investment intensity plays a moderating effect in the impact of livelihood development on CO_2 emissions.

4 The variables, model setting and data description

4.1 Variable selection

4.1.1 Explained variable

CO_2 emissions *per capita* (CE). The measurement of urban CO_2 emissions draws on Han and Xie (2017), which extrapolated urban CO_2 emissions through energy consumption such as electricity, natural gas, and liquefied petroleum gas. The *per capita* CO_2 emissions were then calculated by dividing the total carbon emissions by the population of each city. The specific calculation method is shown in Equations 1, 2.

$$I = C_n + C_p + C_e = \kappa E_n + \gamma E_p + \varphi(\eta \times E_e) \quad (1)$$

$$\mathrm{CE} = I/P \quad (2)$$

Here, I is the urban CO_2 emissions; C_n, C_p, C_e are the CO_2 emissions from the consumption of natural gas, liquefied petroleum gas and electricity, respectively; E_n, E_p, E_e denote the natural gas consumption, liquefied petroleum gas consumption and electricity consumption, respectively; κ is the carbon emission factor of natural gas 2.1622 kg-CO_2/m^3, γ is the carbon emission factor of liquefied petroleum gas 3.1013 kg-CO_2/kg; φ is the GHG emission factor for the coal power fuel chain, with an equivalent CO_2 of 1.3023 kg-CO_2/(kW-h), η is the proportion of coal power generation to total power generation, and P is the number of people in the city at the end of the year.

4.1.2 Core explanatory variable

Human Development Index (HDI). According to the calculation methodology in the Human Development Report 2023–24, the HDI is based on the health, education and standard of living (UNDP, 2024). Then it is measured by calculating the geometric mean of the levels of the indicators in these three dimensions. The calculation method is shown in Equations 3-6.

$$HDI = \sqrt[3]{LEI \times EI \times II} \quad (3)$$

$$LEI = \frac{LE - MinF}{MaxF - MinF} \quad (4)$$

$$EI = \left(\frac{MYS - MinF}{MaxF - MinF}\right) + \left(\frac{EYS - MinF}{MaxF - MinF}\right) \Big/ 2 \quad (5)$$

$$II = \frac{\ln(GNIpc) - \ln(MinF)}{\ln(MaxF) - \ln(MinF)} \quad (6)$$

LEI, EI and II are the health, education and standard of living indices, respectively; LE is the life expectancy at birth, and MYS is the mean years of schooling, and EYS is the expected years of schooling, and $GNIpc$ is the purchasing power-adjusted real GNI *per capita*; $MinF$ is the lower threshold limit for each indicator, and $MaxF$ is the upper threshold for each indicator. The thresholds for each indicator are shown in Table 1. Among them, the calculation of life expectancy and average years of schooling is based on successive national census data measurements to obtain the indicator data for the census years (2000, 2010 and 2020), and then the interpolation and extrapolation methods are used to obtain the data for other years. Data on expected years of schooling are approximated by net or gross enrollment ratios at all levels of education including primary, middle, high school, and university (Liu et al., 2020). For missing data, the enrollment rate of the province was used as a proxy. For the calculation of real GNI *per capita*, the ratio between GDP *per capita* measured in RMB prices in the current year and GNI measured in PPP prices in 2011 was used to obtain a conversion factor, based on which the GNI measured in PPP prices in 2011 was calculated for each city (UNDP et al., 2019; Wang M. et al., 2019).

TABLE 1 Indicator thresholds for each dimension of HDI.

Dimension	Indicator	Minimum	Maximum
Health	Life expectancy at birth (years)	20	85
Education	Expected years of schooling (years)	0	18
	Mean years of schooling (years)	0	15
Standard of living	GNI *per capita* (2011 PPP$)	100	75,000

4.2 Model setting

The STIRPAT model, which is an enhanced version of the IPAT model, was selected as the analytical framework for this paper using the following underlying expression (York et al., 2003). The IPAT model is shown in Equation 7:

$$I = aP^b A^c T^d \varepsilon \tag{7}$$

Where I denotes environmental pressure, P, A and T denote demographic, economic and technological factors; a, b, c and d are the model parameters; ε is the random error term. Referring to the related literature on the impact of HDI on CO_2 emissions, the quadratic term of HDI is added to the model and logarithm is taken on both sides of the model. The expanded baseline regression model is shown in Equation 8.

$$lnCE_{it} = \alpha_0 + \alpha_1 lnHDI_{it} + \alpha_2 (lnHDI_{it})^2 + \alpha_3 \ln CV_{it} + \ln \varepsilon_{it} \tag{8}$$

Where i and t represent cities and years; CE_{it} represents the *per capita* emissions of CO_2 in the city; HDI_{it} represents the human development index; CV_{it} represents a series of control variables, including energy intensity (T), energy structure (S), urbanization rate (U), industrial structure (IS), openness (O), foreign direct investment (FDI), consumption capacity (CON); α is the parameter to be estimated by the model; ε_{it} is the random error term.

Referring to Yang and Niu's research idea to construct the mediation effect model in order to test the mediating effect of innovation inputs (Baron and Kenny, 1986; Yang and Niu, 2023). The model is shown in Equations 9, 10:

$$lnM_{it} = \varphi_0 + \varphi_1 lnHDI_{it} + \varphi_2 (lnHDI_{it})^2 + \varphi_3 \ln CV_{it} + \ln \varepsilon_{it} \tag{9}$$

$$lnCE_{it} = \beta_0 + \beta_1 lnHDI_{it} + \beta_2 (lnHDI_{it})^2 + \beta_3 lnM_{it} + \beta_4 \ln CV_{it} + \ln \varepsilon_{it} \tag{10}$$

Where M_{it} is the mediating variable innovation input; φ, and β are the parameters of the model to be estimated. The other variables are defined as above.

Equation 11 is constructed to test the moderating effect of investment intensity (Yang and Niu, 2023).

$$lnCE_{it} = \gamma_0 + \gamma_1 lnHDI_{it} + \gamma_2 (lnHDI_{it})^2 + \gamma_3 E_{it} + \gamma_4 E_{it} \times lnHDI_{it} + \gamma_5 E_{it} \times (lnHDI_{it})^2 + \gamma_6 \ln CV_{it} + \ln \varepsilon_{it} \tag{11}$$

Where E_{it} is the moderating variable investment intensity; the $E_{it} \times lnHDI_{it}$ and $E_{it} \times (lnHDI_{it})^2$ are the interaction terms of the primary and secondary terms of the explanatory variable HDI with investment intensity; γ are the parameters of the model to be estimated. The other variables are defined as above.

TABLE 2 Variable description statistics.

Variable	Obs	Mean	SD	Min	Max
CE	902	3.660	2.581	0.099	11.591
HDI	902	0.734	0.075	0.522	0.899
T	902	0.191	0.079	0.029	0.614
S	902	0.680	0.092	0.219	0.824
U	902	0.529	0.176	0.029	0.896
IS	902	0.479	0.087	0.216	0.747
O	902	0.321	0.375	0.004	2.882
FDI	902	0.031	0.024	0.000	0.201
CON	902	0.368	0.085	0.163	0.726
TT	902	0.202	0.049	0.017	0.370
FAI	902	0.634	0.303	0.081	2.439

4.3 Data sources and descriptive statistics

This paper takes 41 cities in the Yangtze River Delta urban agglomeration from 2000 to 2021 as the research sample. The data come from China City Statistical Yearbook[1], China Electric Power Yearbook[2], National Statistical Yearbook[3], national population census (2000, 2010, 2020)[4], the World Bank database[5], statistical yearbooks of provinces and cities, and national economic and social development bulletins[6], etc. GDP data were calculated using 2000 as the base period. In addition,

1 China City Statistical Yearbook: https://data.cnki.net/yearBook/single?id=N2024050590&pinyinCode=YZGCA.

2 China Electric Power Yearbook: http://www.ceppc.org.cn/dlnj/.

3 National Statistical Yearbook: https://www.stats.gov.cn/sj/ndsj/.

4 National population census: https://www.stats.gov.cn/sj/pcsj/.

5 World Bank: https://data.worldbank.org.

6 City yearbooks and statistical bulletins: https://data.cnki.net/home.

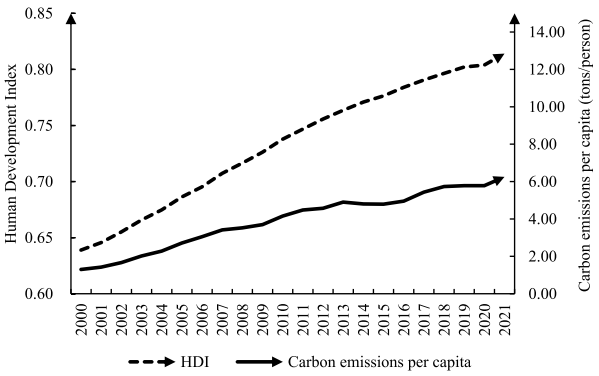


FIGURE 1
Trends in CO_2 emissions and HDI.

we use interpolation and trend extrapolation methods to supplement some missing data. The interpolation method is used to estimate the missing value between two known data points (Fan and Pei, 2023). Meanwhile, the trend extrapolation method predicts future data values based on the historical trends observed in the data, allowing us to estimate values beyond the existing dataset's range (Zhenjun et al., 2023). Therefore, based on the above two methods, we can ensure the consistency and analyzability of data to a certain extent. Table 2 displays the descriptive statistics for each variable.

5 Results

5.1 Analysis of livelihood development and CO_2 emissions

Using the previously mentioned Equations 1–6, data on the evolution of livelihood development and CO_2 emissions during the course of the research period are calculated. The average human development index of 41 cities was chosen as the livelihood development data of the Yangtze River Delta urban agglomerations in order to analyze the data evolution characteristics of these areas. The annual *per capita* carbon emission data of these areas was then calculated by adding and dividing the total carbon emission and population of each city. Figure 1 displays the results of the calculation.

With a rise of 27.41%, the HDI of the Yangtze River Delta urban agglomeration completed the transition from the medium to the very high human development level in 2021, rising steadily from 0.64 in 2000 to 0.81 in 2021, as shown in Figure 1. Between 2000 and 2006, it was at the medium human development. The objective of "building a moderately affluent society in all aspects" was presented during the 16th National Congress of the Communist Party of China in 2002, which introduces new demands for the development of livelihoods. Therefore, the Yangtze River Delta urban agglomeration is working toward greater economic growth, advancements in science and education, and more stable means of subsistence for its residents. After reaching the high human development level in 2007, the HDI hit 0.79 in 2018. During this period, the region's citizens enjoyed an improvement in their standard of life and saw a discernible rise in the level of economic growth. The new rural social pension insurance policy went into effect in 2009, resulting in a large increase in social security payments. The 2010 World Expo was subsequently hosted in Shanghai, which sped up the region's economic upgrading, restructuring, and transformation. It also encouraged the building of transportation infrastructure, which further aided in the

TABLE 3 Regression results.

Variable	(1)	(2)	(3)	(4)
lnHDI	−2.361***			
	(0.563)			
$(lnHDI)^2$	−3.139***			
	(0.541)			
lnLEI		0.486***		
		(0.120)		
lnEI			−0.527***	
			(0.138)	
lnII				0.819***
				(0.110)
lnT	0.988***	0.885***	0.972***	0.918***
	(0.0238)	(0.0104)	(0.0226)	(0.0229)
lnS	0.700***		0.660***	0.611***
	(0.0504)		(0.0494)	(0.0486)
lnU	0.0948***	0.00562	0.0882***	0.0854***
	(0.0170)	(0.00859)	(0.0172)	(0.0167)
lnIS	0.158***	0.128***	0.419***	0.173***
	(0.0576)	(0.0237)	(0.0493)	(0.0526)
lnO	0.0581***	0.00441	0.0665***	0.0705***
	(0.0125)	(0.00626)	(0.0125)	(0.0121)
ln FDI	−0.0190***	−0.00588*	−0.00156	−0.0177**
	(0.00724)	(0.00348)	(0.00718)	(0.00702)
lnCON	−0.105***	0.0150	−0.0401	−0.0559*
	(0.0325)	(0.0160)	(0.0326)	(0.0315)
lnP		−0.980***		
		(0.0169)		
Constant	2.682***	8.602***	3.151***	3.325***
	(0.137)	(0.102)	(0.0680)	(0.0572)
Time-fixed	Yes	Yes	Yes	Yes
City-fixed	Yes	Yes	Yes	Yes
R-squared	0.989	0.997	0.989	0.989

Standard errors in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, below.

region's economic development. Between 2019 and 2021, the Yangtze River Delta urban agglomeration achieved to very high human development. After a reasonably prosperous society was achieved in 2020, there was a notable improvement in people's quality of life, a steady rise in the protection of the rights to development and subsistence, then the new phase of more coordinated growth in human development (Ren et al., 2021).

In addition, the overall trend in the Yangtze River Delta urban agglomeration's *per capita* CO_2 emissions is a sharp rise followed by a slow plateau. In particular, there was an annual growth rate of approximately 9.95% on average in *per capita* CO_2 emissions between 2000 and 2013, rising from 1.29 tons per person in 2000 to 4.90 tons per person in 2013. The nation set goals for 7.5% average annual GDP growth and 47% urbanization rate during the 11th Five-Year Plan period[7]. The Yangtze River Delta urban agglomeration's rapid economic development and the ongoing rise in urbanization have resulted in a rapid increase in CO_2 emissions. Due in large part to China's aggressive push of low-carbon development, *per capita* CO_2 emissions increased negatively in 2014 and 2015. The State Council's adoption and approval of the National Climate Change Response Plan (2014–2020) in 2014 has played a significant role in hastening the reduction of carbon emissions. It lays out explicit guidelines for decreasing CO_2 emissions intensity and expanding forests area. During the "13th Five-Year Plan" period, China has set a target of reducing energy consumption per unit of GDP by 15% by 2020 compared with 2015. The Yangtze River Delta's industrial structure shifted to a larger percentage of tertiary industry as its economic growth method has continuously changed. The pace at which CO_2 emissions increased fell sharply. In 2021, the average person's CO_2 emissions increased to 6.25 tons. As the pandemic spreads during this time, there is a greater chance that a global value chain would break, which could trigger a worldwide energy crisis. This situation may endanger the development of energy in the Yangtze River Delta. It also poses challenges for climate governance and the achievement of the "dual carbon" target CO_2 emissions might have gone up as a result of this.

5.2 Estimation results

The F, LM and Hausman tests led to the selection of the two-way fixed effect model to investigate how livelihood improvement affects carbon emission reduction. Table 3 presents the results of the measurement.

Table 3's column (1) regression findings show that, at the 1% level, the HDI and its squared term coefficient are both significantly negative. Since the HDI has a range of values from 0 to 1, its logarithmic value is negative in the model. Therefore, an important inverted "U" shape is found between the HDI and carbon emissions. This is consistent with the findings of some of the scholars above. Hypothesis 1 is preliminarily tested. It is not rigorous to conclude that the inverted "U" relationship is based solely on the significance of the coefficients of the primary and secondary terms. Then we continued to use the Utest test command to verify the result (Liu and Mu, 2024). The p-value of Utest test for the inverted "U" curve with carbon emission is less than 0.01. The slope of the curve is positive (1.73, $p < 0.01$) and then negative (−1.69, $p < 0.01$). The HDI's extreme point, which is 0.68 and falls within the range of HDI values, suggests that the relationship between carbon emissions and livelihood development is shaped like an inverted "U". The inflection point value is 0.68, meaning that livelihood development will have a suppressive effect on carbon emissions when HDI is higher than 0.68. And after calculation, hypothesis 1 is correct since livelihood development has a dominant effect on reducing carbon emissions at this point. An improvement in the HDI denotes not just a rise in the economic status of the population, but also a notable improvement in their health and education levels. When it comes to this process, individuals with higher levels of education and overall quality typically have stronger concepts related to environmental protection, are more conscious of the significance of climate change and environmental protection, and are more likely to take action to protect the environment. They may even engage in social and political activities to influence policy decisions and encourage the implementation of environmental protection measures to facilitate human development in a sustainable manner (Yumashev et al., 2020).

TABLE 4 Robustness test results.

Variable	(1)	(2)	(3)
lnHDI	−3.498**	−1.604**	−2.899***
	(1.476)	(0.622)	(0.615)
$(lnHDI)^2$	−6.601***	−2.560***	−3.623***
	(1.418)	(0.581)	(0.586)
Control	Yes	Yes	Yes
Constant	1.818***	2.737***	2.644***
	(0.358)	(0.154)	(0.148)
Time-fixed	Yes	Yes	Yes
City-fixed	Yes	Yes	Yes
R-squared	0.942	0.990	0.987

The regression model incorporates the HDI indices of the three dimensions to enhance the examination of the impact of livelihood development on CO_2 emissions. The resulting tables are arranged in columns (2), (3), and (4) of Table 3. Considering the significance of the data, we examined the relationship between the health index and CO_2 emissions using the total population (P) data as a control variable. The findings show that an increase in the health index significantly increases CO_2 emissions. One possible explanation for this could be that although life expectancy has improved dramatically due to improvements in health and medical technology, the energy-intensive nature of medication research and medical services may contribute to a rise in CO_2 emissions. Column (3) data indicates a considerable restraining effect of the

7 Outline of the 11th Five-Year Plan for National Economic and Social Development of the People's Republic of China: https://www.gov.cn/gongbao/content/2006/content_268766.htm.

TABLE 5 Regression results of mediating and moderating effects.

Variable	*lnTT*	*ln CE*	*ln CE*
	(1)	(2)	(3)
lnHDI	5.246***	−1.338**	−3.062***
	(1.141)	(0.524)	(0.739)
$(lnHDI)^2$	4.514***	−2.259***	−4.248***
	(1.096)	(0.503)	(0.865)
lnTT		−0.195***	
		(0.0157)	
$lnHDI \times ln\,FAI$			−0.974**
			(0.392)
$(lnHDI)^2 \times ln\,FAI$			−1.252**
			(0.514)
$ln\,FAI$			−0.188***
			(0.0724)
Control	Yes	Yes	Yes
Constant	−0.836***	2.519***	2.575***
	(0.277)	(0.126)	(0.162)
Time-fixed	Yes	Yes	Yes
City-fixed	Yes	Yes	Yes
R-squared	0.606	0.991	0.989

education index on CO_2 emissions. Education can help people become more aware of environmental issues on a personal and societal level, support the advancement of green technologies, and lower CO_2 emissions. The income index has a considerable impact on the rise in CO_2 emissions, as seen by Column (4). Economic development is reflected in the rising income index, and the Yangtze River Delta region's economic development is heavily reliant on fossil fuels like coal and oil, which can raise CO_2 emissions. In the sub-dimension regression, only the education index can reduce carbon emissions. However, the degree of human development can significantly reduce carbon emissions. This shows that in order to reach the aim of carbon peaking, we need raise the whole level of livelihood development rather than relying solely on one dimension.

5.3 Robustness test

The following robustness tests are carried out to confirm the benchmark regression's scientific validity. The results are shown in Table 4.

(1) Replace the explanatory variables. Replace the CO_2 emissions data with the CO_2 emissions of each city published by China Emission Accounts and Datasets (CEADs) to re-estimate the model. The results are shown in column (1) of Table 4.

(2) Exclude some samples. There is a big difference between municipalities, provincial capitals and sub-provincial cities and ordinary prefecture-level cities in terms of livelihood development. As a result, the regression does not include the aforementioned samples. The outcomes are displayed in Column (2).

(3) Control variable shrinking tail. We employ a 1% shrinking tail treatment to prevent the extreme values of the control variables from significantly affecting the regression findings. The results are shown in column (3). The empirical findings demonstrate the robustness of the benchmark results by demonstrating that the inverted "U" curve link between CO_2 emissions and livelihood development remains constant.

5.4 Mechanism test

5.4.1 Mediating effect

The findings of a step-by-step regression of Equations 9 , 10 to investigate how livelihood development influences urban CO_2 emissions are presented in Table 5. The link between livelihood development and innovation inputs is U-shaped, as seen by column (1). During the examination period, most cities were found to the right of the turning point, suggesting that improvements in living conditions facilitate investment in innovation. Following the addition of mediating variables, column (2) shows that innovation inputs have a regression coefficient of −0.195 on carbon emissions, indicating that innovation inputs suppress carbon emissions. Additionally, the coefficients of lnHDI and $(lnHDI)^2$ are both significant and lower than in the baseline regression model, indicating that innovation inputs play a part in mediating the effect of livelihood development on carbon emissions. Hypothesis 2 is valid.

5.4.2 Moderating effect

The data in column (3) shows that investment intensity has a positive moderating effect on the connection between CO_2 emissions and livelihood development, as seen by the significantly negative coefficients of both lnHDI*lnFAI and $(lnHDI)^2$*lnFAI. Based on Haans and Pieters (Haans et al., 2016), the shift of the turning point and the curve's shape can be used to analyze the moderating effect of investment intensity. The effect of investment intensity on the shape of the curve is mainly reflected by the positivity and negativity of γ_5. It is noticeably negative in column (3), suggesting that the curve steepens with increasing investment intensity. The degree of investment will cause the turning point of the inverted "U" curve to move slightly to the right, as indicated by the new inflection point value of lnHDI ≈ −0.36. Increased investment intensity strengthens the inverted U-shaped link between livelihood development and CO_2 emissions. In other words, it positively regulates the impact of livelihood development on CO_2 emissions. At this point, hypothesis 3 holds true.

5.5 Heterogeneity test

5.5.1 Analysis of regional heterogeneity

To examine geographical differences in the relationship between livelihood development and carbon emissions, group regressions are

TABLE 6 Results of heterogeneity test.

Variable	Central area	Non-central area	Resource-based	Non-resource-based
	(1)	(2)	(3)	(4)
lnHDI	−3.725***	2.694***	3.225**	−3.548***
	(0.789)	(0.757)	(1.522)	(0.564)
$(lnHDI)^2$	−4.194***	2.019***	3.332**	−4.333***
	(0.810)	(0.694)	(1.372)	(0.550)
Control	Yes	Yes	Yes	Yes
Constant	2.598***	3.488***	4.074***	2.579***
	(0.173)	(0.207)	(0.384)	(0.143)
Time-fixed	Yes	Yes	Yes	Yes
City-fixed	Yes	Yes	Yes	Yes
R-squared	0.982	0.996	0.990	0.991

utilized. These regional variations are based on the Outline of the Plan for the Integrated Development of the Yangtze River Delta Region, which classifies 27 cities—including Shanghai, Nanjing, and Changzhou—as the center area and the remaining 14 as non-center area cities. The HDI and its squared term coefficients of the central cities are shown to be significantly negative at the 1% level in columns (1) through (2) of Table 6. The P-value of the Utest test is less than 0.01, indicating that the development of livelihood development and carbon emissions of the central cities have an inverted U-shaped relationship. The city in the central area has now passed the turning point, with an HDI value of 0.64, and the improvement of people's livelihoods has demonstrated a carbon-reducing effect. The HDI and its squared term coefficient of non-central cities show a significant positive relationship, but they fail the U test. The rationale is that there is an incremental relationship between livelihood development and carbon emissions in non-central cities. It is indicated by the fact that all of these cities' HDI are situated on the right side of the positive U-shaped curve's inflection point. According to Lian, the Fisher's Permutation test was used to determine the significance of the variation in coefficients across groups, with the number of samples set at 1000 (Lian et al., 2010). The results show that the p-values for the primary and secondary terms are less than 0.01, which suggests that there is a substantial difference between the two groups' coefficients. Cities in the central region may gain from their better geographic location, quicker advancements in living standards, health, and education, higher degrees of livelihood development, and a population that is more aware of the need to protect the environment. However, when the level of livelihood development rises, non-central region cities will see an increase in energy consumption, which would raise carbon emissions.

5.5.2 Analysis of type heterogeneity

The State Council's National Sustainable Development Plan for Resource-based Cities (2013–2020) criteria is used to divide the cities under investigation into resource-based and non-resource-based categories. This categorization allows for a comparative examination of the ways in which the influence of livelihood development on carbon emissions differs depending on the resource endowment of these cities. The HDI and its squared term in resource-based cities show significantly positive coefficients from columns (3) to (4) of Table 6, but they fail the Utest test at the 5% significant level, suggesting that there is still evidence of a carbon-increasing effect in resource-based cities related to livelihood development. In non-resource cities, the relationship between the livelihood development and carbon emissions is formed like an inverted "U". The results of the significance test for group differences in coefficients demonstrate a significant difference between the two groups' coefficients. The explanation could be that non-resource cities are able to reduce carbon emissions through technological innovation and upgrading of the industrial structure, whereas resource cities have more abundant energy and resources and become unduly dependent on resources in the process of promoting urbanization, which raises carbon emissions (Yan et al., 2021).

6 Conclusion and policy recommendations

6.1 Conclusion

This research measured the human development index and CO_2 emissions from energy consumption using panel data from the Yangtze River Delta urban agglomeration from 2000 to 2021. It then built the STIRPAT model to examine the impact of livelihood development on reducing carbon emissions empirically. The findings of the study were as follows: (1) The relationship between livelihood development and carbon emissions shows an inverted "U" shape, indicating a large reduction in carbon emissions at this level. After a series of robustness tests, the finding holds true. (2) The mechanism test

shows that by boosting investment in innovation, livelihood development lowers CO_2 emissions. The regulation effect of investment intensity on the relationship between livelihood development and CO_2 emissions is positive. The curve is more convex and the inflection point is somewhat pushed to the right under the regulation of investment intensity. (3) In central cities and non-resource cities, the relationship between livelihood development and CO_2 emissions is more substantial in an inverted U shape.

6.2 Policy recommendations

In order to improve the livelihood development and meet the aim of carbon peaking as soon as feasible, this study makes the following recommendations for the Yangtze River Delta urban agglomeration based on the conclusions mentioned above.

Firstly, enhance public service systems for human development. To protect a higher degree of human development, the government should create a strong public service system for the entirety of human existence and implement the sharing of high-quality public services as soon as possible. To lessen the pollution that landfills and incineration contribute to the environment, hospitals and associated organizations should improve waste management and streamline medical service procedures. The government should aggressively maximize the distribution of educational resources, ensure that all citizens have access to high school education, and consistently raise the educational attainment of its citizens. For cities with high levels of HDI (e.g., Shanghai, Nanjing, Suzhou, and Hefei), they should focus on advanced waste management technologies and accelerate cross-jurisdictional sharing of high-quality healthcare and education resources through digital platforms to become regional centers of innovation and service excellence. As for cities with an average level of HDI (e.g., Anqing, Liuan, Fuyang, etc.), these cities should prioritize the improvement of basic waste management infrastructure and the expansion of educational opportunities in order to reduce regional disparities.

Secondly, promote innovation investment and green finance. The government ought to make the most of the regulatory effects of investment intensity and bolster the contribution of innovation investment to the reduction of carbon emissions. Local governments ought to support the green finance system and encourage the development of low-carbon technologies. When assigning fixed-asset investments, they also need to pay attention to green and sustainable projects. For these initiatives, it is imperative to improve environmental evaluations and openness. These initiatives will all have a major impact on reducing carbon emissions.

Thirdly, formulate policies in light of different characteristics of cities. Policies on livelihood development should be developed by the state and pertinent agencies in accordance with local circumstances. We can propose different policy concerns for different types of cities based on the heterogeneity analysis. On the one hand, in the regional heterogeneity analysis, we categorize the 41 cities into central area cities and non-central area cities according to the policy report. Central area cities (e.g., Shanghai, Hangzhou, Wuhu, etc.) should invest more in public services such as education and healthcare, build more low-carbon and energy-saving public facilities, and improve the quality of life for their residents. These central cities should play a leading role in promoting resource sharing and collaborative development with neighboring non-central cities through the establishment of regional cooperation mechanisms. Non-central area cities (e.g., Lianyungang, Lishui, Huangshan, etc.) should focus on improving public transportation and energy efficiency, leveraging their ecological advantages to create ecologically livable cities, and developing low-carbon industries such as eco-agriculture and rural tourism to promote residents' employment and income generation. On the other hand, in the type heterogeneity analysis, we classify cities into resource-based cities and non-resource-based cities. Resource-based cities (e.g., Xuzhou, Suqian, Huzhou, etc.) should increase ecological restoration in resource extraction areas to improve the ecological environment and enhance residents' quality of life. They should also accelerate the optimization of their energy structure, reducing dependence on traditional fossil fuels and increasing the use of renewable energy. Non-resource-based cities (e.g., Changzhou, Nantong, Ningbo, etc.) should promote the greening of public service facilities such as education and healthcare to improve energy efficiency and reduce carbon emissions. Additionally, these cities should strengthen scientific and technological innovation and support enterprises in the research and development and application of low-carbon technologies to enhance industrial competitiveness. These measures will not only reinforce the inverted U-shaped relationship between livelihood development and carbon emissions in central and non-resource-based cities but also facilitate the transition of non-central and resource-based cities to low-carbon development.

7 Limitations and future directions

Although this study provides new insights into how livelihood development affects CO_2 emissions, there are still some limitations. First, this study uses panel data from the Yangtze River Delta urban agglomeration rather than time series data from individual cities. The focus on quantitative analysis may not adequately capture the specific characteristics of each city. Therefore, specific findings and policy recommendations cannot be provided for each city. Additionally, this study focuses on the mediating role of innovation inputs and the moderating role of investment intensity between livelihood development and CO_2 emissions in the Yangtze River Delta urban agglomeration. However, other potential influencing factors, such as public services and social trust, are not included in the analysis. This may affect the comprehensiveness of the mechanism analysis.

In response to these limitations, future research can be expanded and deepened in the following ways. First, conduct specific and in-depth urban analysis. Future research can use county-level data to conduct more specific and in-depth analyses of urban agglomerations, building on the overall impact studies. For example, using county-level carbon emissions data to analyze the heterogeneity of different counties in the relationship between livelihood development and carbon emissions can provide more targeted recommendations for city-level policymaking (Zhu et al., 2024). Second, enrich the mechanism variables. Future studies may consider adding factors such as public services and social trust as mechanism variables to enrich the current findings. For example, the optimization of public services may affect carbon emissions by

improving residents' quality of life and promoting green consumption (Prabhu and Pai, 2012). Social trust may play an important role in environmental protection by reducing CO_2 emissions through social expectations and public opinion pressure (Zhang and Fu, 2023).

Data availability statement

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

Author contributions

ZZ: Conceptualization, Formal Analysis, Funding acquisition, Software, Writing – review and editing. WL: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review and editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was supported by both the Research on Technology Benefit Sharing and Protection Mechanisms of China's Direct Investments in Countries Along the Belt and Road Route under the Program of the National Social Science Foundation of China (20BJL063) and the Jiangsu Provincial Social Science Applied Research Excellence Project, "Research on Carbon Peak Prediction and Carbon Reduction Paths in Jiangsu Urban Agglomeration under the 'Dual Carbon' Target" (22SYB-119).

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.

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 author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2025.1523850/full#supplementary-material

References

Aminetzah, D., Denis, N., Henderson, K., Katz, J., and Mannion, P. (2020). Agriculture and climate change Reducing agriculture emissions through improved farming practices.

Banday, U. J., and Kocoglu, M. (2023). Modelling simultaneous relationships between human development, energy, and environment: fresh evidence from panel quantile regression. *J. Knowl. Econ.* 14 (2), 1559–1581. doi:10.1007/s13132-022-00921-2

Baron, R. M., and Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *J. personality Soc. Psychol.* 51 (6), 1173–1182. doi:10.1037/0022-3514.51.6.1173

Bond, S., Leblebicioğlu, A., and Schiantarelli, F. (2010). Capital accumulation and growth: a new look at the empirical evidence. *J. Appl. Econ.* 25 (7), 1073–1099. doi:10.1002/jae.1163

Chen, M., Liu, Y., Liu, W., and Wang, S. (2020). Measurement, source decomposition and formation mechanism of regional differences in urban livelihood development in China. *Statistical Research* 37 (5), 54–67. doi:10.13653/j.cnki.jqte.2020.01.002

Chen, Z., Wu, S., Ma, W., Liu, X., Cai, B., Liu, J., et al. (2018). Driving forces of carbon dioxide emission for China's cities: empirical analysis based on extended STIRPAT Model. *China Popul. Resour. Environ.* 28 (10), 45–54. doi:10.12062/cpre.20180729

Cracolici, M. F., Cuffaro, M., and Nijkamp, P. (2010). The measurement of economic, social and environmental performance of countries: a novel approach. *Soc. Indic. Res.* 95, 339–356. doi:10.1007/s11205-009-9464-3

Crutzen, P. J. (2002). Geology of mankind. *Nature* 415 (6867), 23. doi:10.1038/415023a

Cumming, G. S., and von Cramon-Taubadel, S. (2018). Linking economic growth pathways and environmental sustainability by understanding development as alternate social–ecological regimes. *Proc. Natl. Acad. Sci.* 115 (38), 9533–9538. doi:10.1073/pnas.1807026115

Fan, Z., and Pei, X. (2023). Spatial-temporal Evolution and Analysis of Influencing Factors of Energy Consumption and in the Yangtze River Economic. *Belt. Resour. Resour. Environ. Yangtze Basin* 32, 2225–2236. doi:10.11870/cjlyzyyhj202311001

Grossman, G. M., and Krueger, A. B. (1995). Economic growth and the environment. *Q. J. Econ.* 110 (2), 353–377. doi:10.2307/2118443

Guan, D., Meng, J., Reiner, D. M., Zhang, N., Shan, Y., Mi, Z., et al. (2018). Structural decline in China's CO2 emissions through transitions in industry and energy systems. *Nat. Geosci.* 11 (8), 551–555. doi:10.1038/s41561-018-0161-1

Haans, R. F., Pieters, C., and He, Z. L. (2016). Thinking about U: theorizing and testing U-and inverted U-shaped relationships in strategy research. *Strategic Manag. J.* 37 (7), 1177–1195. doi:10.1002/smj.2399

Han, F., and Xie, R. (2017). Does the agglomeration of producer services reduce carbon emissions. *J. Quant. Tech. Econ.* 34 (03), 40–58. doi:10.13653/j.cnki.jqte.2017.03.003

He, Y., Lin, Y., Zhou, G., Zhu, Y., and Tang, K. (2021). Spatial pattern and drivers of urbanization in China's mid-level developing urban agglomeration: a case study of Chang-Zhu-Tan. *Reg. Sustain.* 2 (1), 83–97. doi:10.1016/j.regsus.2020.12.001

Hussain, A., and Dey, S. (2021). Revisiting environmental Kuznets curve with HDI: new evidence from cross-country panel data. *J. Environ. Econ. Policy* 10 (3), 324–342. doi:10.1080/21606544.2021.1880486

IEA (2023). Tracking clean energy progress 2023. (Paris).

IEA (2024). CO2 emissions in 2023. (Paris).

Kijewska, A., and Bluszcz, A. (2016). Analysis of greenhouse gas emissions in the European Union member states with the use of an agglomeration algorithm. *J. Sustain. Min.* 15 (4), 133–142. doi:10.1016/j.jsm.2017.02.001

Kuznets, S. (1955). Economic growth and income inequality. *Am. Econ. Rev.* 45 (1), 1–28. doi:10.4324/9780429311208-4

Kvon, G. M., Prokopyev, A. I., Shestak, V. A., Larionova, A. A., and Shikh, E. V. (2019). Features of cost advantages from implementation of energy-saving projects. *Int. J. Energy Econ. Policy* 9 (3), 53–58. doi:10.32479/ijeep.7645

Lian, Y., Peng, F., and Su, Z. (2010). Financing constraints and liquidity management behavior. *Journal of Financial Research* 10, 158–171.

Liu, C., Nie, F., and Ren, D. (2020). Research on the measurement of human development level in China: Research on HDI Expansion Based on New development Concept. *Inquiry into Econ. Issues* 3, 58–73.

Liu, P., and Mu, Y. (2024). Green finance, carbon trading and industrial performance: Influencing mechanism and evidence from the 7 pilot projects of China. *China Soft Sci.* 4, 25–36. doi:10.3969/j.issn.1002-9753.2024.04.003

Liu, Y., Gao, C., and Lu, Y. (2017). The impact of urbanization on GHG emissions in China: the role of population density. *J. Clean. Prod.* 157, 299–309. doi:10.1016/j.jclepro.2017.04.138

Ma, M., Rozema, J., Gianoli, A., and Zhang, W. (2022). The impacts of city size and density on CO 2 emissions: evidence from the Yangtze River Delta urban agglomeration. *Appl. Spatial Analysis Policy* 15, 529–555. doi:10.1007/s12061-021-09406-2

Majewska, A., and Gierałtowska, U. (2022). Impact of economic affluence on CO2 emissions in CEE countries. *Energies* 15 (1), 322. doi:10.3390/en15010322

Maji, I. K. (2019). Impact of clean energy and inclusive development on CO2 emissions in sub-Saharan Africa. *J. Clean. Prod.* 240, 118186. doi:10.1016/j.jclepro.2019.118186

Marra, A., Antonelli, P., Dell'Anna, L., and Pozzi, C. (2015). A network analysis using metadata to investigate innovation in clean-tech–Implications for energy policy. *Energy Policy* 86, 17–26. doi:10.1016/j.enpol.2015.06.025

Michalos, A. C., and Hatch, P. M. (2020). Good societies, financial inequality and secrecy, and a good life: from Aristotle to Piketty. *Appl. Res. Qual. Life* 15, 1005–1054. doi:10.1007/s11482-019-09717-0

Mohmmed, A., Li, Z., Arowolo, A. O., Su, H., Deng, X., Najmuddin, O., et al. (2019). Driving factors of CO2 emissions and nexus with economic growth, development and human health in the Top Ten emitting countries. *Resour. Conservation Recycl.* 148, 157–169. doi:10.1016/j.resconrec.2019.03.048

Morse, S. (2020). To rank or not to rank with indices? That is the question. *Sustainability* 12 (14), 5572. doi:10.3390/su12145572

Pala, O. (2024). Assessment of the social progress on European Union by logarithmic decomposition of criteria importance. *Expert Syst. Appl.* 238, 121846. doi:10.1016/j.eswa.2023.121846

Prabhu, A., and Pai, M. (2012). Buses as low-carbon mobility solutions for urban India: evidence from two cities. *Transp. Res. Rec.* 2317 (1), 15–23. doi:10.3141/2317-03

Ren, D., Cao, G., and Long, S. (2021). Analysis of the coordination degree of social development in China based on the framework of HDI. *J. Quant. Technol. Econ* 38, 88–106. doi:10.13653/j.cnki.jqte.2021.06.004

Sen, A., Stiglitz, J., and Fitoussi, J.-P. (2010). Mis-measuring our lives: why GDP doesn't add up?.

Shao, S., Liu, J., Geng, Y., Miao, Z., and Yang, Y. (2016). Uncovering driving factors of carbon emissions from China's mining sector. *Appl. Energy* 166, 220–238. doi:10.1016/j.apenergy.2016.01.047

Tyagi, S., Tiwari, S., Mishra, A., Hopke, P. K., Attri, S. D., Srivastava, A. K., et al. (2016). Spatial variability of concentrations of gaseous pollutants across the National Capital Region of Delhi, India. *Atmos. Pollut. Res.* 7 (5), 808–816. doi:10.1016/j.apr.2016.04.008

Tyrrell, T. (2011). Anthropogenic modification of the oceans. *Philosophical Trans. R. Soc. A Math. Phys. Eng. Sci.* 369 (1938), 887–908. doi:10.1098/rsta.2010.0334

UNDP (1990). *Human development report 1990*. (New York: United Nations).

UNDP (2024). *Human development report 2023-24*. UNDP (New York: United Nations Development Programme).

UNDP, THU-CIDP, and Center, S.I. (2019). China Institute for Development Planning at Tsinghua University. National Human Development Report Special Edition. (Beijing).

Van Tran, N., Van Tran, Q., Do, L. T. T., Dinh, L. H., and Do, H. T. T. (2019). Trade off between environment, energy consumption and human development: do levels of economic development matter? *Energy* 173, 483–493. doi:10.1016/j.energy.2019.02.042

Wan, Z., el Makhloufi, A., Chen, Y., and Tang, J. (2018). Decarbonizing the international shipping industry: solutions and policy recommendations. *Mar. Pollut. Bull.* 126, 428–435. doi:10.1016/j.marpolbul.2017.11.064

Wang, D., Hou, Y., Li, X., Huang, Y., and Wang, Y. (2022). Spatio-temporal analysis of China's livelihood development: evidence from a functional index model. *Appl. Spatial Analysis Policy* 15 (4), 1493–1523. doi:10.1007/s12061-022-09460-4

Wang, M., Kang, W., and Zhang, B. (2019). A study on the characteristics of China Human Development Index and driving forces since the reform and opening-up. *China Population, Resources and Environment* 29 (10), 70–78. doi:10.12062/cpre.20190632

Wang, S., Huang, Y., and Zhou, Y. (2019). Spatial spillover effect and driving forces of carbon emission intensity at the city level in China. *J. Geogr. Sci.* 29, 231–252. doi:10.1007/s11442-019-1594-1

Wang, S., Luo, Y., Han, Y., and Li, J. (2018). Regional difference and determinants of human well-being in China: based on the analysis of human development index. *Progress in Geography* 37 (8), 1150–1158. doi:10.18306/dlkxjz.2018.08.014

Wei, T. (2011). What STIRPAT tells about effects of population and affluence on the environment? *Ecol. Econ.* 72, 70–74. doi:10.1016/j.ecolecon.2011.10.015

Will, S., Paul, J. C., and John, R. M. (2007). The anthropocene: are humans now overwhelming the great forces of nature. *AMBIO A J. Hum. Environ.* 36 (8), 614–621. doi:10.1579/0044-7447(2007)36[614:TAAHNO]2.0.CO;2

Wu, Y., and Xu, H. (2023). The effect of FDI agglomeration on carbon emission intensity: evidence from city-level data in China. *Sustainability* 15 (2), 1716. doi:10.3390/su15021716

Yan, J., Zhao, J., Yang, X., Su, X., Wang, H., Ran, Q., et al. (2021). Does low-carbon city pilot policy alleviate urban haze pollution? Empirical evidence from a quasi-natural experiment in China. *Int. J. Environ. Res. Public Health* 18 (21), 11287. doi:10.3390/ijerph182111287

Yang, S., Zhang, Y., and Geng, Y. (2022). An LMDI-based investigation of the changes in carbon emissions of the transportation sector in the Yangtze River Economic Belt. *China Environmental Science* 42 (10), 4817–4826. doi:10.3969/j.issn.1000-6923.2022.10.040

Yang, Y., and Niu, X. (2023). Impact of social trust on the effectiveness of environmental regulations on carbon emission reduction: based on panel data from 281 prefecture-level cities in China. *China Popul. Resour. Environ* 33, 82–92. doi:10.12062/cpre.20221030

Ye, X., Xie, C., and Mao, Z. (2018). The sense of gain and the satisfaction of people's livelihood in China: measuring and variance analysis. *The Journal of Quantitative & Technical Economics* 35 (10), 3–20. doi:10.13653/j.cnki.jqte.2018.10.001

York, R., Rosa, E. A., and Dietz, T. (2003). STIRPAT, IPAT and ImPACT: analytic tools for unpacking the driving forces of environmental impacts. *Ecol. Econ.* 46 (3), 351–365. doi:10.1016/s0921-8009(03)00188-5

Yumashev, A., Ślusarczyk, B., Kondrashev, S., and Mikhaylov, A. (2020). Global indicators of sustainable development: evaluation of the influence of the human development index on consumption and quality of energy. *Energies* 13 (11), 2768. doi:10.3390/en13112768

Zalasiewicz, J., Williams, M., Haywood, A., and Ellis, M. (2011). The Anthropocene: a new epoch of geological time? *Philosophical Trans. R. Soc. A Math. Phys. Eng. Sci.* 369 (1938), 835–841. doi:10.1098/rsta.2010.0339

Zhang, Y., and Fu, B. (2023). Social trust contributes to the reduction of urban carbon dioxide emissions. *Energy* 279, 128127. doi:10.1016/j.energy.2023.128127

Zhenjun, Y., Shun, S., Hao, H., Hongyan, A., Wang, L., and Qianhao, L. (2023). Research on the level of fishery mechanization in Beijing based on trend extrapolation. *Journal of Chinese Agricultural Mechanization* 44 (6), 217. doi:10.13733/j.jcam.issn.2095-5553.2023.06.031

Zhu, Z., Qi, X., Jia, Y., and Huang, r. (2024). Analysis of spatial-temporal pattern and influencing factors of CO2 emissions in the Yangtze River Delta urban agglomeration. *Resources and Environment in the Yangtze Basin* 33, 242–253. doi:10.11870/cjlyzyyhj202402002

Zou, Y., Huang, M., Xiang, W., Lu, L., Lu, Y., Gao, J., et al. (2022). The impact of high-tech industry development on energy efficiency and its influencing mechanisms. *Front. Environ. Sci.* 10, 962627. doi:10.3389/fenvs.2022.962627

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 10 April 2025
DOI 10.3389/fenvs.2025.1453151

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Jingkuang Liu,
Guangzhou University, China
Zhenshuang Wang,
Dongbei University of Finance and Economics, China

*CORRESPONDENCE
Ziyu Diao,
2212219027@stmail.ujs.edu.cn

RECEIVED 22 June 2024
ACCEPTED 01 April 2025
PUBLISHED 10 April 2025

CITATION
Li F and Diao Z (2025) The impact of digital infrastructure on the synergistic effects of urban pollution and carbon reduction: empirical evidence from China.
Front. Environ. Sci. 13:1453151.
doi: 10.3389/fenvs.2025.1453151

COPYRIGHT
© 2025 Li and Diao. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

The impact of digital infrastructure on the synergistic effects of urban pollution and carbon reduction: empirical evidence from China

Fanglin Li and Ziyu Diao*

School of Finance and Economics, Jiangsu University, Zhenjiang, Jiangsu, China

Digital infrastructure, as a core component of new infrastructure, plays a powerful engine role in driving urban development. It not only profoundly shapes the future landscape of cities but also plays an irreplaceable role in accelerating the dual transition of industries toward digitization and greening. This process not only promotes the deep integration and synergistic development of urban digitization and greening but also cleverly builds a bridge for the dual benefits of pollution reduction and carbon reduction, laying a solid foundation for achieving an environmentally friendly and resource-saving society. This study adopt a multifaceted approach to explore the impact of digital infrastructure on the synergistic management of urban pollution abatement and carbon reductions. The coefficient for this effect was statistically significant at a 1% significance level (0.1056), demonstrating its capacity to support reductions in both pollution and carbon emissions, with regional variations observed. Furthermore, examining factor flows reveals that digital infrastructure promotes enhanced labor, capital, and innovation flows. Notably, the impact of digital infrastructure on these sectors exhibited coefficients of 57.5616, 0.0097, and 0.0189 respectively. These findings point to a significant nexus between digital infrastructure and sustainable urban development. A nonlinear U-shaped relationship was observed between digital infrastructure and the joint effect of both pollution mitigation and carbon reduction. This study concludes with policy recommendations aiming to optimize the utilization of digital infrastructure for achieving sustainable urban development goals.

KEYWORDS

digital infrastructure, pollution and carbon reduction synergies, labor factor flow, capital factor flow, innovation factor flow

1 Introduction

Air pollution and carbon emissions, recognized as pivotal contributors to global warming (Allen et al., 2009; Amann et al., 2013), present substantial challenges to the attainment of sustainable development goals (SDGs). Therefore, reducing air pollution and mitigating carbon emissions holds a universal imperative for global progress.

China's extensive economic development model has fueled a continuous increase in carbon emissions (Zheng H. et al., 2023), while simultaneously grappling with elevated levels of air pollution compared to other nations. Notably, over 40% of Chinese cities are

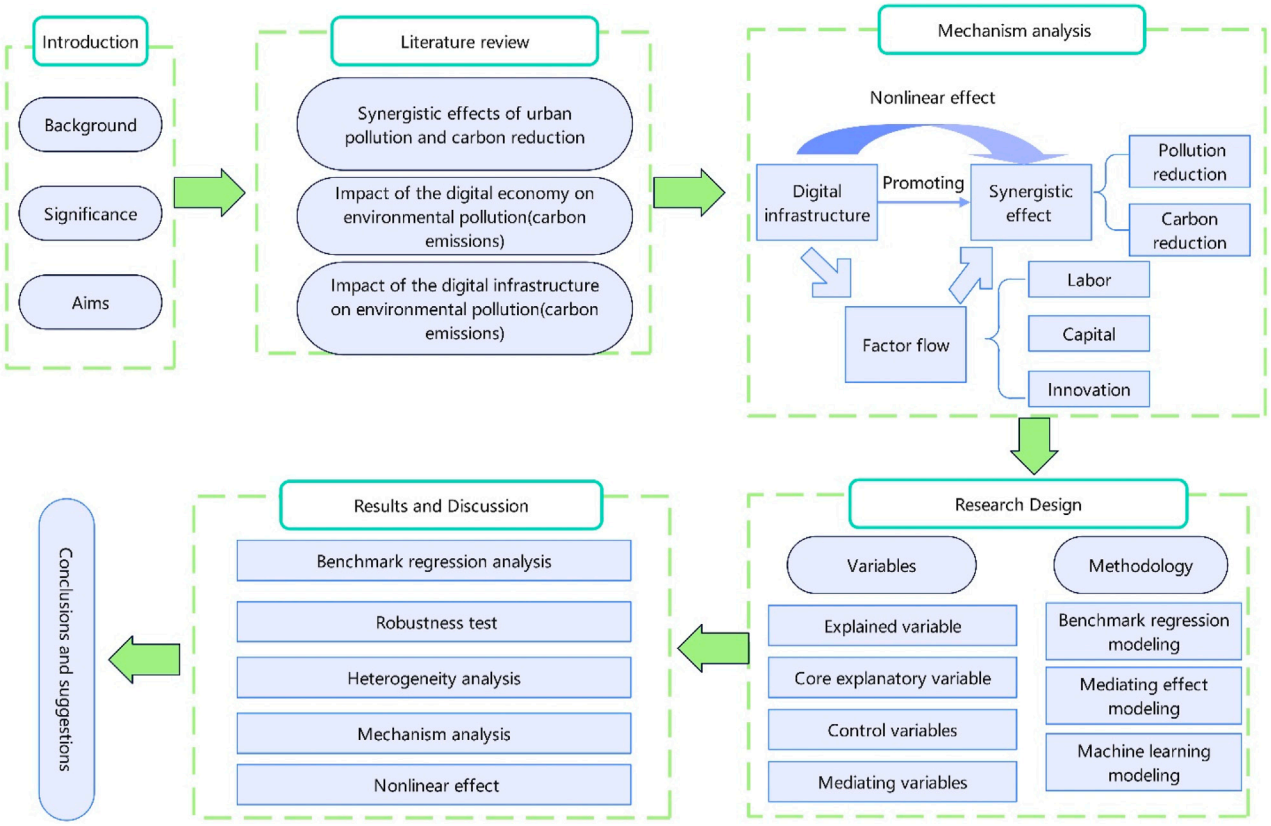


FIGURE 1
Analysis framework.

projected to exceed the international average PM2.5 concentration by 2021 (Hu et al., 2022), impacting both public health and economic wellbeing. Based on this, the Chinese government has implemented a series of measures to reduce pollution and carbon emissions, such as promoting clean energy and strengthening environmental regulation. However, with the acceleration of urbanization and rapid economic development, pollution and carbon emission issues remain severe. Against this backdrop, how to further innovate management methods and enhance the effectiveness of pollution reduction and carbon emission reduction has become an important topic in the management practices of urban pollution and carbon reduction.

Digital infrastructure, as an emerging technological force, is gradually demonstrating its potential in promoting green economic transformation and reducing pollution and carbon emissions. Driven by data innovation, built on communication networks, and centered around data computing facilities, digital infrastructure possesses the powerful ability to break down barriers, optimize resource allocation, and facilitate industrial advancement (Guo et al., 2023; Tranos, 2012).The burgeoning field of digital infrastructure research is exploring the impact on environmental quality (J. Hu et al., 2023; Zhuo et al., 2023). Digital infrastructure plays a critical role in facilitating industrial digitalization by enabling seamless integration with traditional sectors, thereby fostering transformative changes within industrial structures (Ren et al., 2021; Xue et al., 2022). This integration has the potential to mitigate air pollutants and carbon emissions through industrial transformation. However, certain studies raise concerns regarding the possibility of increased energy consumption arising from extensive digital infrastructure deployment (Ren et al., 2021; Xue et al., 2022). However, there is still controversy regarding how digital infrastructure affects air pollutants and carbon emissions, necessitating deeper analysis and discussion. It is essential to clarify the mechanisms by which digital infrastructure influences the synergistic effects of pollution reduction and carbon reduction.

This study examines the impact of digital infrastructure on the synergistic effects of pollution reduction and carbon reduction using relevant data from 282 cities in China from 2011 to 2021. The research objectives are as follows: first, to clarify the specific role of digital infrastructure in current urban pollution and carbon reduction management practices; second, to reveal how digital infrastructure indirectly promotes pollution reduction and carbon reduction by influencing the flow of factors; and finally, to explore potential nonlinear effects of digital infrastructure on the synergistic effects of pollution reduction and carbon reduction, as well as to identify key influencing factors. It is hoped that this research will provide scientific evidence and practical guidance for policymakers, facilitating greater effectiveness in urban pollution and carbon reduction efforts in China and globally.

The paper is structured as follows: the second section presents a comprehensive review of relevant literature; the third section employs mechanism analysis to elucidate causal relationships

between variables; the fourth section details the methodology employed in this study, emphasizing methodological rigor and transparency; the fifth section synthesizes findings and offers an in-depth discussion; and the concluding section provides actionable recommendations for policy development and implementation. The structure of this paper is shown in Figure 1.

2 Literature review

Economic and societal development has driven a substantial increase in carbon emissions and air pollutants (He et al., 2011), posing a severe threat to both the ecological environment and public health (Chen D. et al., 2021). Existing research focuses on measuring the level of coordinated management of carbon emissions and air pollutants, as well as assessing the influencing factors and impacts. For example, Henneman et al. (2016) utilized the GAINS model to investigate the complex interactions between air pollution and carbon emissions under various environmental scenarios. Liu et al. (2024) used an improved Tapio Decoupling Principle and Probit model to explore the factors affecting the synergistic effects of urban pollution reduction and carbon emission mitigation, and ultimately found that environmental regulation is the main influencing factor. Fujimori et al. (2015) emphasized the effectiveness of carbon trading in mitigating both air pollutants and carbon emissions, leading to positive ecological outcomes. In addition, some scholars have conducted research specifically on the construction industry, aiming to explore the actual effects of construction waste sorting on promoting pollution reduction and carbon emission reduction (Liu et al., 2023), as well as the potential impact of this measure on economic growth (Wang Z. et al., 2022; Wang et al., 2024).

The burgeoning digital economy exerts a profound influence on urban development, necessitating comprehensive analysis of its multifaceted relationship with environmental sustainability. Existing research has focused primarily on elucidating the nexus between the digital economy and urban pollution reduction, as well as the regulatory mechanisms governing carbon emissions. Nonetheless, the scholarly discourse regarding the impact of digital economic expansion on pollution reduction remains fragmented. While some scholars espouse a positive outlook, anticipating transformative potential for reducing air quality issues, others advocate a cautious stance, citing concerns about an "energy rebound effect". Heddeghem et al. (2014) posit that the digital economy's growth may trigger increased energy consumption, thereby exacerbating regional atmospheric pollution levels. Che and Wang (2022), on the other hand, leveraged PM2.5 data to assess haze pollution levels and employed multiperiod DID modeling to demonstrate a positive correlation between the digital economy and reduced haze pollution levels. Further research into this complex dynamic is critical for a nuanced understanding of the digital economy's contribution to environmental conservation.

The digital economy presents a nuanced landscape for carbon reduction, with Bai et al. (2023) emphasizing its capacity to curtail emissions through industrial transformation and upgrading. However, their work highlights the potential for such progress to trigger a relocation of heavy industries to underdeveloped regions, thereby exacerbating localized carbon emissions in those areas. Li and Wang (2022), in contrast, investigated the spatial spillover effects of the digital economy on carbon emissions, revealing an inverted U-shaped pattern in their findings. This complexity underscores the need for deeper investigation into this phenomenon. Further research delves into the intricate interplay between the digital economy and pollution reduction strategies. Hu (2023), employing a DID method within a quasi-natural experimental setup in the Big Data Comprehensive Experimental Zone, examined this dynamic. Their findings revealed that advancements in the digital economy effectively mitigate environmental pollution and carbon emissions while highlighting technological innovation and energy efficiency as pivotal drivers of these positive impacts.

Research into the impact of digital infrastructure on urban air pollution and carbon emissions has yielded a complex picture (Tang and Yang, 2023). While Qiao et al. (2021) found that improving energy efficiency through traditional infrastructure upgrades can lead to decreased air pollution, Zou and Pan (2023) emphasize the role of digital infrastructure in mitigating this issue, attributing its positive impact to green innovations. Studies by Zhang P. et al. (2022) further highlight the potential for digital infrastructure to enhance air quality through industrial structure upgrades and technological advancements, particularly within Chinese provinces. However, some scholars caution that digital infrastructure can exacerbate air pollutant emissions. Notably, increased ICT development in specific South American countries has been linked to exacerbated air pollution levels, highlighting the need for careful consideration (Avom et al., 2020; Cheng et al., 2019). Based on an analysis of comprehensive data from 83 countries worldwide, Che et al. (2024) concluded that the development of digital infrastructure has significantly driven the increase in national carbon emissions by promoting capital aggregation and increasing the consumption of fossil energy.

The deployment of digital infrastructure in the context of carbon reduction is multifaceted and subject to ongoing investigation. Dong et al. (2022) employed a double difference model to analyze this relationship, revealing that technological innovation, industrial structure upgrades, optimized factor allocation, and fostering industrial concentration are key drivers of carbon reductions facilitated by digital infrastructure. However, the spatial spillover effects of digital infrastructure on carbon emissions have also been scrutinized, with scholars observing distinct regional variations (Liu and Wan, 2023; Sun and Kim, 2021). Notably, a subset of researchers posit that the relationship between digital infrastructure and carbon emission reduction is not straightforward. Hu et al. (2023) employed threshold and quantile models to delve into this dynamic, uncovering an increasing marginal effect of digital infrastructure on carbon emissions reduction, suggesting potential benefits for cities with advanced low-carbon practices, but perhaps hindering efforts in those lagging behind. Conversely, Sadorsky (2012) conducted a dynamic panel data study focusing on the influence of ICT growth on electricity demand, revealing that its impact surpasses income levels, potentially indicating a negative impact on carbon reduction efforts by expansion of digital infrastructure. Wang and Zhong (2023), further explored this point, identifying an energy-intensive distribution scenario resulting from digital

infrastructure expansion, which ultimately leads to diminished energy efficiency and subsequently heightened carbon emissions.

Despite a wealth of research endeavoring to elucidate the implications of the digital economy for environmental pollution and carbon emissions, the existing body of literature is notably sparse with respect to the specific influence of digital infrastructure on these critical issues. The majority of extant studies have concentrated on the direct effects of the digital economy on environmental indicators, often overlooking the complex, synergistic interplay between digital infrastructure and the mitigation of pollution. This gap in understanding stems from a lack of comprehensive analysis of the intricate nonlinear dynamics that govern the relationship between digital infrastructure and environmental conservation, which are influenced by a myriad of factors, including evolving energy demands and advancements in energy efficiency technologies. Therefore, there is an urgent need for further research to delve into the complex interplay between digital infrastructure and carbon mitigation strategies. Such an investigation is essential for a nuanced evaluation of the role digital infrastructure plays in environmental conservation, particularly through a thorough examination of its nonlinear dynamics. An integrated analysis of the governance of pollution and carbon reduction will be instrumental in achieving a more accurate assessment of the contribution of digital infrastructure to sustainable urban development.

3 Mechanism analysis

Digital infrastructure, a cornerstone of the contemporary infrastructure paradigm, plays a crucial role in modernizing daily life through the integration of information technology. Unlike traditional infrastructure reliant on physical components like iron and concrete, digital infrastructure offers inherent eco-friendly advantages, consuming significantly less energy than its counterpart (Lan and Zhu, 2023). This results in reduced ecological footprints within urban environments. Moreover, digital infrastructure fosters cleaner industrial practices by enabling residents to embrace more sustainable lifestyles. Smart home technologies empower individuals to exert precise control over their energy consumption, while intelligent air conditioning systems adapt output based on temperature fluctuations to minimize wastage (Favoretto et al., 2022; Ghosh et al., 2022). Similarly, smart lighting systems intelligently adjust based on ambient light conditions. The integration of digital infrastructure into daily routines supports the decarbonization of household routines and contributes to reduced energy usage, air pollution, as well as environmental sustainability in various sectors. Specifically, digital infrastructure promotes a notable enhancement in manufacturing sector's energy efficiency (Rathore et al., 2018; Yong et al., 2020), achieved by leveraging big data and cloud computing to optimize production processes, streamline operations, and reduce unnecessary energy and carbon emissions. Furthermore, digital infrastructure supports collaborative efforts between industries, encourages resource recycling, waste reduction, thereby decreasing pollutants and greenhouse gas emissions. In transportation, where significant emissions are prevalent, digital infrastructure provides crucial solutions for reducing carbon footprints through smart transportation systems, data-driven traffic forecasting, congestion prediction, and route optimization (Chen et al., 2016; Guerrero-ibanez et al., 2015). The adoption of new energy vehicles fueled by digital infrastructure further mitigate pollution and carbon emissions in transit operations (Li J. et al., 2024). These advancements underpin the research hypothesis that:

H1: Digital infrastructure can accelerate the process of urban pollution reduction and carbon reduction and realize the synergy of pollution reduction and carbon reduction.

Digital infrastructure has revolutionized the dynamics of production factors, transcending geographical barriers to facilitate a self-sustaining and efficient circulation of resources within a more robust market ecosystem. This transformation is driven by digital infrastructure's ability to break down physical limitations and foster interconnectedness (Ndubuisi et al., 2021).This expansion dramatically broadens information dissemination, mitigating informational disparities within the workforce (Hu et al., 2023), thereby streamlining workforce integration into suitable roles and enhancing labor mobility. Furthermore, digital infrastructure enhances knowledge access through online platforms, empowering individuals to acquire essential skills for diverse occupational contexts (Raab et al., 2001), ultimately elevating overall workforce education levels and fostering greater versatility (Tang and Zhao, 2023). This enhanced skill acquisition further promotes labor market fluidity. Digital infrastructure's impact is not limited to labor; it also drives capital mobility at unprecedented speeds. Digital trading platforms facilitate swift mutual understanding between trading entities (He et al., 2020), accelerating the financing process and optimizing capital utilization. These innovations stimulate financial markets through novel financial products, derived from digital integration (Stein, 2002). Consequently, the flow of capital is facilitated significantly. Furthermore, enhancing digital infrastructure fosters financial innovation, which involves integrating digital technologies to create new financial products (Li et al., 2022). This expansion in investment options for investors leads to increased market activity and further accelerates the movement of capital. Third, digital infrastructure facilitates the movement of factors that drive creativity. By leveraging internet platform connectivity and interaction capabilities, digital infrastructure enables unrestricted innovation factor exchange across geographical boundaries (Hu et al., 2023). This dismantles traditional limitations imposed by geographic locations, fostering greater knowledge spillover effects (Wood et al., 2018), thereby accelerating the exchange of innovative ideas between cities.

The enhanced mobility of production factors stands as a key driver in accelerating the reduction of urban pollution and the effective management of carbon emissions. This transformation is mediated by several interconnected mechanisms, all contributing to the broader goal of achieving environmental sustainability within urban environments: First, labor mobility holds the potential to significantly expedite efforts aimed at decreasing urban pollutants and carbon emissions. By addressing labor supply and demand imbalances, labor mobility promotes a more efficient allocation of human capital (Yashiv, 2007), ultimately leading to enhanced talent availability in energy-intensive sectors. This increased capacity for

specialized workforce development paves the way for a smoother transition toward sustainable practices, thereby resulting in reduced emissions of both carbon and other pollutants (Ouyang and Sun, 2015). Furthermore, labor mobility fosters environmental conservation ethos by facilitating the transfer of skilled individuals to smaller cities, stimulating regional industries and driving innovation (Chen et al., 2021b; Wu et al., 2022). Second, capital factor flows can act as a catalyst for mitigating urban pollution and reducing carbon emissions. Capital flows can direct capital toward green industries (Wang and Wang, 2021; Wei et al., 2015), offering financial assistance for the eco-friendly transformation of energy-consuming sectors. This process facilitates the upgrading of urban industries and contributes to a more coordinated approach to managing urban pollution and carbon reduction (Hao et al., 2020; Wu and Chen, 2001).Cross-border capital movement also introduces advanced production management knowledge, ultimately boosting industrial labor productivity while curtailing emissions, thereby meeting environmental objectives (Wu and Chen, 2001).Third, the flow of innovative elements accelerates clean energy technology adoption within urban settings, a phenomenon known as the "Porter effect." This transformative force revitalizes urban energy frameworks and increases the share of clean energy, ultimately enhancing the cityscape's overall environmental footprint (Malhotra et al., 2019; Steffen et al., 2018). Moreover, this increased adoption of clean energy technologies can trigger stronger governmental regulations surrounding environmental protection, prompting enterprises to implement stricter environmental policies. This, in turn, helps curb urban carbon and pollutant emissions (Liao, 2018), demonstrating the interconnected nature of innovation, policy, and environmental sustainability. In light of these insights, a compelling hypothesis emerges:

H2: Digital infrastructure promotes the synergistic effect of urban pollution reduction and carbon reduction by accelerating the flow of factors (labor, capital and innovation).

Digital infrastructure plays a pivotal role in addressing urban pollution and carbon reduction efforts, exhibiting complex nonlinear dynamics that render simplistic linear models inadequate. The expansion of digital infrastructure historically results in heightened energy consumption as the demand for essential components such as data centers and communication stations surges (Dayarathna et al., 2015; Sharma et al., 2020). This increased demand can lead to significant environmental resource depletion and ecological damage, potentially exacerbating both urban pollution and carbon emissions (Dian et al., 2023). However, advancements in digital infrastructure innovation are driving a shift towards greener and more sustainable practices. These innovations have significantly enhanced the energy efficiency of IT equipment and communication networks through the implementation of cutting-edge energy-saving techniques, optimization strategies, and the integration of renewable sources (Uddin et al., 2012). This transition has positioned digital infrastructure as a key player in achieving urban pollution and carbon reduction targets. Digital infrastructure is evolving from a significant energy consumer to a green and sustainable energy carrier (Wu et al., 2021), fueling the sustainable development of cities. Through intelligent management, digital infrastructure facilitates the rational allocation and economic utilization of resources, reducing unnecessary energy consumption and emissions. Furthermore, its extensive deployment underpins urban environmental surveillance, pollution control, and eco-friendly transportation, further advancing the objectives of urban pollution reduction (Bibri, 2018). Based on these insights, the following research hypothesis is proposed:

H3: The impact of digital infrastructure on the synergistic effect of pollution reduction and carbon reduction in cities is nonlinear.

4 Research design

4.1 Variable definitions

The explained variable is the synergistic effect of pollution reduction and carbon reduction (*se*).To elucidate the intricate relationship between pollution reduction and carbon reduction subsystems, a comprehensive index system for evaluating their synergistic effects is developed in line with the methodology of Yi et al. (2022). This system, detailed in Table 1, provides a framework to quantify mutual influence between these two subsystems. Given the lack of carbon emission data at the urban level, this study references the research by Chen et al. (2020) and uses nighttime light data along with provincial carbon emission data to estimate the annual carbon dioxide emissions for cities (measured in tons).Utilizing coupling coordination models (as exemplified by Equations 1,2), the analysis delves into the intrinsic connections and dynamic patterns of change between pollution reduction and carbon reduction, shedding light on their interconnected nature.

$$C = \left\{ \frac{X_{it} Y_{it}}{(X_{it} + Y_{it})^2} \right\}^{\frac{1}{2}} \tag{1}$$

$$se = \sqrt{C \times (\alpha X + \beta Y)} \tag{2}$$

where X is the pollution reduction index and Y is the carbon reduction index, both of which are measured via the projection tracing method. The value range of C is [0,1]. α and β are weight values, both of which are set to 0.5. *se* is the system coupling coordination degree of pollution reduction and carbon reduction.

Core Explanatory Variable: Digital infrastructure (*inform*). Digital infrastructure refers to the foundational facilities that support the digital operation and smart development of cities, including but not limited to communication networks, data centers, cloud computing platforms, and Internet of Things (IoT) devices. Given the data accessibility at the city level, we utilize the indicator system developed by Tang and Yang (2023), as presented in Table 2. Additionally, we employ the projection pursuit model, optimized using a genetic algorithm, to assess the extent of urban digital infrastructure development. Regarding the construction level of digital infrastructure, we rely on the research conducted by Wen et al. (2022) to select the frequency of words related to digital infrastructure in government work reports each year as a metric for measuring the extent of digital infrastructure development.

Control variables: Based on a synthesis of multiple studies (Lee and Zhao, 2023; Tang and Yang, 2023), this paper controls for relevant variables to explore the synergistic effects of urban pollution

TABLE 1 Evaluation index system of the synergistic effect of urban pollution reduction and carbon reduction.

Target level	Primary indicators	Secondary indicators
Synergistic management degree of pollution reduction and carbon reduction	Pollution reduction	pm2.5
		Industrial soot emissions
		Growth rate of industrial soot
		Intensity of industrial soot emissions
	Carbon reduction	Carbon emissions
		Carbon Emission Growth Rate
		Carbon Emission Intensity

TABLE 2 Digital infrastructure indicator system.

Target level	Primary indicators	Secondary indicators
Digital infrastructure	Construction level	The interaction between digital infrastructure mentions in government reports and the secondary sector's value-added is analyzed
	Business Revenue	Revenue from telecommunication services
	Coverage	Number of international internet users
		Total mobile subscriber count at the year-end

TABLE 3 Descriptive statistics.

Variable	Obs	Mean	Std. dev	Min	Max
se	2,820	0.8646	0.0591	0.4513	0.9686
inform	2,820	0.1395	0.1520	0.0022	1.2781
pgdp	2,820	5.5127	3.1274	0.0000	21.8118
urb	2,820	0.5694	0.1472	0.1815	1.0000
hum	2,820	0.0200	0.0254	0.0000	0.1398
trans	2,820	1.1211	0.5233	0.0702	2.7780
is	2,820	0.0435	0.0102	0.0115	0.0907
energy	2,820	7.9925	91.3584	0.0252	1,204.9430
lff	2,820	3.8294	12.8139	−184.6440	151.0165
cff	2,820	0.0037	0.1866	−4.5326	4.6165
iff	2,820	0.0002	0.0093	−0.1172	0.0792

reduction and carbon emission reduction in depth.: Economic development level(pgdp) is measured by *per capita* development, which typically shows a positive correlation with urban pollution reduction and carbon emission reduction outcomes. (Zhang H. et al., 2022); urbanization rate(urb) is reflected by the proportion of the resident urban population; the advancement of urbanization helps improve resource use efficiency and achieve emission reduction targets. Human capital(hum) is measured by the number of higher education students per ten thousand people; enhancing human capital can increase public environmental awareness and promote sustainable development actions. (Fan et al., 2024).The level of transportation infrastructure(trans) is assessed by the ratio of urban road mileage to administrative area; well-developed transportation infrastructure is a key factor in enhancing urban energy efficiency (Zhang X. et al., 2023). Industrial structure upgrading(is) is indicated by the proportion of the tertiary industry in GDP, reflecting the development status of urban services and the level of industrial advancement. Finally, energy consumption intensity (energy) is benchmarked by energy consumption per ten thousand GDP; its reduction directly reflects the improvements in urban energy efficiency and the effectiveness of pollution reduction and carbon emission reduction efforts.

The mediating factors include labor factor flows (*lff*), capital factor flows (*cff*), and innovation factor flows (*iff*). The labor factor flow (*lff*), capital factor flow (*cff*), and innovation factor flow (*iff*) play vital and decisive roles in economic progress, serving as the primary driving forces behind the promotion of sustainable urban transformation. Hence, we utilize the Jones et al. (1986) model on factor flow to develop separate calculation models for labor factor flow, capital factor flow, and innovation factor flow. As exemplified by Equations 3-5.

$$lff_{it} = \frac{labor_{it}/gdp_{it}}{\sum_i labor_{it}/\sum_i gdp_{it}} - \frac{labor_{i,t-1}/gdp_{i,t-1}}{\sum_i labor_{i,t-1}/\sum_i gdp_{i,t-1}} \quad (3)$$

$$cff_{it} = \frac{capital_{it}/gdp_{it}}{\sum_i capital_{it}/\sum_i gdp_{it}} - \frac{capital_{i,t-1}/gdp_{i,t-1}}{\sum_i capital_{i,t-1}/\sum_i gdp_{i,t-1}} \quad (4)$$

$$iff_{it} = \frac{patent_{it}/gdp_{it}}{\sum_i patent_{it}/\sum_i gdp_{it}} - \frac{patent_{i,t-1}/gdp_{i,t-1}}{\sum_i patent_{i,t-1}/\sum_i gdp_{i,t-1}} \quad (5)$$

In this context, $labor_{it}$ denotes the total number of individuals who are currently employed inside the city. $capital_{it}$ represents the

fixed amount of capital resources available in the city. $patent_{it}$ signifies the total number of patents awarded, which is calculated by summing the number of invention patents, utility model patents, and design patents.

4.2 Econometric modeling

4.2.1 Benchmark regression modeling

This research aims to investigate the correlation between digital infrastructure and the synergistic effect of urban pollution and carbon emissions. To achieve this, an econometric model is constructed as outlined below:

$$se_{it} = \alpha_0 + \alpha_1 inform_{it} + \beta controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

In this context, se_{it} refers to the explained variable, specifically the magnitude of the synergistic management degree of pollution reduction and carbon reduction in city i during year t. Similarly, $inform_{it}$ refers to the core explanatory variable, namely, the level of digital infrastructure in city i during year t μ_i represents the control variables considered in this study, while λ_t represents an individual fixed effect. Additionally, there is a time fixed effect denoted by ε_{it}, which represents the random error term that varies across individuals and time periods.

4.2.2 Mediating effect modeling

This paper examines the precise mechanism through which digital infrastructure influences the synergistic effect of reducing urban pollution and carbon emissions. It does so by analyzing the flow of labor factors, capital factors, and innovation factors from three different perspectives. According to Yi et al. (2022), the following mediated effect model is established:

$$M_{it} = \delta_0 + \delta_1 inform_{it} + \gamma controls + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

The variable M_{it} serves as the mediating factor. δ_1 represents the effect of digital infrastructure on the mediator variable, while the remaining variables are consistent with Equation 6.

4.2.3 Machine learning modeling

To further investigate the nonlinear effects between digital infrastructure and the collaborative effects of urban pollution reduction and carbon emission reduction, this study first employs a random forest model to explore the nonlinear relationship between the two, and then uses the SHAP method to rank and interpret the results.

4.2.3.1 Random forest model

The random forest model, as an efficient ensemble learning method, consists of multiple decision trees. When constructing the model, it first randomly selects samples and subsets of features from the original dataset to build several decision trees, ensuring that each tree is trained independently. Finally, during the prediction phase, it uses a voting method for classification tasks and an averaging method for regression tasks to combine the predictions of all the decision trees, resulting in a final prediction that is accurate and stable. As exemplified by Equation 8. In this study, we have constructed such a random forest model to deeply explore the complex nonlinear relationship between digital infrastructure and the collaborative effects of urban pollution reduction and carbon emission reduction:

$$se_{it} = \Phi\left(inform_{it}, controls_{it}, \mu_k, \lambda_t, \varepsilon_{it}\right) \quad (8)$$

$\Phi(\cdot)$ for fitting using a random forest model.

4.2.3.2 SHAP interpretation method

SHAP is a powerful method for interpreting machine learning model predictions. It is based on the Shapley value from game theory, which assigns an importance score to each feature, quantifying its contribution to the model's predictions. A key concept within the SHAP framework is the SHAP decomposition method, which allows us to break down the model's predictions into the contributions of individual features.

The core idea of the SHAP decomposition method is to express the model output (i.e., the prediction) as a weighted sum of the contributions from all features, plus a baseline value. The baseline value represents the model's predicted outcome when no features are provided. The contribution of each feature (the SHAP value) reflects its marginal impact on the model's prediction. This decomposition method enables us to intuitively understand how each feature influences the model's predictions.

Furthermore, to reveal the marginal effects of digital infrastructure on the collaborative effects of pollution reduction and carbon emission reduction, we can construct partial dependence functions $(x_1, \hat{\Phi}(x_1))$. $\hat{\Phi}(x_1)$ denotes the partial function of the dependent variable on x_1, while also accounting for the influences of other variables $x_1, x_{j2}, \cdots, x_{jp}$ on the dependent variable that have been eliminated via integration; then, the sample is utilized to estimate the entire equation to yield Equation 9:

$$\hat{\Phi}(x_1) = \frac{1}{n}\sum_{j=1}^{n} f\left(x_1, x_{j2}, \cdots, x_{jp}\right) \quad (9)$$

4.3 Data source

This study investigates the impact of *inform* on *se* in China, utilizing a dataset comprising 282 prefecture-level cities between 2012 and 2021. Primary data sources include the China Statistical Yearbook and China Urban Statistical Yearbook. Carbon emissions at the city level are estimated through assimilating DMSP and VIIRS nighttime lighting data (Wu et al., 2022). PM2.5 data were sourced from the Atmospheric Composition Analysis Group at Dalhousie University, Canada. Missing data points are interpolated using linear interpolation methods. Descriptive statistics of variables are shown in Table 3.

5 Results and discussion

5.1 Benchmark regression analysis

To disentangle the specific impact of *inform* on *se*, we employed stepwise regression analysis, incorporating control variables to account for their influence. The results presented in Table 4

TABLE 4 Benchmark regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
inform	0.1146***	0.1114***	0.1099***	0.1112***	0.1066***	0.1056***	0.1056***
	(3.9660)	(3.5241)	(3.5805)	(3.5511)	(3.2502)	(3.4408)	(3.4398)
pgdp		0.0005	0.0006	0.0006	0.0007	0.0021**	0.0021**
		(0.5126)	(0.6040)	(0.6749)	(0.7960)	(2.2023)	(2.2026)
urb			0.0501*	0.0515*	0.0485*	0.0464*	0.0464*
			(1.8770)	(1.9513)	(1.8505)	(1.8357)	(1.8354)
hum				−0.2644	−0.2313	−0.2419	−0.2419
				(-1.2876)	(-1.1508)	(-1.2957)	(-1.2956)
trans					0.0203***	0.0175***	0.0175***
					(2.7518)	(2.6246)	(2.6243)
is						1.1166***	1.1164***
						(4.7732)	(4.7714)
energy							0.0000
							(1.1081)
_cons	0.8325***	0.8308***	0.8052***	0.8087***	0.7889***	0.7471***	0.7471***
	(257.0257)	(222.5188)	(56.9837)	(54.2749)	(51.5299)	(39.4868)	(39.4807)
city	Yes	yes	yes	yes	yes	yes	yes
year	Yes	yes	yes	yes	yes	yes	yes
N	2,820	2,820	2,820	2,820	2,820	2,820	2,820
R^2	0.503	0.503	0.506	0.507	0.512	0.527	0.527

Note: Standard errors for robust clustering at the city level are in parentheses, * stands for significant at the 10% level, ** stands for significant at the 5% level, *** stands for significant at the 1% level, and the same applies below.

demonstrate that core explanatory variables exhibit statistically significant positive relationships at a 1% significance level. Importantly, the inclusion of additional control variables yielded no alterations in outcomes, suggesting the critical role of digital infrastructure in fostering synergy between urban pollution reduction and carbon abatement (Du et al., 2023). This finding further supports the validity of hypothesis H1.

Control variable analysis reveals a strong synergistic relationship between digital infrastructure and the reduction of pollution and carbon emissions. Higher levels of economic development, urbanization rates, transportation infrastructure, and industrial structure upgrading all positively impact combined reductions in pollutants and greenhouse gases. This synergy can be attributed to the positive correlation between higher economic development, technological progress, and strengthened environmental standards, which drive enterprises towards adopting more sustainable production practices, leading to decreased pollution. Furthermore, urban sprawl is linked to resource efficiency, the promotion of eco-friendly infrastructure, and the emergence of environmentally focused facilities. In transportation, advancements contribute to increased network efficiency, reduced traffic congestion, and limited vehicular emissions. Meanwhile, the transformation of industrial structures involves restructuring heavily polluting industries towards cleaner production methods and green innovations, resulting in reduced carbon emissions (Mentel et al., 2022). In contrast, previous studies have shown that human capital can positively influence environmental outcomes when accompanied by sufficient technological expertise and investment in education(Wang Q. et al., 2022). This suggests that the negative impact observed in this analysis may stem from a current mismatch between educational outcomes and industry needs in China, leading to inefficiencies in carbon reduction initiatives. Additionally, other research highlights that energy intensity's impact on emissions varies significantly across regions, with some regions achieving better results through targeted energy-saving technologies(Hosan et al., 2022). The negligible influence of energy intensity in this study may indicate a broader systemic issue, where cities fail to implement effective energy-saving strategies, as suggested by the persistent high energy consumption rates in many Chinese urban centers.

5.2 Robustness test

To confirm the trustworthiness of the benchmark regression results, this research performs robustness tests in the following manner:

TABLE 5 Robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)
inform	1.4649**	0.1812***	0.0834***	0.1056***	0.1079***	0.0906***
	(2.0691)	(2.8392)	(2.8200)	(3.4219)	(3.8716)	(3.8831)
pgdp	−0.0083	0.0022**	0.0021*	0.0021**	0.0016*	0.0012
	(-1.4262)	(2.0026)	(1.9180)	(2.1912)	(1.8930)	(1.2316)
urb	0.0219	0.0442	0.0158	0.0464*	0.0253	0.0448*
	(0.5908)	(1.4075)	(0.5314)	(1.8259)	(1.3554)	(1.9055)
hum	−0.7170	−0.2963	−0.2335	−0.2419	−0.3087*	−0.1288
	(-1.0914)	(-1.4827)	(-1.2165)	(-1.2889)	(-1.9344)	(-0.7141)
trans	−0.0087	0.0171**	0.0128*	0.0175***	0.0167***	0.0182***
	(-0.2271)	(2.4173)	(1.9419)	(2.6107)	(2.6216)	(2.6978)
is	1.0309**	1.1500***	0.9448***	1.1164***	1.0034***	1.0759***
	(2.4364)	(4.6954)	(4.2255)	(4.7467)	(4.7710)	(4.8654)
energy	−0.0000	0.0000	0.0000**	0.0000	−0.0330**	−0.0000
	(-1.2449)	(1.5790)	(2.5154)	(1.1024)	(-2.4020)	(-0.8569)
appcp						−0.0106***
						(-3.7788)
bluesky						0.0218***
						(5.0215)
unidentifiable tests	3.821	9.019				
	(0.0506)	(0.0027)				
weak instrumental variable tests	15.385	2,144.370				
	(8.96)	(84.862)				
_cons	−0.6798	0.4376***	0.7731***	0.7484***	0.7753***	0.7522***
	(-1.0876)	(5.5065)	(35.6894)	(34.1756)	(47.6759)	(42.1249)
city	yes	yes	yes	yes	city	yes
year	yes	yes	yes	yes	year	yes
N	2,820	2,538	2,256	2,820	2,820	2,820
R2	0.507	0.885	0.519	0.890	0.909	0.556

Note: P values in parentheses for unidentifiable tests; 10% threshold for weak instrumental variable tests in parentheses for weak instrumental variable tests.

5.2.1 Endogeneity test

To investigate potential reciprocal relationships between the advancement of digital infrastructure and integrated pollution and carbon reduction management in urban areas, an endogeneity test is conducted. Drawing upon Gao et al. (2022), post offices from 1984 are selected as instrumental variables for 2SLS estimation alongside digital infrastructure level data from the preceding year. This approach acknowledges the historical role of postal services as crucial information exchange channels, reflecting a precursor to modern digital infrastructure. Notably, the shift towards contemporary communication technologies renders the post office less relevant today. Moreover, 1984 falls outside the study's timeframe, ensuring its exogeneity and applicability for this analysis. Considering cross-sectional data, an interaction term is constructed by incorporating both the number of post offices in 1984 and national internet investment levels from the preceding year. This approach aligns with the methodology of Nunn and Qian (2014), further emphasizing the instrumental variable strategy. We also utilize the digital infrastructure level from the previous year as an additional instrumental variable to account for its dynamic nature and impact on current-year development.

The regression results are presented in columns (1) and (2) of Table 5. These findings demonstrate that coefficients of primary explanatory factors maintain statistically significant positive

correlations, highlighting the continued relevance of digital infrastructure in facilitating coordinated pollution and carbon reduction management. In addition to this, both instrumental variables successfully passed the nonidentification test and weak instrumental variable test, strengthening their validity and emphasizing the significance of digital infrastructure for mitigating urban pollution and carbon emissions.

5.2.2 Controlling for high-dimensional fixed effects

To account for potential unobservable province-level characteristics, province fixed effects are incorporated into the baseline regression model. This adjustment mitigates their influence on the regression coefficients, as shown in column (3) of Table 5. These results reveal notably positive regression coefficients for key explanatory variables, suggesting that digital infrastructure demonstrably fosters a synergistic effect in reducing urban pollution and carbon emissions. This implies a substantial impact of digital infrastructure on achieving these goals.

5.2.3 Bilateral tailoring process

This paper addresses the issue of distorted or biased regression coefficients stemming from unrealistic extreme values. To achieve this, we analyze bilateral shrinkage of the tail in the upper and lower 1% quartiles as shown in Table 5 column (4). The results reveal consistently positive regression coefficients for digital infrastructure that are consistent with those obtained from a benchmark regression model.

5.2.4 Adjusting the sample interval

The implementation of the Broadband China pilot policy in 2013 directly correlates with digital infrastructure development, thus rendering this study's focus on the period between 2014 and 2021 particularly relevant. Column (5) of Table 5 reveals significant positive impacts at the 1% level for key explanatory variables, indicating reliable and strong conclusions derived from the benchmark regression analysis.

5.2.5 Control of other policies

The influence of environmental policies such as the Action Plan for Prevention and Control of Air Pollution (2013–2017) and the Three-Year Action Plan for Winning the Battle for the Blue Sky, as documented by Li L. et al. (2024) and Liu et al. (2021), exerts a significant influence on collaborative pollution reduction and carbon abatement efforts. To account for potential perturbations caused by these policies on air pollutants and carbon emissions, this study integrates both policies as dummy variables into the benchmark regression (column 6 of Table 5). Remarkably, even after incorporating policy shocks, primary explanatory variables consistently demonstrate significant positive effects, affirming the role of digital infrastructure in accelerating synergy between pollution reduction and carbon abatement. This underscores its crucial contribution to advancing collaborative urban environmental enhancement efforts.

5.3 Heterogeneity analysis

The impact of digital infrastructure development varies across cities, influencing their collaborative capabilities for pollution reduction and carbon mitigation strategies. Geographic location, city size, and available resources all contribute to these distinct impacts.

5.3.1 Geographic location heterogeneity

To investigate the influence of *inform* on *se*, it is crucial to account for regional variations. Studies conducted by Liang et al. (2021) and Pu et al. (2020) have categorized the country into three regions: East, Central-West, and North-South. Utilizing a permutation test, this study assessed the variation in regression coefficients across these groups. The findings are presented in Table 6.

Statistical analysis reveals significant intergroup differences between regions classified as Eastern, Central-Western, and North-South. Regression coefficients for core explanatory variables within the Eastern and Central-Western regions demonstrate significantly positive values with the Eastern region exhibiting a coefficient exceeding that of the Central-West region. This indicates that in the eastern region, the role of digital infrastructure in promoting pollution reduction and carbon emission mitigation is more pronounced, which may not be consistent with the conclusions of existing studies (Zhong et al., 2024). This could be due to the more rapid development of digital infrastructure in the eastern region (Ma and Lin, 2023), which makes it easier to leverage the connectivity advantages of digital infrastructure. This facilitates cross-regional cooperation and resource sharing, and more effectively integrates resources, thereby improving the efficiency of coordinated pollution reduction and carbon emission mitigation efforts. Analysis comparing the Northern and Southern regions reveals a significant regression coefficient of 0.2077 for the Northern region (passing the 1% significance test), aligning with research by Zhang et al. (2023) who highlight the Northern region's position as a major heavy industrial base in China and its distinct air pollution challenges due to severe winter climate conditions. This emphasizes the need to bolster environmental governance and infrastructure development, leveraging digital technology effectively for monitoring and addressing environmental challenges within the region.

5.3.2 Heterogeneity of city size

Considering that urban size may have an impact on the pollution reduction and carbon emission effects of digital infrastructure, this study explores the heterogeneity of urban size from the perspective of population scale[1]. As shown in columns (1) and (2) of Table 7, the differences in coefficients between the aforementioned groups are highly significant. Notably, the coefficient for large cities is notably smaller at 0.0728. This is in

1 According to the "Notice from the State Council on Adjusting the Standards for Urban Size Classification," based on the resident population of municipal districts in 2015, cities with a population of over one million are classified as large cities, those with a population between 500,000 and one million are classified as medium-sized cities, and those with a population of less than 500,000 are classified as small cities

TABLE 6 Geographic location heterogeneity test.

	(1)	(2)	(3)	(4)
	East	Central-West	North	South
inform	0.1904***	0.0648***	0.2077***	0.0404***
	(3.0693)	(2.6365)	(2.9996)	(2.6442)
pgdp	−0.0015	0.0043***	0.0027*	0.0016*
	(-0.8490)	(3.9561)	(1.7943)	(1.6606)
urb	0.0952**	0.0113	0.0200	0.0522**
	(2.2468)	(0.4989)	(0.5742)	(2.5038)
hum	−0.0551	−0.1930	−0.3614	−0.2787*
	(-0.1439)	(-0.8633)	(-1.1720)	(-1.8463)
trans	0.0223	0.0210***	0.0592**	0.0090
	(1.1785)	(3.1259)	(2.5801)	(1.5284)
is	0.8275	1.2470***	1.5843***	0.5370***
	(1.3984)	(5.3421)	(4.4640)	(2.8181)
energy	0.0000***	−0.0001***	−0.0404***	0.0000***
	(3.1568)	(-3.5270)	(-2.7595)	(4.3289)
experienced p value	0.007***		0.002***	
_cons	0.7070***	0.7619***	0.6845***	0.8012***
	(13.8055)	(50.6600)	(21.6762)	(57.9569)
city	yes	yes	yes	yes
year	yes	yes	yes	yes
N	1,000	1820	1,290	1,530
R2	0.513	0.596	0.469	0.703

Note: Empirical p values are used to test for differences in coefficients between groups and are obtained by 1,000 bootstrap replicates, as follows.

line with the research of other scholar(Liao and Liu, 2024), which may be due to the fact that larger cities require more resource elements during the digital transformation process, resulting in poor coverage of digital infrastructure(Lin and Ma, 2022). This discrepancy could be attributed to the resource-intensive nature of digital transformation within larger cities, leading to inadequate digital infrastructure coverage and hindering its role in synergistic pollution and carbon reduction processes. Furthermore, large cities' broader regional scope necessitates increased coordination and investment in resources for policy implementation, potentially posing greater challenges compared to smaller cities(Yang, Yeh and Wang, 2018).

5.3.3 Resource endowment heterogeneity

Given the significant differences in industrial structure, energy consumption patterns, and environmental challenges between resource-based and non-resource-based cities, we will categorize the samples into these two types of cities to explore in more detail the differing roles of digital infrastructure in helping them achieve pollution reduction and carbon emission targets. The results are shown in columns (3) and (4) of Table 7. A significant positive correlation is observed in the regression coefficients of primary explanatory variables, evident across both resource-based and non-resource-based cities. The disparity between these groups is highly statistically significant. Digital infrastructure plays a crucial role in enabling cities to achieve their pollution and carbon reduction objectives, particularly for resource-based cities, where industries heavily reliant on extractive and heavy energy sources dominate(Cai and Lin, 2022). Consequently, environmental pollution and carbon emissions become increasingly pronounced, highlighting the urgent need for enhanced environmental governance measures. In resource-based cities, digital infrastructure deployment can accelerate industrial digital transformation, improve energy utilization efficiency, and simultaneously mitigate carbon and pollutant emissions (Pan et al., 2023), fostering a mutually beneficial outcome in achieving both pollution and carbon reduction goals.

5.4 Mechanism analysis

To validate the hypothesis H2, regression analysis was conducted using Equation 7, as presented in Table 8. The

TABLE 7 Heterogeneity test of urban scale and resource endowments.

	(1)	(2)	(3)	(4)
	Large	Small-medium	Resource	Non-resource
inform	0.0728***	0.2829**	0.2437**	0.0836***
	(2.7880)	(2.2467)	(2.0091)	(3.1626)
pgdp	0.0004	0.0029**	0.0009	0.0024*
	(0.2748)	(2.0456)	(0.5774)	(1.8730)
urb	0.0501	0.0345	−0.0116	0.0986**
	(1.2620)	(1.2160)	(-0.4886)	(2.4328)
hum	−0.2756	−0.1240	0.1782	−0.3166
	(-1.1585)	(-0.3696)	(0.3632)	(-1.4956)
trans	0.0039	0.0485***	0.0389***	0.0052
	(0.5209)	(3.4590)	(3.7686)	(0.6765)
is	0.8152***	1.3977***	1.0526***	1.0800***
	(2.8142)	(3.8979)	(2.7054)	(4.0217)
energy	−0.0287	−0.0000	−0.0001***	0.0000**
	(-0.9520)	(-0.1730)	(-3.4133)	(2.4786)
experienced p-value	0.000***		0.001***	
_cons	0.7684***	0.7281***	0.7613***	0.7320***
	(29.4566)	(25.5191)	(33.0673)	(26.9225)
city	yes	yes	yes	yes
year	yes	yes	yes	yes
N	1,440	1,380	1,110	1710
R2	0.600	0.484	0.496	0.569

TABLE 8 Mechanism test results.

	(1)	(2)	(3)
	lff	cff	iff
inform	57.5616***	0.0097*	0.0189**
	(3.9654)	(1.8449)	(1.9942)
pgdp	2.0928***	−0.0004*	−0.0008***
	(4.5587)	(-1.9415)	(-3.2716)
urb	−12.3511	−0.0016	0.0078
	(-1.5974)	(-0.3580)	(1.6303)
hum	−90.9089	0.0420	0.1453**
	(-1.2832)	(1.0068)	(2.3653)
trans	−1.2135	0.0048***	−0.0031
	(-0.6788)	(3.1111)	(-1.0482)
is	−3.3e+02***	0.1607***	0.1446***
	(-2.8932)	(3.6368)	(3.4032)
energy	0.0008	0.0000	−0.0000*
	(0.9585)	(0.4028)	(-1.8928)
_cons	6.1562	−0.0122***	−0.0068*
	(1.3616)	(-3.5843)	(-1.6562)
city	yes	yes	yes
year	yes	yes	yes
N	2,820	2,820	2,820
R2	0.255	0.037	0.033

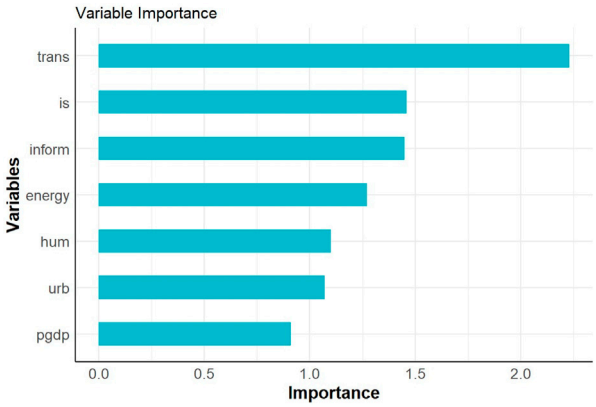


FIGURE 2
Variable importance.

results clearly demonstrate a significantly positive correlation between digital infrastructure and the flow of labor, capital, and innovation factors. This suggests that digital infrastructure fosters a synergistic effect by accelerating these factor flows, ultimately contributing to cleaner air and reduced carbon emissions.

Digital infrastructure facilitates efficient movement of all three factors. For instance, the adoption of digital technologies enhances transparency in labor markets, reduces labor mobility costs (Hua and Zhang, 2024), and optimizes labor allocation. In relation to capital flow, digital infrastructure offers enhanced trading platforms and risk management tools within the capital market, leading to improved liquidity and allocation efficiency (Dong et al., 2022). Regarding innovation factors, digital infrastructure serves as a strong catalyst for scientific and technological advancements (Bygstad and Øvrelid, 2020), fostering efficient sharing and integration of innovation resources and promoting urban industrial structure upgrades. The acceleration of these factor flows ultimately alters the city's industrial structure by optimizing resource allocation, enhancing production efficiency, improving energy utilization efficiency, reducing energy waste, and lowering pollutant emissions. Simultaneously, industrial restructuring promotes environmentally friendly and sustainable practices, further bolstering pollution reduction and carbon mitigation efforts.

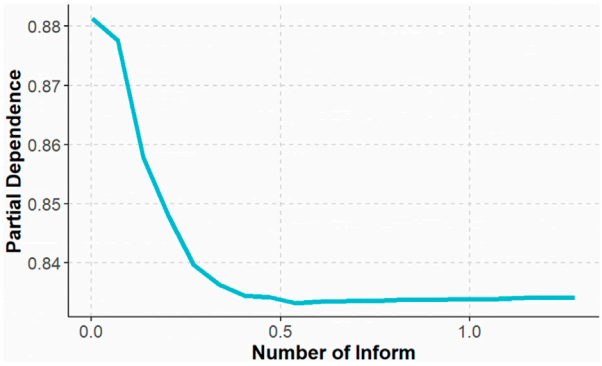


FIGURE 3
Bias dependence diagram.

5.5 Nonlinear effect

This study employs a random forest model with regression trees as the base learner to investigate the relationship between *inform* and *se*, utilizing the minimum mean square error criterion (Li et al., 2018). A biased dependence model is employed to elucidate the marginal influence of digital infrastructure on this synergistic effect. Figure 2 presents the ranking of importance for various feature variables, revealing that the driving factors for the synergistic effect of urban pollution reduction and carbon mitigation are, in order: transportation infrastructure level, industrial structure level, digital infrastructure level, energy consumption intensity, human capital, urbanization rate, and *per capita* economic development level. To analyze the manner in which digital infrastructure influences the synergistic effect of urban pollution reduction and carbon mitigation, this paper further employs a partial dependence plot to illustrate the dependency relationship between digital infrastructure and the synergistic effect of urban pollution reduction and carbon mitigation.

Figure 3 displays a diagram illustrating these relationships. Specifically, the synergistic impact of digital infrastructure on urban pollution reduction and carbon mitigation exhibits a distinct U-shaped relationship. This discrepancy can be attributed to the stage of development in urban digital infrastructure: early stages may not effectively contribute to enhanced synergistic effects in both pollution and carbon reduction. However, once digital infrastructure reaches a certain degree of maturity, it facilitates the adoption of sustainable practices across various sectors, accelerating progress towards cleaner air and reduced emissions.

In contrast, other studies have indicated a more linear relationship between digital infrastructure and environmental outcomes (Tao et al., 2023; Zheng et al., 2023c).These studies suggest that even at early stages of digital infrastructure development, there can be immediate benefits in terms of efficiency improvements and better data management for pollution control. The differences in findings may arise from varying contextual factors, such as the specific technological tools implemented or the regulatory environments of different regions. For instance, regions that prioritize smart technologies and have supportive policies may experience immediate improvements, while others may lag due to insufficient investment or planning.

6 Conclusions and suggestions

6.1 Conclusions

This study employs a multi-faceted approach to analyze panel data from 282 Chinese cities, employing a two-way fixed-effect model, a mediated-effects model, and a machine learning model for comprehensive assessment. The objective is to investigate the influence of digital infrastructure on coordinated urban pollution and carbon emissions reduction, quantifying its impact through an evaluation of urban digital infrastructure levels.

The study reveals:

(1) The study provides a deeper understanding of how digital infrastructure plays a pivotal role in amplifying the efficacy of urban pollution and carbon emissions reduction initiatives, leading to their synergistic governance. By examining geographical disparities, urban dimensions, and resource endowments, it is evident that regions in the east, northern cities, and smaller or resource-dependent municipalities witness a more pronounced beneficial effect. This suggests that the spatial distribution and characteristics of cities significantly influence the capacity of digital infrastructure to drive environmental improvements.

(2) The research underscores the transformative impact of digital infrastructure in harmonizing urban pollution and emission reduction efforts. It does so by enabling the smooth circulation of labor, capital, and innovative elements, which are crucial for optimizing resource distribution. This optimization is instrumental in steering the economy towards a greener trajectory. As a result, there is a notable enhancement in energy efficiency, a reduction in emissions, and a subsequent decline in environmental pollution levels, highlighting the critical role of digital infrastructure in advancing sustainable urban development.

(3) Employing a random forest model, the study reveals the complex, non-linear dynamics between digital infrastructure and the concurrent management of pollution and carbon emissions. It is observed that during the initial stages of digital infrastructure expansion, high energy consumption may counteract environmental efforts. However, as the infrastructure evolves, it becomes a catalyst for industry-wide digital transformation, which is essential for environmental conservation and emission reduction. This transition underscores the importance of maturation in digital infrastructure as a key factor in aligning pollution and carbon mitigation strategies effectively.

This study deepens the integration of digital economy and sustainable development theories, clarifying how digital infrastructure accelerates urban pollution reduction and carbon reduction processes in a nonlinear manner by facilitating the flow of labor, capital, and innovation factors. More importantly, this research provides policymakers with a theoretical foundation for precise policy implementation, aiding them in making more informed decisions while promoting regional differentiated development, optimizing resource allocation, and seeking a balance between digital infrastructure construction and

environmental protection goals. This not only aligns closely with the national strategy of actively promoting "new infrastructure" and achieving "dual carbon" goals but also offers practical strategies and pathways for achieving a green transformation of the economy and society.

6.2 Recommendations for countermeasures

Based on these findings, the paper recommends several strategic approaches to maximize the impact of digital infrastructure on urban pollution and carbon emissions mitigation:

(1) Policymakers will use differentiated strategies based on New Infrastructure Plan and carbon peaking/neutrality targets to promote digital infrastructure development for emission reduction. Areas with strong economies and tech capabilities (east and north) should focus on optimizing existing infrastructure to maximize emission reductions potential. Smaller cities and resource-rich areas can leverage regional development policies to increase digital infrastructure investment, enabling green transitions in traditional industries through technology. Finally, promoting interregional digital infrastructure connectivity aligned with initiatives like the Belt and Road Initiative will facilitate resource sharing and collaborative governance for stronger emissions reduction effect.

(2) To enhance the green economy, governments will promote green industries and low-carbon fields through the strategy on developing a quality workforce. This includes providing job training and information to help workers develop green skills. Additionally, policies like green finance encourage capital investment in green projects. Digital innovation platforms will also be created to attract new talent and innovation resources for emissions reduction and accelerate the city's green transformation.

(3) During digital infrastructure development, prioritize environmental management and oversight throughout construction to control energy consumption and emissions. Post-completion, encourage industries to leverage digital technologies for green transformation (energy efficiency, reducing carbon and pollution) and maximize the impact of this infrastructure on emission reduction and coordinated governance. Leveraging big data and AI technology can establish a dynamic evaluation mechanism for timely policy adjustments, enabling more precise and effective management.

6.3 Research outlook

This study examines how digital infrastructure impacts pollution and carbon reduction efforts, contributing to a dual-carbon strategy. However, further optimizations are necessary:

(1) While this research focuses on Chinese cities, future studies should broaden to include diverse nations and regions worldwide. Comparative analyses across these distinct contexts will reveal the varying influences of digital infrastructure on climate change mitigation strategies. Such insights can yield actionable guidelines for global climate efforts.

(2) The impact of digital infrastructure is particularly potent when integrated into crucial sectors like manufacturing and transportation. Deeper research should focus on assessing the specific effects of this integration on the collaborative management of pollution and emissions reduction. A thorough analysis can highlight the vital role of digital infrastructure in pollution and carbon mitigation, providing a more robust foundation for policy development and implementation.

Data availability statement

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

Author contributions

FL: Formal Analysis, Funding acquisition, Methodology, Project administration, Resources, Writing – review and editing. ZD: Conceptualization, Data curation, Investigation, Methodology, Writing – original draft.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article.

This study is supported by the National Natural Science Foundation of China under the "Analysis of Corporate Environmental Behavior and Reconstruction of Guiding Mechanisms for Reimbursable Use and Trading of Emission Rights" (71974081) and the Postgraduate Research and Practice Innovation Program of Jiangsu Province (KYCX24_3882).

Acknowledgments

The authors are very grateful to all the reviewers and editors for their comments on this paper.

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.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated

organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Allen, M., Frame, D., Huntingford, C., Jones, C., Lowe, J., Meinshausen, M., et al. (2009). Warming caused by cumulative carbon emissions towards the trillionth tonne. *Nature* 458 (7242), 1163–1166. doi:10.1038/nature08019

Amann, M., Klimont, Z., and Wagner, F. (2013). Regional and global emissions of air pollutants: recent trends and future scenarios. *Annu. Rev. Environ. Resour.* 38 (1), 31–55. doi:10.1146/annurev-environ-052912-173303

Avom, D., Nkengfack, H., Fotio, H. K., and Totouom, A. (2020). ICT and environmental quality in Sub-Saharan Africa: effects and transmission channels. *Technol. Forecast. Soc. Change* 155, 120028. doi:10.1016/j.techfore.2020.120028

Bai, T., Qi, Y., Li, Z., and Xu, D. (2023). Digital economy, industrial transformation and upgrading, and spatial transfer of carbon emissions: the paths for low-carbon transformation of Chinese cities. *J. Environ. Manag.* 344, 118528. doi:10.1016/j.jenvman.2023.118528

Bibri, S. E. (2018). The IoT for smart sustainable cities of the future: an analytical framework for sensor-based big data applications for environmental sustainability. *Sustain. Cities Soc.* 38, 230–253. doi:10.1016/j.scs.2017.12.034

Bygstad, B., and Øvrelid, E. (2020). Architectural alignment of process innovation and digital infrastructure in a high-tech hospital. *Eur. J. Inf. Syst.* 29 (3), 220–237. doi:10.1080/0960085x.2020.1728201

Cai, Y., and Lin, G. (2022). Pathways for sustainable municipal energy systems transition: a case study of Tangshan, a resource-based city in China. *J. Clean. Prod.* 330, 129835. doi:10.1016/j.jclepro.2021.129835

Che, S., and Wang, J. (2022). Digital economy development and haze pollution: evidence from China. *Environ. Sci. Pollut. Res.* 29 (48), 73210–73226. doi:10.1007/s11356-022-20957-w

Che, S., Wen, L., and Wang, J. (2024). Global insights on the impact of digital infrastructure on carbon emissions: a multidimensional analysis. *J. Environ. Manag.* 368, 122144. doi:10.1016/j.jenvman.2024.122144

Chen, D., Lu, X., Hu, W., Zhang, C., and Lin, Y. (2021a). How urban sprawl influences eco-environmental quality: empirical research in China by using the Spatial Durbin model. *Ecol. Indic.* 131, 108113. doi:10.1016/j.ecolind.2021.108113

Chen, J., Gao, M., Cheng, S., Hou, W., Song, M., Liu, X., et al. (2020). County-level CO2 emissions and sequestration in China during 1997–2017. *Sci. Data* 7 (1), 391. doi:10.1038/s41597-020-00736-3

Chen, Y., Ardila-Gomez, A., and Frame, G. (2016). Achieving energy savings by intelligent transportation systems investments in the context of smart cities. *Transp. Res. Part D Transp. Environ.* 54, 381–396. doi:10.1016/j.trd.2017.06.008

Chen, Y., Tian, W., Zhou, Q., and Shi, T. J. J. o. C. P. (2021b). Spatiotemporal and driving forces of Ecological Carrying Capacity for high-quality development of 286 cities in China. *J. Clean. Prod.* 293, 126186. doi:10.1016/j.jclepro.2021.126186

Cheng, Z., Li, L., and Liu, J. (2019). The effect of information technology on environmental pollution in China. *Environ. Sci. Pollut. Res.* 26 (32), 33109–33124. doi:10.1007/s11356-019-06454-7

Dayarathna, M., Wen, Y., and Fan, R. J. (2015). Data center energy consumption modeling: a survey. *A Surv.* 18 (1), 732–794. doi:10.1109/comst.2015.2481183

Dian, J., Song, T., and Li, S. (2023). Facilitating or inhibiting? Spatial effects of the digital economy affecting urban green technology innovation. *Energy Econ.* 129, 107223. doi:10.1016/j.eneco.2023.107223

Dong, F., Li, Y., Qin, C., Zhang, X., Chen, Y.-H., Zhao, X., et al. (2022). Information infrastructure and greenhouse gas emission performance in urban China: a difference-in-differences analysis. *J. Environ. Manag.* 316, 115252. doi:10.1016/j.jenvman.2022.115252

Du, Y., Zhou, J., Bai, J., and Cao, Y. (2023). Breaking the resource curse: the perspective of improving carbon emission efficiency based on digital infrastructure construction. *Resour. Policy* 85, 103842. doi:10.1016/j.resourpol.2023.103842

Fan, X., Zhou, Y., and Xie, Q. (2024). Assessment on the synergistic effect of pollution and carbon reductions in low-carbon city pilot policy: based on effectiveness and efficiency perspectives. *Environ. Dev. Sustain.* doi:10.1007/s10668-023-04421-4

Favoretto, C., Mendes, G. H. d. S., Filho, M. G., Gouvea de Oliveira, M., Ganga, G. M., and Marketing, I. (2022). Digital transformation of business model in manufacturing companies. *challenges Res. agenda*. 37(4), 748–767. doi:10.1108/jbim-10-2020-0477

Fujimori, S., Masui, T., and Matsuoka, Y. (2015). Gains from emission trading under multiple stabilization targets and technological constraints. *Energy Econ.* 48, 306–315. doi:10.1016/j.eneco.2014.12.011

Gao, D., Li, G., and Yu, J. (2022). Does digitization improve green total factor energy efficiency? Evidence from Chinese 213 cities. *Energy* 247, 123395. doi:10.1016/j.energy.2022.123395

Ghosh, S., Hughes, M., Hodgkinson, I., and Hughes, P. J. T. (2022). Digital transformation of industrial businesses. *A Dyn. Capab. approach*, 113.102414. doi:10.1016/j.technovation.2021.102414

Guerrero-ibanez, J. A., Zeadally, S., and Contreras-Castillo, J. (2015). Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies. *IEEE Wirel. Commun.* 22 (6), 122–128. doi:10.1109/mwc.2015.7368833

Guo, Q., Geng, C.-x., Yao, N., and Zhao, L. (2023). Can digital infrastructure enhance economic efficiency? Evidence from China. *Qual. and Quantity* 58 (2), 1729–1752. doi:10.1007/s11135-023-01710-y

Hao, Y., Wu, Y., Wu, H., and Ren, S. (2020). How do FDI and technical innovation affect environmental quality? Evidence from China. *Environ. Sci. Pollut. Res.* 27 (8), 7835–7850. doi:10.1007/s11356-019-07411-0

He, C., Pan, F., and Yan, Y. (2011). Is economic transition harmful to China's urban environment? Evidence from industrial air pollution in Chinese cities. *Urban Stud.* 49 (8), 1767–1790. doi:10.1177/0042098011415719

He, X., Meng, X., Wu, Y., Chan, C. S., and Pang, T. (2020). Semantic matching efficiency of supply and demand texts on online technology trading platforms: taking the electronic information of three platforms as an example. *Inf. Process. and Manag.* 57 (5), 102258. doi:10.1016/j.ipm.2020.102258

Heddeghem, W. V., Lambert, S., Lannoo, B., Colle, D., Pickavet, M., and Demeester, P. (2014). Trends in worldwide ICT electricity consumption from 2007 to 2012. *Comput. Commun.* 50, 64–76. doi:10.1016/j.comcom.2014.02.008

Henneman, L. R. F., Rafaj, P., Annegarn, H., and Klausbruckner, C. (2016). Assessing emissions levels and costs associated with climate and air pollution policies in South Africa. *Energy Policy* 89, 160–170. doi:10.1016/j.enpol.2015.11.026

Hosan, S., Karmaker, S. C., Rahman, M. M., Chapman, A. J., and Saha, B. (2022). Dynamic links among the demographic dividend, digitalization, energy intensity and sustainable economic growth: empirical evidence from emerging economies. *J. Clean. Prod.* 330, 129858. doi:10.1016/j.jclepro.2021.129858

Hu, J. (2023). Synergistic effect of pollution reduction and carbon emission mitigation in the digital economy. *J. Environ. Manag.* 337, 117755. doi:10.1016/j.jenvman.2023.117755

Hu, J., Zhang, H., and Irfan, M. (2023). How does digital infrastructure construction affect low-carbon development? A multidimensional interpretation of evidence from China. *J. Clean. Prod.* 396, 136467. doi:10.1016/j.jclepro.2023.136467

Hu, Y., Ji, J. S., and Zhao, B. (2022). Deaths attributable to indoor PM2.5 in urban China when outdoor air meets 2021 WHO air quality guidelines. *Environ. Sci. and Technol.* 56 (22), 15882–15891. doi:10.1021/acs.est.2c03715

Hua, Y., and Zhang, H. (2024). Labour misallocation and digital infrastructure: evidence from a quasi-natural experiment of 'broadband China strategy. *Appl. Econ. Lett.*, 1–7. doi:10.1080/13504851.2024.2332574

Jones, R. W., Coelho, I., and Easton, S. T. (1986). The theory of international factor flows: the basic model. *J. Int. Econ.* 20 (3-4), 313–327. doi:10.1016/0022-1996(86)90024-3

Lan, M., and Zhu, Y. (2023). Digital infrastructure construction, carbon total factor productivity, and carbon rebound effect. *Environ. Sci. Pollut. Res.* 30 (38), 88968–88985. doi:10.1007/s11356-023-28738-9

Lee, C.-C., and Zhao, Y.-N. (2023). Heterogeneity analysis of factors influencing CO2 emissions: the role of human capital, urbanization, and FDI. *Renew. Sustain. Energy Rev.* 185, 113644. doi:10.1016/j.rser.2023.113644

Li, C., Tao, Y., Ao, W., Yang, S., and Bai, Y. (2018). Improving forecasting accuracy of daily enterprise electricity consumption using a random forest based on ensemble empirical mode decomposition. *Energy* 165, 1220–1227. doi:10.1016/j.energy.2018.10.113

Li, F., Wu, Y., Liu, J., and Zhong, S. (2022). Does digital inclusive finance promote industrial transformation? New evidence from 115 resource-based cities in China. *PLOS ONE* 17 (8), e0273680. doi:10.1371/journal.pone.0273680

Li, J., Jiang, M., and Li, G. (2024a). Does the New Energy Vehicles subsidy policy decrease the carbon emissions of the urban transport industry? Evidence from Chinese cities in Yangtze River Delta. *Energy* 298, 131322. doi:10.1016/j.energy.2024.131322

Li, L., He, M., Liang, X., Deng, H., and Yang, R. (2024b). How does the impact of a two-stage air pollution control policy on air quality different? Evidence from 258 cities in China. *Atmos. Pollut. Res.* 15 (7), 102148. doi:10.1016/j.apr.2024.102148

Li, Z., and Wang, J. (2022). The dynamic impact of digital economy on carbon emission reduction: evidence city-level empirical data in China. *J. Clean. Prod.* 351, 131570. doi:10.1016/j.jclepro.2022.131570

Liang, L., Chen, M., Luo, X., and Xian, Y. (2021). Changes pattern in the population and economic gravity centers since the Reform and Opening up in China: the widening gaps between the South and North. *J. Clean. Prod.* 310, 127379. doi:10.1016/j.jclepro.2021.127379

Liao, K., and Liu, J. (2024). Digital infrastructure empowerment and urban carbon emissions: evidence from China. *Telecommun. Policy* 48 (6), 102764. doi:10.1016/j.telpol.2024.102764

Liao, Z. (2018). Environmental policy instruments, environmental innovation and the reputation of enterprises. *J. Clean. Prod.* 171, 1111–1117. doi:10.1016/j.jclepro.2017.10.126

Lin, B., and Ma, R. (2022). How does digital finance influence green technology innovation in China? Evidence from the financing constraints perspective. *J. Environ. Manag.* 320, 115833. doi:10.1016/j.jenvman.2022.115833

Liu, G., and Wan, S. (2023). The impact of information and communication technology on carbon emissions in China: spatial effect and mechanism discussion. *Environ. Sci. Pollut. Res.* 30 (6), 16178–16194. doi:10.1007/s11356-022-23201-7

Liu, J., Li, Y., and Wang, Z. (2023). The potential for carbon reduction in construction waste sorting: a dynamic simulation. *Energy* 275, 127477. doi:10.1016/j.energy.2023.127477

Liu, K., Ren, G., Dong, S., and Xue, Y. (2024). The synergy between pollution reduction and carbon reduction in Chinese cities and its influencing factors. *Sustain. Cities Soc.* 106, 105348. doi:10.1016/j.scs.2024.105348

Liu, Z., Xue, W., Ni, X., Qi, Z., Zhang, Q., and Wang, J. (2021). Fund gap to high air quality in China: a cost evaluation for PM2.5 abatement based on the Air Pollution Prevention and control Action Plan. *J. Clean. Prod.* 319, 128715. doi:10.1016/j.jclepro.2021.128715

Ma, R., and Lin, B. (2023). Digital infrastructure construction drives green economic transformation: evidence from Chinese cities. *Humanit. Soc. Sci. Commun.* 10 (1), 1–10. doi:10.1057/s41599-023-01839-z

Malhotra, A., Schmidt, T. S., and Huenteler, J. (2019). The role of inter-sectoral learning in knowledge development and diffusion: case studies on three clean energy technologies. *Technol. Forecast. Soc. Change* 146, 464–487. doi:10.1016/j.techfore.2019.04.018

Mentel, G., Tarczyński, W., Azadi, H., Abdurakmanov, K., Zakirova, E., and Salahodjaev, R. (2022). R&D human capital, renewable energy and CO2 emissions: evidence from 26 countries. *Energies* 15 (23), 9205. doi:10.3390/en15239205

Ndubuisi, G., Otioma, C., and Tetteh, G. K. (2021). Digital infrastructure and employment in services: evidence from Sub-Saharan African countries. *Telecommun. Policy* 45 (8), 102153. doi:10.1016/j.telpol.2021.102153

Nunn, N., and Qian, N. (2014). US food aid and civil conflict. *Am. Econ. Rev.* 104 (6), 1630–1666. doi:10.1257/aer.104.6.1630

Ouyang, X., and Sun, C. (2015). Energy savings potential in China's industrial sector: from the perspectives of factor price distortion and allocative inefficiency. *Energy Econ.* 48, 117–126. doi:10.1016/j.eneco.2014.11.020

Pan, M., Zhao, X., Lv, K., Rosak-Szyrocka, J., Mentel, G., and Truskolaski, T. (2023). Internet development and carbon emission-reduction in the era of digitalization: where will resource-based cities go? *Resour. Policy* 81, 103345. doi:10.1016/j.resourpol.2023.103345

Pu, L., Wang, X., Tan, Z., Wang, H., Yang, J., and Wu, J. (2020). Is China's electricity price cross-subsidy policy reasonable? Comparative analysis of eastern, central, and western regions. *Energy Policy* 138, 111250. doi:10.1016/j.enpol.2020.111250

Qiao, L., Li, L., and Fei, J. (2021). Information infrastructure and air pollution: empirical analysis based on data from Chinese cities. *Econ. Analysis Policy* 73, 563–573. doi:10.1016/j.eap.2021.12.014

Raab, R. T., Ellis, W. W., and Abdon, B. R. (2001). Multisectoral partnerships in e-learning: a potential force for improved human capital development in the Asia Pacific. *Internet High. Educ.* 4 (3-4), 217–229. doi:10.1016/s1096-7516(01)00067-7

Rathore, M. M., Paul, A., Hong, W.-H., Seo, H., Awan, I., and Saeed, S. (2018). Exploiting IoT and big data analytics: defining smart digital city using real-time urban data. *Sustain. Cities Soc.* 40, 600–610. doi:10.1016/j.scs.2017.12.022

Ren, S., Hao, Y., Xu, L., Wu, H., and Ba, N. (2021). Digitalization and energy: how does internet development affect China's energy consumption? *Energy Econ.* 98, 105220. doi:10.1016/j.eneco.2021.105220

Sadorsky, P. (2012). Information communication technology and electricity consumption in emerging economies. *Energy Policy* 48, 130–136. doi:10.1016/j.enpol.2012.04.064

Sharma, P. K., Kumar, N., and Park, J. H. J. I. N. (2020). Blockchain technology toward green IoT: opportunities and challenges. *IEEE Netw.* 34 (4), 263–269. doi:10.1109/mnet.001.1900526

Steffen, B., Matsuo, T., Steinemann, D., and Schmidt, T. S. (2018). Opening new markets for clean energy: the role of project developers in the global diffusion of renewable energy technologies. *Bus. Polit.* 20 (4), 553–587. doi:10.1017/bap.2018.17

Stein, J. C. (2002). Information production and capital allocation: decentralized versus hierarchical firms. *J. Finance* 57 (5), 1891–1921. doi:10.1111/0022-1082.00483

Sun, H., and Kim, G. (2021). The composite impact of ICT industry on lowering carbon intensity: from the perspective of regional heterogeneity. *Technol. Soc.* 66, 101661. doi:10.1016/j.techsoc.2021.101661

Tang, J., and Zhao, X. (2023). Does the new digital infrastructure improve total factor productivity? *Bull. Econ. Res.* 75 (4), 895–916. doi:10.1111/boer.12388

Tang, K., and Yang, G. (2023). Does digital infrastructure cut carbon emissions in Chinese cities? *Sustain. Prod. Consum.* 35, 431–443. doi:10.1016/j.spc.2022.11.022

Tao, M., Poletti, S., Wen, L., Sheng, M. S., Wang, J., Wang, G., et al. (2023). Appraising the role of the digital economy in global decarbonization: a spatial non-linear perspective on globalization. *J. Environ. Manag.* 347, 119170. doi:10.1016/j.jenvman.2023.119170

Tranos, E. (2012). The causal effect of the internet infrastructure on the economic development of European city regions. *Spat. Econ. Anal.* 7 (3), 319–337. doi:10.1080/17421772.2012.694140

Uddin, M., Rahman, A. A., and Reviews, S. E. (2012). Energy efficiency and low carbon enabler green IT framework for data centers considering green metrics. 16(6), 4078–4094.

Wang, Q., Zhang, F., and Li, R. (2022a). Revisiting the environmental kuznets curve hypothesis in 208 counties: the roles of trade openness, human capital, renewable energy and natural resource rent. *Environ. Res.* 216, 114637. doi:10.1016/j.envres.2022.114637

Wang, X., and Wang, Q. (2021). Research on the impact of green finance on the upgrading of China's regional industrial structure from the perspective of sustainable development. *Resour. Policy* 74, 102436. doi:10.1016/j.resourpol.2021.102436

Wang, X., and Zhong, M. (2023). Can digital economy reduce carbon emission intensity? Empirical evidence from China's smart city pilot policies. *Environ. Sci. Pollut. Res.* 30 (18), 51749–51769. doi:10.1007/s11356-023-26038-w

Wang, Z., Han, F., Xia, B., Liu, J., and Zhang, C. (2022b). Regional differences and heterogeneity of construction and demolition waste with economic growth: evidence from China. *Constr. Manag. Econ.* 41 (1), 44–59. doi:10.1080/01446193.2022.2137882

Wang, Z., Hu, T., and Liu, J. (2024). Decoupling economic growth from construction waste generation: comparative analysis between the EU and China. *J. Environ. Manag.* 353, 120144. doi:10.1016/j.jenvman.2024.120144

Wei, Z., Yuguo, J., and Jiaping, W. (2015). Greenization of venture capital and green innovation of Chinese entity industry. *Ecol. Indic.* 51, 31–41. doi:10.1016/j.ecolind.2014.10.025

Wen, H., Zhong, Q., and Lee, C.-C. (2022). Digitalization, competition strategy and corporate innovation: evidence from Chinese manufacturing listed companies. *Int. Rev. Financial Analysis* 82, 102166. doi:10.1016/j.irfa.2022.102166

Wood, A. J., Lehdonvirta, V., and Graham, M. (2018). Workers of the Internet unite? Online freelancer organisation among remote gig economy workers in six Asian and African countries. *New Technol. Work Employ.* 33 (2), 95–112. doi:10.1111/ntwe.12112

Wu, H.-L., and Chen, C.-H. (2001). An assessment of outward foreign direct investment from China's transitional economy. *Europe-Asia Stud.* 53 (8), 1235–1254. doi:10.1080/09668130120093219

Wu, Y., Shi, K., Chen, Z., Liu, S., and Chang, Z. (2022). Developing improved time-series DMSP-OLS-like data (1992–2019) in China by integrating DMSP-OLS and SNPP-VIIRS. *IEEE Trans. Geoscience Remote Sens.* 60, 1–14. doi:10.1109/tgrs.2021.3135333

Wu, Y., Wu, Y., Guerrero, J., and Vasquez, J. (2021). A comprehensive overview of framework for developing sustainable energy internet: from things-based energy network to services-based management system. *Renew. Sustain. Energy Rev.* 150, 111409. doi:10.1016/j.rser.2021.111409

Xue, Y., Tang, C., Wu, H., Liu, J., and Hao, Y. (2022). The emerging driving force of energy consumption in China: does digital economy development matter? *Energy Policy* 165, 112997. doi:10.1016/j.enpol.2022.112997

Yang, F. F., Yeh, A. G., and Wang, J. J. A. G. (2018). Regional effects of producer services on manufacturing productivity in China, 97, 263–274.

Yashiv, E. (2007). Labor search and matching in macroeconomics. *Eur. Econ. Rev.* 51 (8), 1859–1895. doi:10.1016/j.euroecorev.2007.06.024

Yi, H., Zhao, L., Qian, Y., Zhou, L., and Yang, P. (2022). How to achieve synergy between carbon dioxide mitigation and air pollution control? Evidence from China. *Sustain. Cities Soc.* 78, 103609. doi:10.1016/j.scs.2021.103609

Yong, X., Xinxin, T., Su, Z., Yao, W., and Rui, C. (2020). Construction and application of digital creative platform for digital creative industry based on smart city concept. *Comput. and Electr. Eng.* 87, 106748. doi:10.1016/j.compeleceng.2020.106748

Zhang, H., Sun, X., Bi, C., Ahmad, M., and Wang, J. (2022a). Can sustainable development policy reduce carbon emissions? Empirical evidence from resource-based cities in China. *Sci. Total Environ.* 838, 156341. doi:10.1016/j.scitotenv.2022.156341

Zhang, P., Chen, P., Xiao, F., Sun, Y., Ma, S., and Zhao, Z. (2022b). The impact of information infrastructure on air pollution: empirical evidence from China. *Int. J. Environ. Res. Public Health* 19 (21), 14351. doi:10.3390/ijerph192114351

Zhang, W., Fan, H., and Zhao, Q. (2023). Seeing green: how does digital infrastructure affect carbon emission intensity? *Energy Econ.* 127, 107085. doi:10.1016/j.eneco.2023.107085

Zhang, X., He, P., Liu, X., and Lu, T. (2023a). The effect of low-carbon transportation pilot policy on carbon performance: evidence from China. *Environ. Sci. Pollut. Res.* 30 (19), 54694–54722. doi:10.1007/s11356-023-25940-7

Zheng, H., Zhang, Z., Dietzenbacher, E., Zhou, Y., Többen, J., Feng, K., et al. (2023b). Leveraging opportunity of low carbon transition by super-emitter cities in China. *Sci. Bull.* 68 (20), 2456–2466. doi:10.1016/j.scib.2023.08.016

Zheng, R., Wu, G., Cheng, Y., Liu, H., Wang, Y., and Wang, X. (2023c). How does digitalization drive carbon emissions? The inverted U-shaped effect in China. *Environ. Impact Assess. Rev.* 102, 107203. doi:10.1016/j.eiar.2023.107203

Zhong, W., Liu, Y., Dong, K., and Ni, G. (2024). Assessing the synergistic effects of artificial intelligence on pollutant and carbon emission mitigation in China. *Energy Econ.* 138, 107829. doi:10.1016/j.eneco.2024.107829

Zhuo, C., Wen, Y., and Wu, H. (2023). The environmental externality of China's digital infrastructure: does institution supply matter? *Appl. Econ.* 56, 4875–4888. doi:10.1080/00036846.2023.2219887

Zou, W., and Pan, M. (2023). Does the construction of network infrastructure reduce environmental pollution?evidence from a quasi-natural experiment in "Broadband China". *Environ. Sci. Pollut. Res.* 30 (1), 242–258. doi:10.1007/s11356-022-22159-w

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 09 May 2025
DOI 10.3389/fenvs.2025.1529622

Check for updates

OPEN ACCESS

EDITED BY
Mariarosaria Lombardi,
University of Foggia, Italy

REVIEWED BY
Christian Bux,
University of Foggia, Italy
Aihemaiti Namaiti,
Tianjin University, China

*CORRESPONDENCE
Meichen Fu,
fumeichen@cugb.edu.cn

RECEIVED 18 November 2024
ACCEPTED 06 March 2025
PUBLISHED 09 May 2025

CITATION
Zhang J, Wang L, Fu M, Wen H and Li S (2025) Accelerating land use carbon emissions in shrinking counties: a systematic analysis of land use dynamics in the Beijing-Tianjin-Hebei region, 2000–2020.
Front. Environ. Sci. 13:1529622.
doi: 10.3389/fenvs.2025.1529622

COPYRIGHT
© 2025 Zhang, Wang, Fu, Wen and Li. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Accelerating land use carbon emissions in shrinking counties: a systematic analysis of land use dynamics in the Beijing-Tianjin-Hebei region, 2000–2020

Jianwen Zhang[1], Li Wang[2], Meichen Fu[1]*, Hongyan Wen[3] and Sijia Li[1]

[1]School of Land Science and Technology, China University of Geosciences (Beijing), Beijing, China, [2]State Key Laboratory of Remote Sensing Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, China, [3]Wu'an Natural Resources and Planning Bureau, Shijiazhuang, China

Urban shrinkage, characterized by population loss and economic decline, poses unique challenges to carbon neutrality goals. While existing studies focus on energy-related emissions in shrinking cities, the role of land use dynamics remains underexplored. This study systematically investigates land use carbon emissions (LUCE) in shrinking counties to address this gap. Focusing on the Beijing-Tianjin-Hebei (BTH) region (2000–2020), we integrated population indices, land use data, energy statistics, and nightlight imagery to classify counties into non-shrinking, continuous, temporary, and potential shrinkage types. Direct and indirect carbon emissions were estimated using emission coefficients and energy consumption models. Key findings include: (1) Non-shrinking counties, concentrated in urban cores, exhibit higher LUCE but slower growth rates, whereas shrinking peripheral counties show lower emissions but faster LUCE growth. (2) Continuous shrinkage counties experience the highest LUCE growth due to inefficient built-up area expansion, despite having significant carbon sinks. (3) Severe shrinkage counties demonstrate the fastest total carbon emissions (TCE) growth, with per capita emissions (PCE) positively correlated to shrinkage intensity. These findings highlight the need for differentiated policies: prioritizing land-use efficiency in shrinking counties, integrating regional equity into emission governance, and leveraging carbon sinks in ecologically rich areas.

KEYWORDS

shrinking cities, carbon emissions, land use dynamics, counties, Beijing-Tianjin-Hebei

1 Introduction

The carbon emission pressure has become increasingly severe, constituting a serious menace to both the regional ecological environment and sustainable human development. According to the International Energy Agency (IEA, 2023), China accounted for around 28% of global CO_2 emissions in 2022, totaling 12.1 billion tonnes. The industrial and energy sectors dominate national emissions, accounting for 65% of the total, while rapid urbanization has driven a 40% increase in carbon emissions from urban construction

and transportation since 2010. For instance, built-up areas expanded by 25% in the Beijing-Tianjin-Hebei (BTH) region from 2000 to 2020, directly correlating with a 38% rise in regional carbon emissions (National Bureau of Statistics of China, 2023). These trends underscore the urgency of reconciling urban development with emission reduction goals, particularly in regions experiencing population shrinkage (Zhang et al., 2022a). To address the carbon emissions challenge, the Chinese government has put forward a plan to reach the peak of carbon emissions by 2030 and attain carbon neutrality by 2060 (Zhang et al., 2022). As China's economy enters the transition stage, the constraints on the available resources and the environment continue to increase, as well as the Matthew effect of the factor agglomeration (Zhang et al., 2022). This effect further enlarges the dominant position of the economically developed regions in various fields, aggravates the imbalance of regional development, intensifies the spatial concentration and dispersion of the population, and some cities show a shrinking trend. The predominant manifestations of this effect encompass population depletion, economic recession, escalating unemployment, deserted land, unoccupied houses, and environmental deterioration, among other aspects (Guo et al., 2021). Conversely, a decline in population can to a certain degree ease the pressure on the environment and resources, and consequently lead to a reduction in carbon emissions (Herrmann et al., 2016). In the face of the new trend of urban shrinkage, clarifying the differences in carbon emissions among different regional cities with various development types is of significant importance for formulating regional carbon reduction plans and promoting urban sustainable development.

The concept of urban shrinkage originated in Europe in the 1980s, particularly in post-industrial regions such as Germany's Ruhr Valley and Eastern Europe, where deindustrialization and population aging triggered sustained population decline (Häußermann and Siebel, 1988). Recent research has highlighted that it is prevalent in both developed and developing countries and is a global phenomenon. In Europe, cities such as Leipzig and Dresden have implemented "smart shrinkage" policies that focus on urban greening and compact development to address population decline and economic stagnation (Artmann et al., 2019; Kim et al., 2020). In the United States, rust belt cities such as Detroit and Cleveland experienced significant shrinkage due to deindustrialization, leading to widespread urban decay and population loss (Sutradhar et al., 2024). Similarly, Japan is facing shrinking cities due to an aging population and declining birth rate, with cities such as Kitakyushu adopting compact urban forms and renewable energy integration to mitigate this impact (Onodera et al., 2024).

The urban shrinkage in China has some unique factors such as population aging and the decline of resource-based cities. For example, cities in Northeast China, which once relied on heavy industry and natural resources, are facing significant economic decline and population loss due to resource depletion and industrial restructuring (Chen, 2024; Xie et al., 2022). In addition, China's aging population exacerbates urban shrinkage as younger generations migrate to economically active areas, leaving behind an older, less economically active population (Kang et al., 2024). These factors set China's urban shrinkage apart from other countries and require a targeted policy response.

Compared with non-shrinking cities, shrinking cities exhibit distinct transformation dynamics in population, economy, society, and land use patterns, which may catalyze novel pathways for carbon emission evolution. Scholars globally have initiated systematic investigations into the interplay between urban shrinkage and carbon emissions, yielding preliminary insights into their complex relationship. For instance, Maerz et al. (2013) conducted a seminal analysis of low-carbon transition barriers and enablers in German shrinking cities, emphasizing structural economic constraints. Schwartz et al. (2020) demonstrated that strategic optimization of urban green spaces in shrinking contexts could reduce emissions by up to 15%, highlighting the role of ecological planning. In the Chinese context, Yang et al. (2022) revealed divergent carbon emission trajectories between growing and shrinking cities, with the latter showing accelerated *per capita* emissions despite population decline. A notable contribution by Xiao et al. (2019) quantified emission disparities, identifying a persistent upward trend in rapidly shrinking cities, whereas Tong X. et al. (2022) reported an inverted U-shaped emission curve in such contexts. Complementing these findings, Liu X. et al. (2020) and Zeng et al. (2022a) established scale-dependent correlations, showing that shrinkage-induced emission increases were disproportionately pronounced in smaller urban units. Further granularity was added by Zeng et al. (2022b), who delineated shrinkage-driven reductions in both energy consumption efficiency and carbon emission performance.

Despite these advancements, three critical limitations persist in the current scholarship. First, extant literature predominantly focuses on energy-related emissions, overlooking the mediating role of land use dynamics in shaping emission pathways. While land cover alterations (e.g., deforestation, urbanization) directly release sequestered carbon (Zhang et al., 2022b), indirect emissions from land use-associated activities—such as transportation networks and construction sprawl (Yang et al., 2022)—remain underexplored in shrinkage contexts. Second, the prevailing reliance on prefecture-level city analyses in Chinese studies inadequately captures localized shrinkage mechanisms. Given their administrative granularity and economic vulnerability, counties serve as more sensitive indicators of shrinkage impacts (Guan et al., 2021; Tong et al., 2022b). Third, although population size and shrinkage intensity have been incorporated into emission models, the temporal trajectories of shrinkage (e.g., continuous vs. episodic) and their emission implications remain virtually unaddressed in empirical research.

This study advances shrinkage research by addressing three critical gaps in prior work: First, while existing literature predominantly focuses on energy-related emissions, we establish land use dynamics as a key mediator between shrinkage and carbon outcomes. Second, our county-level analysis reveals spatial heterogeneities obscured in prefecture-level studies. Third, we pioneer the classification of shrinkage trajectories (continuous, temporary, potential), demonstrating their distinct emission pathways. By elucidating the relationship between urban shrinkage and accelerated LUCE, our findings provide critical insights for tailoring carbon reduction strategies to different shrinkage trajectories. For policymakers, the results underscore the need to prioritize land-use efficiency in shrinking counties and integrate regional equity into emission governance.

Ultimately, this work contributes to bridging the gap between urban shrinkage studies and low-carbon transition policies, offering actionable pathways for achieving China's 2030/2060 carbon goals.

2 Materials and methods

2.1 Study area

The Beijing-Tianjin-Hebei region is located in the heart of China's Bohai Sea region, between 113°27′-119°50′E and 36°05′-42°40′N (Figure 1). It has a land area of 216,000 km2 and is considered the most densely populated and economically active urban area in northern China. Moreover, it has two municipalities directly under the central government of Beijing and Tianjin and Hebei province, with a total of 199 county-level administrative districts and a resident population of 107 million by the end of 2020. From 2000 to 2010, 34 districts and counties lost their resident population, while during the decade 2010-2020, 114 districts and counties lost their resident population, accounting for more than half of the number of counties and districts in the Beijing-Tianjin-Hebei region, which corresponds to an increase of nearly three times, with the regional population loss intensifying and the trend of shrinkage coming into the fore. Additionally, the region faces severe economic disparities, with GDP *per capita* in shrinking counties being significantly lower than in non-shrinking counties (Wang et al., 2020). In 2020, the carbon emissions of the Beijing-Tianjin-Hebei city cluster will be 601 million tons, which is equivalent to an increase of 335 million tons compared with 2009 (266 million tons). The BTH region exhibits a prominent trend of population shrinkage and severe pressure for carbon emission reduction. It is an important experimental field for exploring urban carbon emission reduction in the context of shrinkage.

2.2 Data sources

The demographic information was sourced from the fifth (2000), sixth (2010), and seventh (2020) national censuses of China, publicly available through the National Bureau of Statistics (http://www.stats.gov.cn). The land use data for the years 2000, 2010, and 2020 were obtained from the esteemed Data Center for Resources and Environmental Sciences, affiliated with the Chinese Academy of Sciences, accessible via their official website (http://www. resdc.cn). These land use datasets were classified into six fundamental categories: cropland, forestland, grassland, water, construction land, and unused land. Each category has a spatial granularity of 30 m. The regional energy consumption data in the BTH region were derived from China Energy Statistical Yearbook. The data of the administrative territory originated from the 1:100,000 Chinese Geographical Information Resources Directory Service System (http://www.webmap.cn). The nightlight dataset (Version 2.0, 1000 m resolution) was obtained from the Global Change Scientific Research Data Publishing System (https://www.geodoi.ac.cn). Specifically, we utilized the comprehensive Chinese Long Time Series Night Light Dataset spanning from 2000 to 2020. To address administrative boundary changes (e.g., mergers or splits of counties), we standardized all data to the 2020 county boundaries using spatial overlay and area-weighted interpolation in ArcGIS 10.8. Historical census data were adjusted to match the 2020 administrative divisions.

2.3 Research methods

2.3.1 Methodological framework

This study adopts a systematic approach to analyze LUCE in shrinking cities within the Beijing-Tianjin-Hebei (BTH) region. The methodological framework comprises four key steps: (1) Data Preparation: Integration of multi-source datasets, including population census, land use maps, energy statistics, and nighttime light imagery, standardized to 2020 administrative boundaries. (2) Shrinkage Identification: Classification of counties into non-shrinking and shrinking types (continuous, temporary, potential) based on population dynamics (2000–2020). (3) Land Use Dynamics Analysis: Quantification of land use changes using dynamic degree indices and correlation with LUCE trends. (4) Carbon Emission Estimation: Calculation of direct emissions (via land use coefficients) and indirect emissions (via energy consumption models).

2.3.2 Identification of shrinking counties

Based on the relevant works in the literature (Hu et al., 2021; Yang et al., 2022; Zhou et al., 2021), the characteristics of shrinking cities are usually manifested in three aspects: population loss, economic decline, and spatial decay. However, in the specific identification of shrinking cities, the scientific community has not yet established a uniform standard. Nevertheless, population loss is generally regarded as the main characteristic of shrinking cities. Moreover, the shrinkage of cities in China is manifested primarily by population outflow from those cities facing vulnerable competition, whereas economic recession and spatial decay are not as pronounced (Chen et al., 2022).

Therefore, county-level administrative areas were used here as the research unit, and population loss was taken as the identification sign of the county shrinkage. The census data of permanent residents were used in this work, which were divided into T1 and T2 phases with a 10-year interval between censuses. T1 was 2000–2010 and T2 was 2010–2020. The years 2000, 2010, and 2020 were selected as temporal nodes for three key reasons: 1. Data Consistency: China conducts its national population census every decade (2000, 2010, 2020), providing authoritative and standardized demographic data essential for longitudinal analysis. 2. Shrinkage Trajectory: Before 2000, county shrinkage in the BTH region was negligible (Liu et al., 2020b). From 2000 to 2010, shrinkage intensified (34 counties), and by 2010–2020, over half of counties experienced population loss, marking a critical transition from localized to widespread shrinkage. 3. Policy Relevance: The 20-year span captures China's urbanization and carbon policy shifts, enabling analysis of LUCE trends under varying shrinkage intensities and governance phases. Meanwhile, PI (population index) was used to define

TABLE 1 Types of shrinking counties.

Shrinkage trajectory	Description	Shrinkage intensity	Description
Continuous shrinkage	Shrinkage occurs in each time period; which is, 2000–2010 < 0, 2010–2020 < 0	Slight shrinkage	−1% ≤ PI < 0
Potential shrinkage	Growth in the former period and shrinks in the latter period; which is, 2000–2010 > 0, 2010–2020 < 0	Moderate shrinkage	−2% ≤ PI < −1%
Temporary shrinkage	Shrinks in the former period and growth in the latter period; which is, 2000–2010 < 0, 2010–2020 > 0	Severe shrinkage	−5% ≤ PI < - 2%
Non shrinkage	Each time period growth; which is, 2000–2010 > 0, 2010–2020 > 0	Extreme shrinkage	PI < −5%

population shrinkage rate of each county and district in each period.

$$PI = \frac{POP_{i2} - POP_{i1}}{POP_{i1}} \times 0.1 \times 100\% \quad (1)$$

In Formula (1), PI stands for the population index. Meanwhile, POP_{i1} and POP_{i2} represent the populations as cited in the national censuses conducted in $i1$ and $i2$, respectively. The factor of 0.1 is used to convert the population change over a 10-year period into an annualized rate.

2.3.3 Types of shrinking counties

To comprehensively analyze the unique characteristics and variations observed in county shrinkage, a review of the relevant works in the literature was conducted (Gao et al., 2022; Guan et al., 2021; Wolff and Wiechmann, 2018). This research categorized counties into eight distinct types, based on their respective shrinkage trajectories and degrees (Table 1).

2.3.4 Land use dynamic degree

The land use dynamic degree serves as an indicator, offering insights into the tempo and magnitude of alterations occurring within various land use categories within the designated study area, spanning across a specified time frame (Du et al., 2022; Huang et al., 2018). The computation of the dynamic degree pertaining to a specific land use type can be performed using the following Formula (2):

$$S_i = \left[(U_{it2} - U_{it1}) / U_{it1} \right] \times (t_2 - t_1)^{-1} \times 100\% \quad (2)$$

where Si is the single dynamic degree of land use type i, U_{it2} is the area of land use type i in the study area at time t_2, U_{it1} is the area of land use type i at time t_1, and t_2~t_1 is the study period.

2.3.5 Estimation of LUCE

LUCE encompass two distinct categories: direct and indirect emissions (Hong et al., 2023; Yang and Liu, 2023). Direct carbon emissions are the emissions that directly originate from different land use types during their utilization. Specifically, they comprise emissions from cropland, forest, grassland, water, and unused land. Conversely, indirect carbon emissions are related to the energy consumption linked with socioeconomic activities, production procedures, and the inhabitation of land allocated for construction (Rong et al., 2023; Song et al., 2023).

(1) The estimation of direct carbon emissions emanating from diverse land-use categories was conducted employing the carbon emission coefficient methodology. Specifically, the coefficients assigned to cropland, forest, grassland, water, and unused land were quantified as 0.422, −0.623, −0.021, −0.253, and −0.007 tons per hectare per annum (t/hm^2 a), respectively (Wang et al., 2021; Yan et al., 2022; Zhang et al., 2024; Zhu et al., 2019). The Formula (3) utilized for calculating direct carbon emissions is presented as follows:

$$C_d = \sum e_i = \sum_{i=1}^{5} A_i \times \alpha_i \quad (3)$$

where C_d is the total amount of direct carbon emissions, e_i states the carbon emission generated by the i land use type, A_i denotes the area of land use type i, and α_i represents the carbon emission coefficient of land use type i.

(2) Indirect carbon emissions: The construction land also account for a significant portion of the energy expenditure generated by human activities. Carbon emissions can be estimated indirectly by considering the energy consumed during the utilization of the construction land. The Equation (4) for this estimation is as follows:

$$C_i = \sum E_j = \sum m_j \times \beta_j \times \gamma_j \quad (4)$$

where C_i is the indirect carbon emissions, E_j represents the carbon emissions from various fossil energy sources, m_j stands for the fossil energy consumption, β_j is standard coal conversion coefficient, and γ_j refers to the carbon emission coefficient.

To this end, the conversion coefficient of the energy standard coal issued by the (IPCC, 2006) was used in combined with the carbon emission coefficient studied by the scientific community in the BTH region (Cui et al., 2019; Zhou Ying et al., 2021), and the relevant parameters are presented in Table 2. Due to the lack of county-level energy consumption statistics, the night light data is combined with energy consumption statistics to estimate carbon emissions. According to (Wang et al., 2021; Yang et al., 2022; Zhou Yuan et al., 2021) uses a regression model in which nightlight data is used as a proxy for energy consumption. The model was validated against available energy consumption statistics at the regional level, ensuring the reliability of the estimates.

TABLE 2 Standard coal conversion coefficients and carbon emission coefficients.

Energy sources	Standard coal conversion coefficient	Carbon emission coefficient
Coal	0.7143 (kgce/kg)	0.7559
Coke	0.9714 (kgce/kg)	0.8550
Crude Oil	1.4286 (kgce/kg)	0.5857
Fuel Oil	1.4286 (kgce/kg)	0.6185
Gasoline	1.4714 (kgce/kg)	0.5538
Kerosene	1.4714 (kgce/kg)	0.5714
Diesel Oil	1.4571 (kgce/kg)	0.5921
Natural Gas	1.3301 (kgce/m^3)	0.4483
Electricity	0.1299 (kgce/kWh)	0.7935

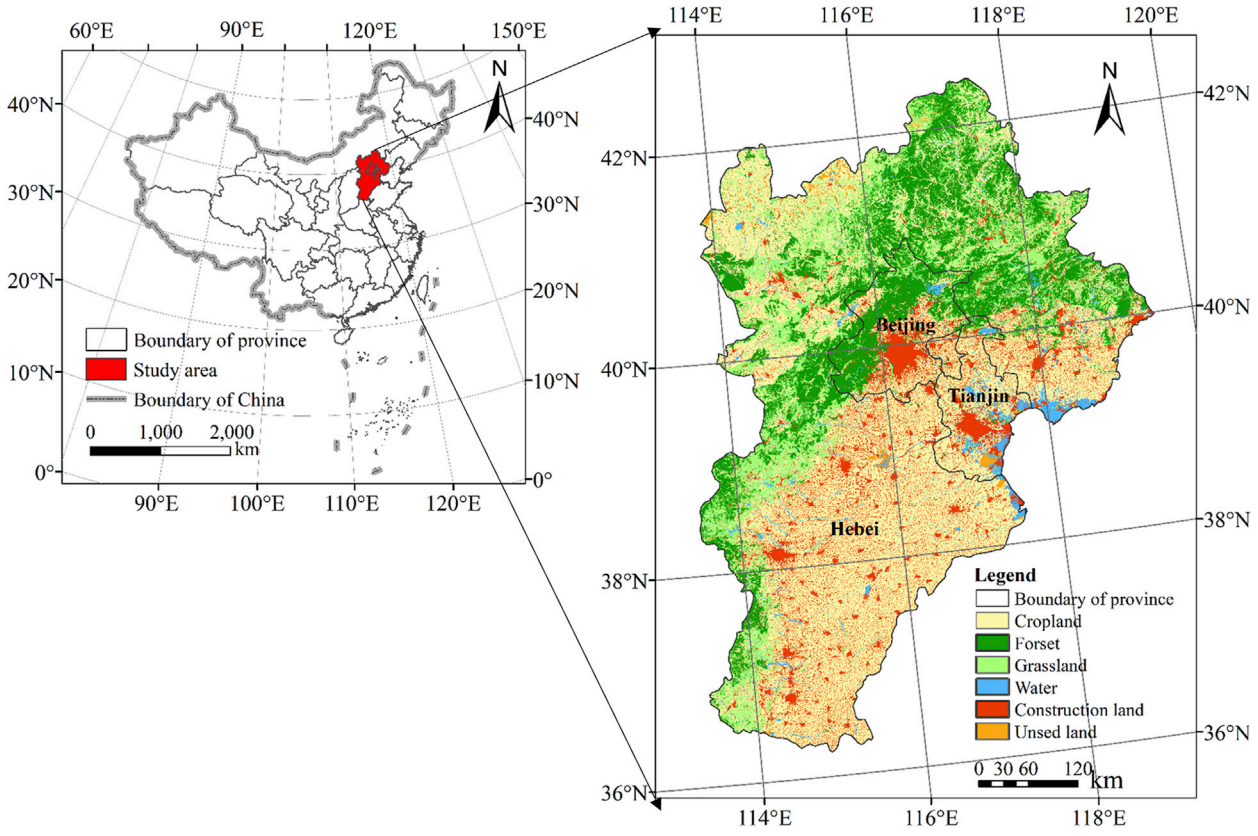


FIGURE 1
Geographical location of the studied area.

3 Results and analysis

3.1 LUCE in shrinking and non-shrinking counties

To gain a deeper comprehension of the LUCE peculiarities within shrinking counties, we compared and analyzed the LUCE in shrinking counties with those in non-shrinking counties. In general, non-shrinking counties are predominantly clustered in the environs of Beijing, Tianjin, and Hebei, and the shrinking counties are distributed in the periphery. Non-shrinking counties have obvious regional advantages and strong capacity for the agglomeration of regional development factors. The outflow of development factors in shrinking counties, primarily characterized by population outflow, is the result of the interplay between the development capabilities of these counties and their associated counties. The corresponding areas with high LUCE values are mainly distributed in non-shrinking counties, and the LUCE in

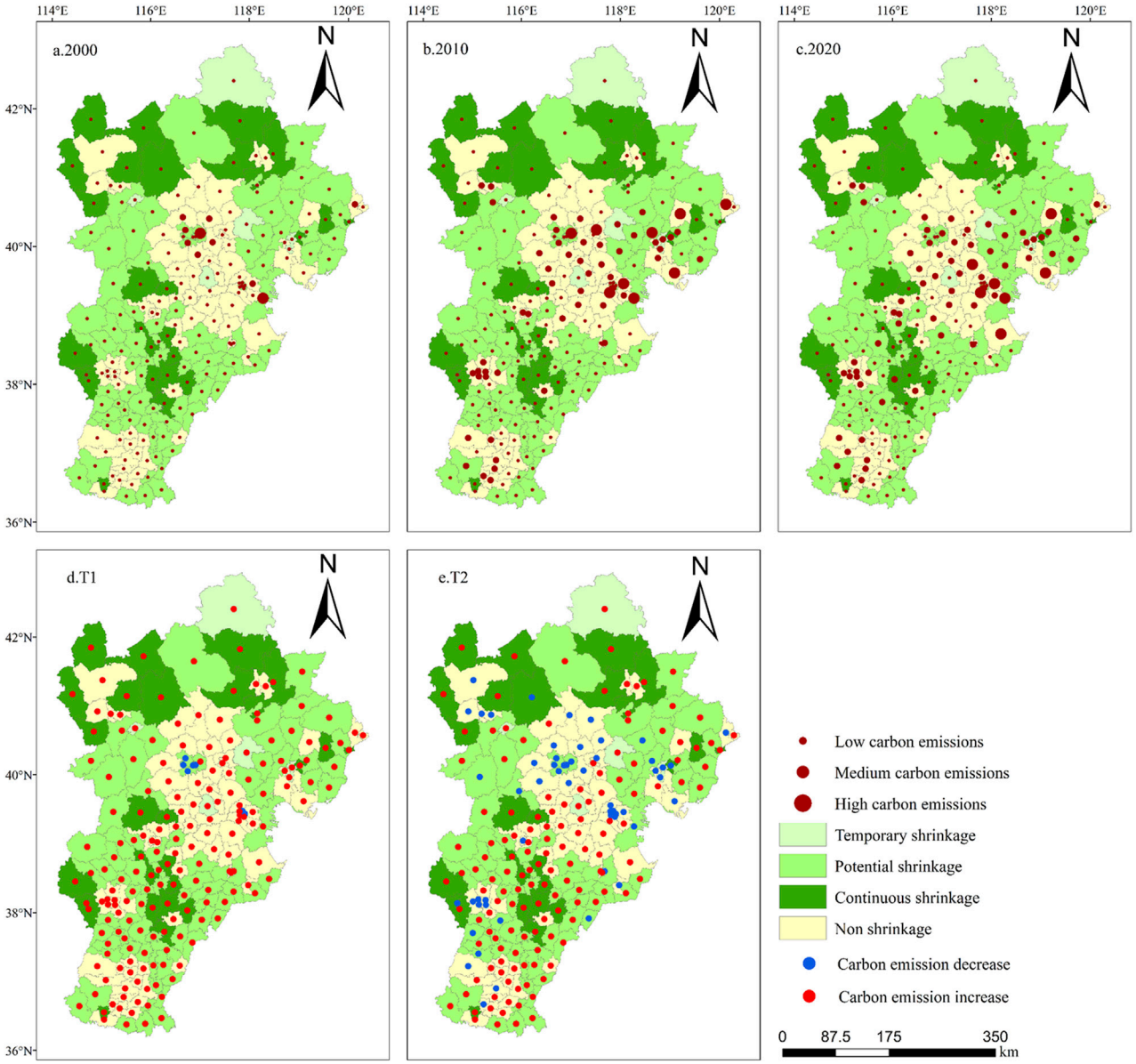


FIGURE 2
Spatial distribution and changes in TCE. **(a)** 2000 **(b)** 2010 **(c)** 2020 **(d)** T1:2000-2010 **(e)** T2:2010-2020.

shrinking counties is generally relatively low (Figure 2). At the same time, the adaptability of the non-shrinking counties to low-carbon development is stronger, while that of shrinking counties is weaker. It is predominantly manifested in the facilitation of green and low-carbon development in the region at T2 stage. Moreover, the counties where TCE and PCE are reduced are mainly non-shrinking counties (Figure 3).

Under the influence of the overall regional trend, the land use change of both shrinking and non-shrinking types exhibited continuous expansion of the built-up areas and continuous reduction of the cropland. Compared with the T1 stage, the growth rate of the construction land expansion and reduction rate of the cropland in the T2 stage slowed down (Table 3). The areas of the forest and grassland remained largely stable, while the water and unused land with low carbon sequestration potential, although experiencing significant fluctuations, were less distributed in the BTH region, accounting for only 4% of the total area, resulting in weak carbon uptake (Figure 4). A strong consistency between the continuous expansion of the construction land and the continuous increase in the LUCE can also be observed. During T1 stage, non-shrinking counties experienced a TCE growth rate of 17.6% annually (vs. 12.6% in shrinking counties), driven by construction land expansion at 4.29% per year (Table 3). In the T2 stage, the expansion of the construction land in non-shrinking counties slowed down sharply, and the TCE grew at a low speed, with a growth rate of only 0.4% annually, lower than 1.4% in shrinking areas. Furthermore, the growth rate of PCE was significantly lower than that in shrinking counties (Figure 5B). Thereby, it can be inferred that shrinking counties have weak adaptability to low-carbon development of land use, which may stem from their

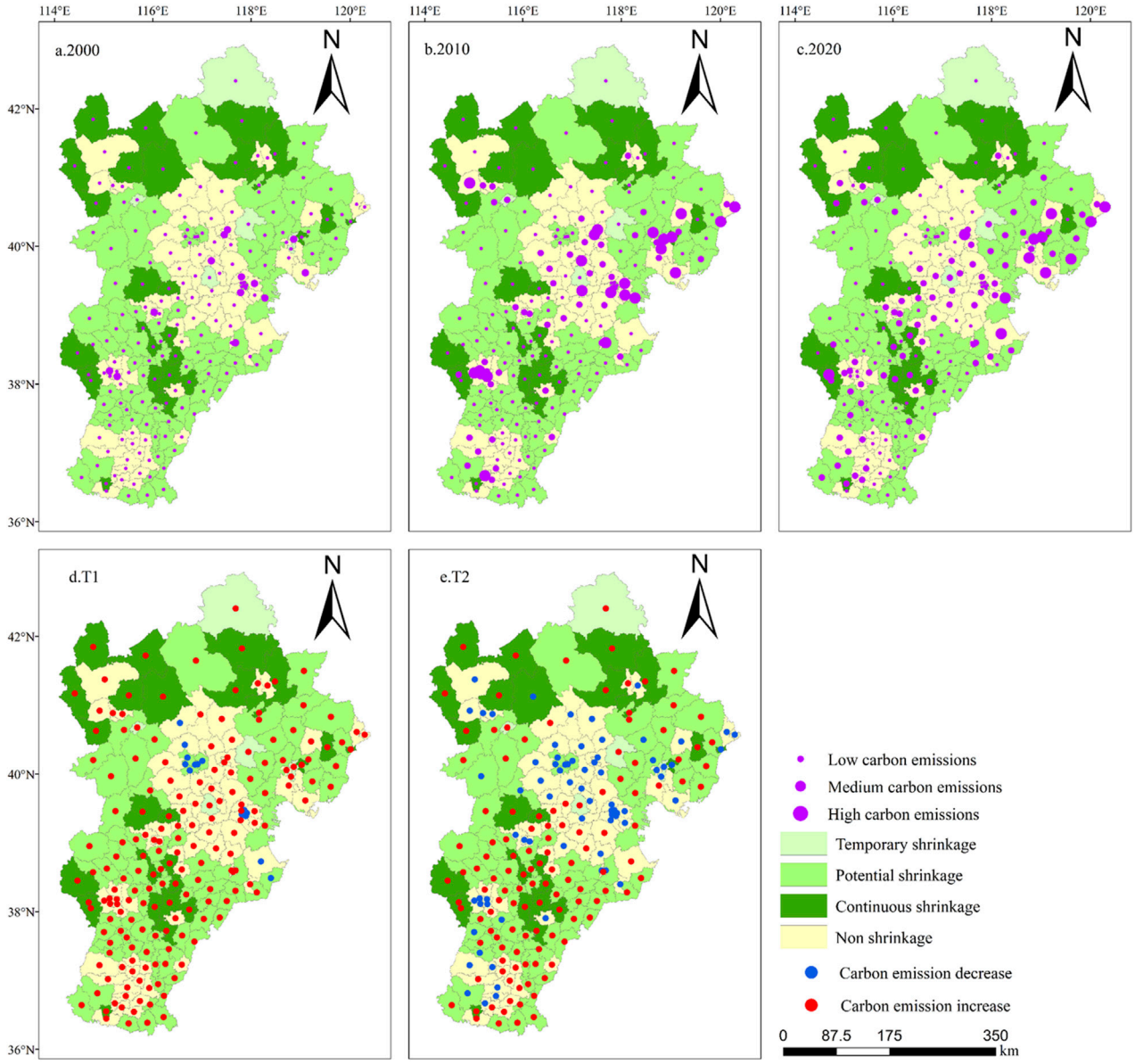


FIGURE 3
Spatial distribution and changes in PCE. **(a)** 2000 **(b)** 2010 **(c)** 2020 **(d)** T1:2000-2010 **(e)** T2:2010-2020.

relatively low development stage and economic level, lower land use efficiency and energy use efficiency, or they are located in low-carbon emission areas with less pressure on carbon emission reduction (Ge and Liu, 2021; Zhou et al., 2021).

3.2 LUCE with different shrinkage trajectories

To further analyze the LUCE of the shrinking types, the LUCE of the different shrinking types were systematically explored by identifying the population index. A total of 27 counties and districts continued to shrink, mainly distributed in the northern plateau and central plain. The economic development level was relatively backward, and the continuous population decline indicated that the region was less attractive and lacked the driving force for economic development. Ecological lands (forest and grassland) were widely distributed, and the carbon sink was about one-third of that in the BTH region, and remained basically stable. Besides, both the TCE and PCE were relatively low (Figure 4). However, Continuous shrinkage counties showed the highest annual TCE growth rate (3.7% in T2), followed by potential shrinkage (1.2%) and temporary shrinkage (0.07%) (Figure 5A). This disparity correlates with construction land expansion rates: 1.37% in continuous shrinkage vs. 0.60% in potential shrinkage (Table 3). In the cases of insufficient economic power, the government mostly transfers land use rights to increase fiscal revenue (land finance), so as to maintain Gross Domestic Product (GDP) growth. However, due to the lack of economic development power, the land use efficiency is low, resulting in the waste of land resources and the

TABLE 3 Single land use dynamic degree corresponding to different shrinkage types.

Types of urban shrinkage	Time	Cropland	Forest	Grassland	Water	Construction land	Unused land
Non shrinkage	T1	−0.80	−0.10	−0.87	−0.60	5.57	−5.37
	T2	−0.62	0.15	0.71	3.56	0.68	2.32
Continuous shrinkage	T1	−0.09	0.15	−0.55	−1.65	4.45	−0.63
	T2	−0.35	0.26	−0.01	0.66	1.37	−0.24
Potential shrinkage	T1	−0.42	0.16	−0.22	−1.77	3.92	−6.77
	T2	−0.29	0.03	−0.16	2.35	0.60	24.40
Temporary shrinkage	T1	−0.32	−0.14	0.88	−0.98	3.22	−5.19
	T2	−0.09	−0.10	0.03	0.45	1.04	−0.52
Slight shrinkage	T1	−0.11	0.20	−0.47	−1.56	4.03	−2.00
	T2	−0.30	0.07	−0.04	1.66	0.79	2.57
Moderate shrinkage	T1	−0.62	−1.07	1.68	3.84	12.98	0.00
	T2	−0.25	0.05	−0.30	2.79	0.53	95.02
Severe shrinkage	T2	−0.55	1.88	0.45	1.82	1.72	−0.90

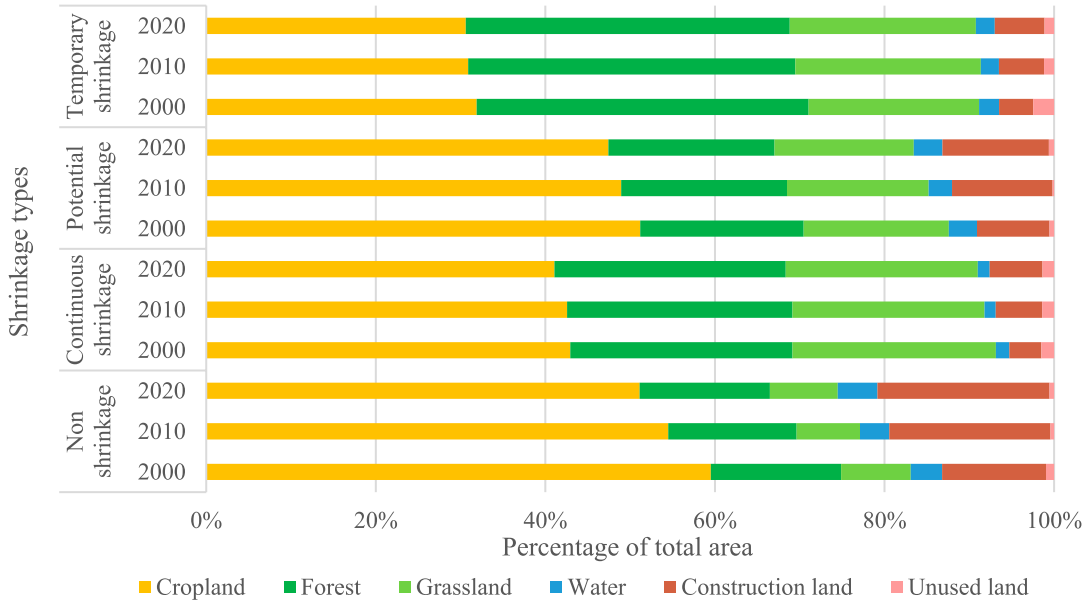


FIGURE 4
The proportion of land use area in different shrinkage types (2000–2020).

increase of LUCE. This outcome is consistent with the research of Wang et al. (2020), suggesting that land finance accelerates the further shrinkage of the urban population. Therefore, shrinking counties need to achieve regional green and low-carbon quality development through intensive land use.

In addition to continuous shrinkage, shrinkage at different stages can be classified into two categories. The first category is marked by shrinkage at T1 and growth at T2. In this work, it is referred to as temporary shrinkage. There are only seven counties of this type, and their distribution is relatively scattered (Figure 2). The growth rate of LUCE in the T2 stage is the lowest among all shrinkage types. Counties and districts are transition from shrinkage to growth, indicating the success of the development transformation, energy structure adjustment, and energy efficiency improvement, to achieve "smart shrinkage". Besides, 3 counties and regions with reduced LUCE were detected (Figure 4), accounting for 42.86%, which is the highest proportion among the different types of shrinkage trajectories. These regions were distributed in Tianjin and Tangshan, Hebei Province, where the economic development level was relatively good. The development of the construction land has

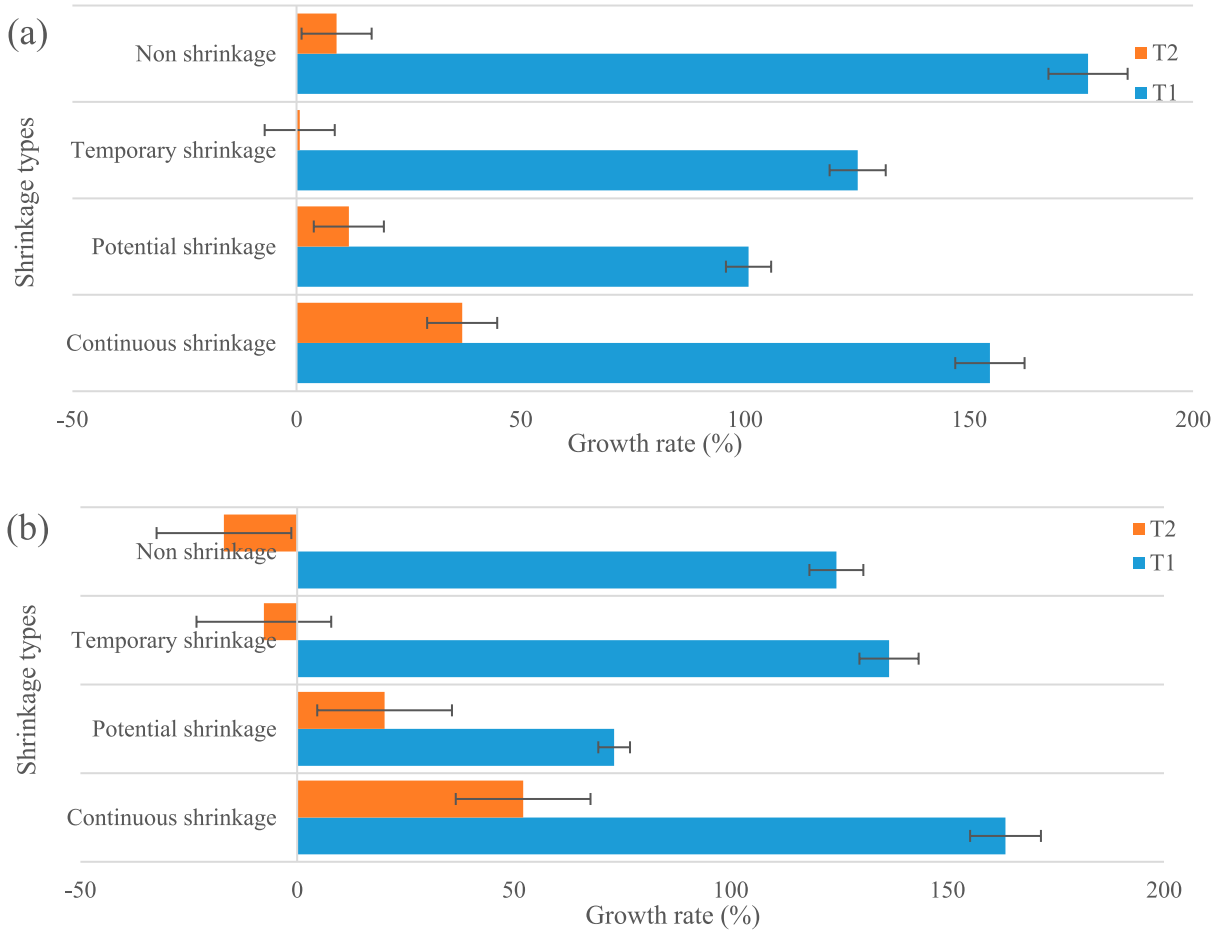


FIGURE 5
Change rate in LUCE: **(a)** Total carbon emissions (TCE); **(b)** Per capita emissions (PCE). Time periods (T1: 2000–2010, T2: 2010–2020).

shown saturation, and the land use change has basically remained stable. Due to the small sample size and the large differences in TCE among the samples, the overall trend is more influenced by counties with high LUCE.

The second category is marked by population growth during the T1 stage and population shrinkage in the T2 stage, which we term the potential shrinkage type in this work. Counties of this type are primarily distributed in the surrounding areas of Beijing and Tianjin, as well as around cities in Hebei Province, and exhibit a contiguous distribution. The proportion of carbon sink lands, such as forest and grassland, is relatively low, whereas the proportion of carbon source land, such as construction land is relatively high. Counties that have high levels of LUCE are predominantly located in this category. Both TCE and PCE continue to grow, with the growth rate of the TCE and PCE in the T1 stage is the lowest among all shrinkage types. In contrast, the growth rate of TCE and PCE in the T2 stage is only higher than that of the potential shrinkage type (Figure 5). Thus, it can be argued that the urban shrinkage is negatively correlated with the growth rate of the LUCE. Despite the overall growth trend of LUCE, some counties and districts exhibited a downward trend, primarily located in the main urban areas of Beijing and Tianjin, which possess the highest regional economic level (Figure 2). The primary reason for this phenomenon may be that urban development has reached a stage of high-quality development. To enhance urban functions, improve urban quality, and optimize the energy consumption structure, cities have taken proactive measures to reduce their populations, leading to a continuous decrease in both TCE and PCE. Additionally, the development of construction land has shifted towards reducing volume and increasing efficiency. It is evident that urban shrinkage is influenced by complex driving mechanisms, and the LUCE in shrinking counties vary significantly under different mechanisms. Currently, the spatial distribution of counties experiencing active shrinkage is concentrated, with a relatively small proportion of regions affected. However, this may become a trend in the development of megacities in the future.

3.3 LUCE under different shrinkage degrees

In the T1 stage, the BTH region exhibited local shrinkage of less developed areas, with 34 shrinking counties, accounting for 17%. Only two counties experienced moderate shrinkage, and the trend in LUCE was reversed. However, due to the small sample size, it lacks regularity. There were 32 counties with slight shrinkage, and both TCE and PCE displayed an upward trend. Compared to the entire

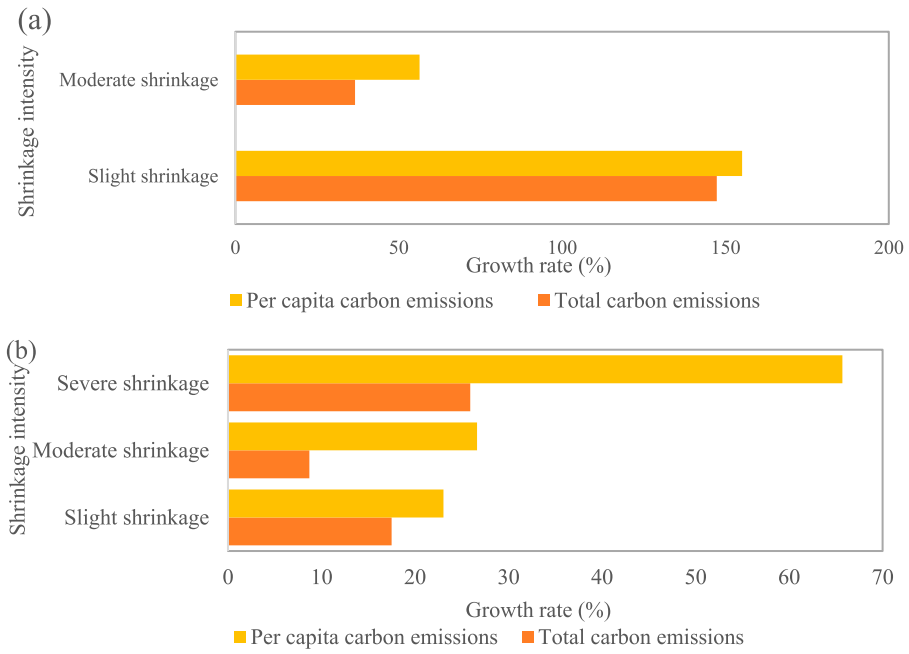


FIGURE 6
Change rate of LUCE under different shrinkage degrees: **(a)** T1 (2000–2010); **(b)** T2 (2010–2020).

BTH region, the TCE grew at a lower rate, while the PCE grew at a higher rate, and the expansion rate of construction land was lower in the T1 stage. It is evident that the expansion of the built-up area is highly correlated with the growth of TCE, and population loss leads to rapid growth in PCE. In the T2 stage, the number of shrinking counties increased rapidly, transitioning from local to global shrinkage, with severe shrinkage counties emerging. Nonetheless, the region was still predominantly characterized by mild shrinkage. LUCE for each shrinkage degree and type also exhibited an upward trend. The percentages of counties with decreased LUCE were 17%, 23%, and 18% for severe, moderate, and mild shrinkage, respectively, with the moderate shrinkage type having the highest proportion. Among shrinking counties, the growth rate of TCE was highest in severe shrinkage, followed by mild shrinkage, and lowest in moderate shrinkage. Similarly, the growth rate of PCE was highest in severe shrinkage, followed by moderate shrinkage, and lowest in mild shrinkage (Figure 6). The expansion of the construction land is relatively consistent with the growth rate of TCE, confirming a positive correlation between the two. In general, during the stage of urban expansion, a stronger degree of shrinkage leads to more drastic expansion of the construction land and a faster growth rate of TCE. Due to differences in the extent of population loss, the growth rate of PCE was lowest in moderately contracted counties.

Since counties with the same degree of shrinkage are at different stages of development and exhibit significant differences in LUCE trends, it was found that the regularity is more obvious by eliminating counties with large differences in overall trends within the same shrinkage degree. Generally speaking, severe population loss in counties and districts indicates low economic development vitality and limited avenues for driving economic growth and attracting the population. Consequently, further urban development is often driven by increasing the land quota for construction, which simultaneously promotes urban expansion and construction (Hu et al., 2021; Wu and Yao, 2021). Due to the extensive development model, low land use efficiency, and persistent severe population loss, multiple factors could contribute to a relatively high growth rate of PCE.

4 Discussion

4.1 LUCE in shrinking counties

Our findings reveal that non-shrinking counties exhibit a lower growth rate in LUCE compared to shrinking counties, which aligns with previous studies highlighting the challenges of carbon reduction in shrinking cities (Xiao et al., 2019; Yang et al., 2022). However, our study provides a more nuanced understanding by emphasizing the stage differences in LUCE trends. During the early stages of urban expansion, non-shrinking counties experience rapid growth in LUCE due to intense built-up area expansion. In contrast, during the later stages of urban transformation, the growth rate of LUCE in non-shrinking counties slows significantly, reflecting successful efforts in industrial upgrading and energy efficiency improvements. Severely shrinking counties, despite having the lowest initial LUCE, exhibit the fastest growth rate in total carbon emissions (TCE). This anomaly can be attributed to the extensive development model prevalent in these regions, where low land use efficiency and persistent population loss exacerbate carbon emissions. This finding challenges the conventional assumption that population decline inherently reduces carbon emissions and underscores the need for targeted interventions in severely shrinking regions.

4.2 LUCE in shrinking counties under different driving mechanisms

Urban shrinkage is driven by a combination of factors, and our study identifies two distinct mechanisms: passive shrinkage and proactive shrinkage.

Passive Shrinkage: In the T1 stage (2000–2010), shrinkage in the BTH region was primarily driven by the depletion of resources in industrial and mining counties, leading to population loss and economic decline. These counties, located on the periphery of urban agglomerations, experienced spatial deprivation of development factors, resulting in low LUCE but rapid growth rates due to inefficient land use.

Proactive Shrinkage: In the T2 stage (2010–2020), a new form of shrinkage emerged, characterized by policy-driven suburbanization in Beijing. This proactive shrinkage aimed to optimize urban spatial distribution, alleviate congestion, and control population size. Counties experiencing proactive shrinkage exhibited stable or decreasing LUCE, reflecting successful efforts in land use optimization and energy efficiency improvements. The Dongcheng District of Beijing, a severely shrinking county dominated by tertiary industries, demonstrated a continuous decrease in LUCE. This finding highlights the potential for high-quality urban development in shrinking cities, where proactive policies can lead to significant carbon emission reductions. This contrasts with the typical narrative of shrinkage as a negative phenomenon and offers a new perspective on the potential benefits of managed urban decline.

Unique to the BTH region, the coexistence of these pathways highlights the critical role of regional equity policies. For example, Tangshan's waterfront industrial zone absorbed Beijing's relocated steel plants, exacerbating emissions in a shrinking county. This anomaly, absent in Western cases (Miljanović et al., 2023), underscores the need for trans-regional carbon accounting in China's coordinated development plans.

4.3 Limitations and directions for improvement

Although some research results were achieved in this work, it still has the following limitations:

(1) Census data have inherent limitations, including a 10-year temporal resolution and delayed publication (e.g., 2020 census results were released in 2021). This may introduce gaps in capturing rapid population shifts. Additionally, nightlight data at 1000 m resolution may overlook fine-scale land use changes, particularly in peri-urban or rural counties.

With the advancements in the Internet and remote sensing geographic information technology, it is now possible to obtain spatio-temporal big data that can accurately represent human activities over a wide range and with high precision. In the future, big data can be utilized to better identify shrinking cities at different scales.

(2) LUCE exert a certain impact on urban shrinkage. However, whether the interaction between shrinking cities will amplify this impact remains unknown. In the future, the impact of interactions between shrinking cities on LUCE can be further explored.

(3) This study qualitatively analyzed the differences in LUCE patterns between actively shrinking counties and passively shrinking counties. The LUCE in shrinking cities with different driving mechanisms are significantly different, and the underlying processes of urban shrinkage in different development periods are obviously heterogeneous. Therefore, in future studies on the LUCE effects of shrinking cities, it is necessary to further analyze LUCE under different development stages and driving mechanisms from a quantitative perspective.

4.4 Policy recommendations for mitigating shrinkage and LUCE

4.4.1 Policy recommendations

Based on the findings, the following policy recommendations are proposed to address urban shrinkage and its impact on LUCE at the county level:

First, strict control of built-up area expansion in shrinking counties should be prioritized. For example, zoning policies could enforce "infill development" by reusing vacant industrial lands and abandoned residential areas, rather than permitting urban sprawl. This aligns with the observed correlation between built-up area expansion and LUCE growth (Figure 5). Second, establishing cross-county cooperation platforms is critical to mitigate the "center-periphery" imbalance. For instance, fiscal transfer mechanisms could incentivize core cities (e.g., Beijing) to share industrial and technological resources with shrinking peripheral counties. This would reduce reliance on land finance-driven GDP growth. Third, subsidies for renewable energy adoption and circular economy practices should target shrinking counties with high LUCE growth rates. Heavy industrial bases like Tangshan could integrate carbon capture technologies, while agricultural counties might transition to agroforestry systems to enhance carbon sinks. Tax breaks for green enterprises and stricter emission standards for coal-dependent industries would accelerate this transition.

4.4.2 Feasibility and challenges

While these policies are theoretically viable, their implementation faces three key challenges: First, hrinking counties often lack fiscal autonomy. Central government grants or public-private partnerships (PPPs) may be necessary to fund green infrastructure projects. Second, many counties lack granular energy consumption data. Integrating nighttime light data and IoT sensors could improve LUCE monitoring (Zheng et al., 2023). Third, existing administrative barriers hinder resource sharing. Legally binding regional agreements, as seen in the BTH Coordinated Development Plan, could serve as a model.

These recommendations align with China's "dual carbon" goals and emphasize adaptive governance tailored to shrinkage

trajectories. Future policies should balance equity and efficiency, ensuring shrinking counties are not marginalized in national decarbonization efforts.

4.4.3 International comparisons and Lessons

Globally, municipalities experiencing urban contraction confront shared systemic challenges while employing divergent adaptive approaches. Illustrated by the German model, proactive smart shrinkage strategies in metropolitan centers like Leipzig and Dresden prioritize structural demolition of underutilized properties and their ecological conversion, effectively mitigating urban sprawl and carbon footprints (Ali et al., 2020).

This contrasts fundamentally with China's land-finance-driven development model, highlighting divergent policy orientations between immediate fiscal optimization and long-term ecological planning. Regarding demographic contraction driven by aging populations, Japanese cities like Kitakyushu demonstrate an integrated sustainability framework through compact city design and systematic renewable energy integration, simultaneously achieving emission reduction targets and enhancing economic adaptability (Peng et al., 2022). The American experience, particularly post-industrial urban centers in the Rust Belt such as Detroit, exemplifies innovative public-private partnership (PPP) mechanisms in financing green infrastructure - an empirical validation of fiscal decentralization theories (LaFrombois et al., 2023). Conversely, China's state-led suburbanization paradigm, manifested in Beijing's strategic relocation of non-core urban functions, reveals unique institutional mechanisms for coordinating contraction management with regional development synergies. This distinctive approach provides valuable insights into spatial governance.

5 Conclusion

This study systematically investigates the spatio-temporal disparities of land use carbon LUCE in shrinking counties within the Beijing-Tianjin-Hebei (BTH) region from 2000 to 2020. By integrating population dynamics, land use transitions, and carbon accounting methodologies at the county level, two key contributions emerge:

(1) Contrary to the assumption that population decline inherently reduces environmental pressure, this study reveals that urban shrinkage paradoxically accelerates LUCE growth in peripheral counties. Continuous shrinkage counties exhibited the highest LUCE growth rates (14% in T2), driven by inefficient built-up area expansion and low land use efficiency. This challenges conventional wisdom and underscores the need for context-specific carbon governance frameworks.

(2) Distinct LUCE patterns were observed across shrinkage trajectories. Temporary shrinkage counties achieved the lowest *per capita* emission growth (3.2% in T2) through smart land use transitions, while potential shrinkage counties faced escalating emissions due to industrial relocation. These findings enrich the theoretical understanding of how shrinkage mechanisms interact with land use systems.

This research bridges critical gaps between urban shrinkage studies and low-carbon transition policies. By quantifying the LUCE effects of shrinkage trajectories, it provides a decision-making toolkit for policymakers to balance equity and efficiency in regional decarbonization. The methodological framework also advances the integration of demographic dynamics into land use carbon accounting, offering replicable insights for megacity regions globally facing similar shrinkage challenges.

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

JZ: Conceptualization, Methodology, Software, Visualization, Writing–original draft. LW: Supervision, Writing–review and editing, Validation. MF: Conceptualization, Funding acquisition, Supervision, Writing–review and editing. HW: Project administration, Writing–review and editing. SL: Investigation, Writing–review and editing.

Funding

The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by the National Natural Science Foundation of China (Grant No. 41771204).

Acknowledgments

We are deeply indebted to the reviewers and the editor for their helpful comments and suggestions.

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 author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Ali, L., Haase, A., and Heiland, S. (2020). Gentrification through green regeneration? Analyzing the interaction between inner-city green space development and neighborhood change in the context of regrowth: the case of lene-voigt-park in Leipzig, eastern Germany. *Land* 9, 24. doi:10.3390/land9010024

Artmann, M., Inostroza, L., and Fan, P. (2019). Urban sprawl, compact urban development and green cities. How much do we know, how much do we agree? *Ecol. Indic. urban sprawl compact green cities – Indic. multi-scale multi-dimensional analysis* 96, 3–9. doi:10.1016/j.ecolind.2018.10.059

Chen, D., Wu, Y., Lin, Z., and Xu, Z. (2022). County-level city shrinkage in China: representation, cause, and response. *Land* 11, 1845. doi:10.3390/land11101845

Chen, Y. (2024). Regional decline and structural changes in Northeast China: an exploratory space–time approach. *Asia-Pac J. Reg. Sci.* 8, 397–427. doi:10.1007/s41685-023-00328-0

Cui, X., Wei, X., Liu, W., Zhang, F., and Li, Z. (2019). Spatial and temporal analysis of carbon sources and sinks through land use/cover changes in the Beijing-Tianjin-Hebei urban agglomeration region. *Phys. Chem. Earth, Parts A/B/C* 110, 61–70. doi:10.1016/j.pce.2018.10.001

Du, W., Zhao, X., Zhao, Z., Chen, C., and Qian, D. (2022). Assessment and dynamic mechanisms of the land-use dominant morphology transition: a case study of Hainan Province, China. *Environ. Monit. Assess.* 194, 419. doi:10.1007/s10661-022-09988-5

Gao, W., Zhao, X., Li, J., Zhang, D., Rui, Y., Li, T., et al. (2022). Spatiotemporal pattern identification and driving mechanism of urban shrinkage in the yellow river basin from 2000 to 2020. *Land* 11, 1325. doi:10.3390/land11081325

Ge, X. J., and Liu, X. (2021). Urban land use efficiency under resource-based economic transformation-A case study of shanxi province. *Land* 10, 850. doi:10.3390/land10080850

Guan, D., He, X., and Hu, X. (2021). Quantitative identification and evolution trend simulation of shrinking cities at the county scale, China. *Sustain. Cities Soc.* 65, 102611. doi:10.1016/j.scs.2020.102611

Guo, F., Qu, X., Ma, Y., and Tong, L. (2021). Spatiotemporal pattern evolution and influencing factors of shrinking cities: evidence from China. *Cities* 119, 103391. doi:10.1016/j.cities.2021.103391

Häußermann, H., and Siebel, W. (1988). "Die Schrumpfende Stadt und die Stadtsoziologie," in *Soziologische stadtforschung*. Editor J. Friedrichs (Wiesbaden: VS Verlag für Sozialwissenschaften), 78–94. doi:10.1007/978-3-322-83617-5_5

Herrmann, D. L., Schwarz, K., Shuster, W. D., Berland, A., Chaffin, B. C., Garmestani, A. S., et al. (2016). Ecology for the shrinking city. *BioScience* 66, 965–973. doi:10.1093/biosci/biw062

Hong, T., Huang, X., Zhang, X., and Deng, X. (2023). Correlation modelling between land surface temperatures and urban carbon emissions using multi-source remote sensing data: a case study. *Phys. Chem. Earth, Parts A/B/C* 132, 103489. doi:10.1016/j.pce.2023.103489

Hu, Y., Wang, Z., and Deng, T. (2021). Expansion in the shrinking cities: does place-based policy help to curb urban shrinkage in China? *Cities* 113, 103188. doi:10.1016/j.cities.2021.103188

Huang, B., Huang, J., Pontius, R. G., and Tu, Z. (2018). Comparison of Intensity Analysis and the land use dynamic degrees to measure land changes outside versus inside the coastal zone of Longhai, China. *Ecol. Indic.* 89, 336–347. doi:10.1016/j.ecolind.2017.12.057

IEA (2023). *International Energy Agency*. Available online at: https://www.iea.org/reports/world-energy-outlook-2023.

IPCC (2006). 2006 IPCC guidelines for national greenhouse Gas inventories — IPCC. Available online at: https://www.ipcc-nggip.iges.or.jp/public/2006gl/(Accessed April 3, 25).

Kang, H., Fu, M., Kang, H., Li, L., Dong, X., and Li, S. (2024). The impacts of urban population growth and shrinkage on the urban land use efficiency: a case study of the northeastern region of China. *Land* 13, 1532. doi:10.3390/land13091532

Kim, G., Newman, G., and Jiang, B. (2020). Urban regeneration: community engagement process for vacant land in declining cities. *Cities* 102, 102730. doi:10.1016/j.cities.2020.102730

LaFrombois, M. E. H. E., Park, Y., and Yurcaba, D. (2023). How US shrinking cities plan for change: comparing population projections and planning strategies in depopulating US cities. *J. Plan. Educ. Res.* 43, 81–93. doi:10.1177/0739456X19854121

Liu, X., Wang, M., Qiang, W., Wu, K., and Wang, X. (2020a). Urban form, shrinking cities, and residential carbon emissions: evidence from Chinese city-regions. *Appl. Energy* 261, 114409. doi:10.1016/j.apenergy.2019.114409

Liu, Z., Qi, W., Qi, H., and Liu, S. (2020b). The evolution of regional population decline and its driving factors at the county level in China from 1990 to 2015. *Geogr. Res.* 39, 1565–1579. doi:10.11821/dlyj020190599

Maerz, S., Bierwirth, A., and Hauptstock, D. (2013). Rethink the target.

Miljanović, D., Vuksanović-Macura, Z., and Doljak, D. (2023). Rethinking the spatial transformation of postsocialist cities: shrinking, sprawling or densifying. *Cities* 140, 104443. doi:10.1016/j.cities.2023.104443

National Bureau of Statistics of China (2023). *China Statistical Yearbook*. Availbale online at: https://www.stats.gov.cn/english/ (April 26, 2025).

Onodera, H., Delage, R., and Nakata, T. (2024). The role of regional renewable energy integration in electricity decarbonization—a case study of Japan. *Appl. Energy* 363, 123118. doi:10.1016/j.apenergy.2024.123118

Peng, W., Fan, Z., Duan, J., Gao, W., Wang, R., Liu, N., et al. (2022). Assessment of interactions between influencing factors on city shrinkage based on geographical detector: a case study in Kitakyushu, Japan. *Cities* 131, 103958. doi:10.1016/j.cities.2022.103958

Rong, T., Zhang, P., Li, G., Wang, Q., Zheng, H., Chang, Y., et al. (2023). Spatial correlation evolution and prediction scenario of land use carbon emissions in the Yellow River Basin. *Ecol. Indic.* 154, 110701. doi:10.1016/j.ecolind.2023.110701

Schwartz, E., Papuga, S. A., and Hwang, K. (2020). *CO2 in the shrinking city: the role of vegetation phenology in carbon dynamics of post-industrial urban Detroit 2020*, GC102–0007.

Song, H., Zhang, X., Zou, J., Gu, L., Li, Y., and Tang, J. (2023). A study on the value of carbon compensation in the Huai River basin based on land use from 2000 to 2020. *Phys. Chem. Earth* 132, 103490. doi:10.1016/j.pce.2023.103490

Sutradhar, U., Spearing, L., and Derrible, S. (2024). Depopulation and associated challenges for US cities by 2100. *Nat. Cities* 1, 51–61. doi:10.1038/s44284-023-00011-7

Tong, X., Guo, S., Duan, H., Duan, Z., Gao, C., and Chen, W. (2022a). Carbon-emission characteristics and influencing factors in growing and shrinking cities: evidence from 280 Chinese cities. *Int. J. Environ. Res. Public Health* 19, 2120. doi:10.3390/ijerph19042120

Tong, Y., Liu, W., Li, C., Rong, Y., Zhang, J., Yang, Y., et al. (2022b). County town shrinkage in China: identification, spatiotemporal variations and the heterogeneity of influencing factors. *J. Rural Stud.* 95, 350–361. doi:10.1016/j.jrurstud.2022.09.029

Wang, C., Zhan, J., Zhang, F., Liu, W., and Twumasi-Ankrah, M. J. (2021). Analysis of urban carbon balance based on land use dynamics in the Beijing-Tianjin-Hebei region, China. *J. Clean. Prod.* 281, 125138. doi:10.1016/j.jclepro.2020.125138

Wang, Z., Cao, C., Chen, J., and Wang, H. (2020). Does land finance contraction accelerate urban shrinkage? A study based on 84 key cities in China. J. Urban plann. *Dev* 146, 04020038. doi:10.1061/(ASCE)UP.1943-5444.0000613

Wolff, M., and Wiechmann, T. (2018). Urban growth and decline: Europe's shrinking cities in a comparative perspective 1990–2010. *Eur. Urban Regional Stud.* 25, 122–139. doi:10.1177/0969776417694680

Wu, K., and Yao, C. (2021). Exploring the association between shrinking cities and the loss of external investment: an intercity network analysis. *Cities* 119, 103351. doi:10.1016/j.cities.2021.103351

Xiao, H., Duan, Z., Zhou, Y., Zhang, N., Shan, Y., Lin, X., et al. (2019). CO2 emission patterns in shrinking and growing cities: a case study of Northeast China and the Yangtze River Delta. *Appl. Energy* 251, 113384. doi:10.1016/j.apenergy.2019.113384

Xie, M., Feng, Z., and Li, C. (2022). How does population shrinkage affect economic resilience? A case study of resource-based cities in Northeast China. *Sustainability* 14, 3650. doi:10.3390/su14063650

Yan, H., Guo, X., Zhao, S., and Yang, H. (2022). Variation of net carbon emissions from land use change in the beijing-tianjin-hebei region during 1990–2020. *Land* 11, 997. doi:10.3390/land11070997

Yang, S., Yang, X., Gao, X., and Zhang, J. (2022). Spatial and temporal distribution characteristics of carbon emissions and their drivers in shrinking cities in China: empirical evidence based on the NPP/VIIRS nighttime lighting index. *J. Environ. Manag.* 322, 116082. doi:10.1016/j.jenvman.2022.116082

Yang, X., and Liu, X. (2023). Path analysis and mediating effects of influencing factors of land use carbon emissions in Chang-Zhu-Tan urban agglomeration. *Technol. Forecast. Soc. Change* 188, 122268. doi:10.1016/j.techfore.2022.122268

Zeng, T., Jin, H., Gang, X., Kang, Z., and Luan, J. (2022a). County economy, population, construction land, and carbon intensity in a shrinkage scenario. *Sustainability* 14, 10523. doi:10.3390/su141710523

Zeng, T., Jin, H., Geng, Z., Kang, Z., and Zhang, Z. (2022b). The effect of urban shrinkage on carbon dioxide emissions efficiency in Northeast China. *IJERPH* 19, 5772. doi:10.3390/ijerph19095772

Zhang, R., Tai, H., Cheng, K., Zhu, Y., and Hou, J. (2022). Carbon emission efficiency network formation mechanism and spatial correlation complexity analysis: taking the Yangtze River Economic Belt as an example. *Sci. Total Environ.* 841, 156719. doi:10.1016/j.scitotenv.2022.156719

Zhang, X., Brandt, M., Tong, X., Ciais, P., Yue, Y., Xiao, X., et al. (2022a). A large but transient carbon sink from urbanization and rural depopulation in China. *Nat. Sustain* 5, 321–328. doi:10.1038/s41893-021-00843-y

Zhang, X., Fan, H., Hou, H., Xu, C., Sun, L., Li, Q., et al. (2024). Spatiotemporal evolution and multi-scale coupling effects of land use carbon emissions and ecological environmental quality. *Sci. Total Environ.* 922, 171149. doi:10.1016/j.scitotenv.2024.171149

Zhang, Z., Hu, G., Mu, X., and Kong, L. (2022). From low carbon to carbon neutrality: a bibliometric analysis of the status, evolution and development trend. *J. Environ. Manage.* 322, 116087. doi:10.1016/j.jenvman.2022.116087

Zheng, Q., Seto, K. C., Zhou, Y., You, S., and Weng, Q. (2023). Nighttime light remote sensing for urban applications: progress, challenges, and prospects. *ISPRS J. Photogrammetry Remote Sens.* 202, 125–141. doi:10.1016/j.isprsjprs.2023.05.028

Zhou, Y., Chen, M., Tang, Z., and Mei, Z. (2021a). Urbanization, land use change, and carbon emissions: quantitative assessments for city-level carbon emissions in Beijing-Tianjin-Hebei region. *Sustain. Cities Soc.* 66, 102701. doi:10.1016/j.scs.2020.102701

Zhou, Y., Li, C., Zheng, W., Rong, Y., and Liu, W. (2021b). Identification of urban shrinkage using NPP-VIIRS nighttime light data at the county level in China. *Cities* 118, 103373. doi:10.1016/j.cities.2021.103373

Zhu, E., Deng, J., Zhou, M., Gan, M., Jiang, R., Wang, K., et al. (2019). Carbon emissions induced by land-use and land-cover change from 1970 to 2010 in Zhejiang, China. *China. Sci. Total Environ.* 646, 930–939. doi:10.1016/j.scitotenv.2018.07.317

frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 12 May 2025
DOI 10.3389/fenvs.2025.1579001

Check for updates

OPEN ACCESS

EDITED BY
Ji Zheng,
The University of Hong Kong, Hong Kong SAR China

REVIEWED BY
Bingnan Guo,
Jiangsu University of Science and Technology, China
Mingshi Wang,
Henan Polytechnic University, China

*CORRESPONDENCE
Shaojian Wang,
wangshj8@mail.sysu.edu.cn

RECEIVED 19 February 2025
ACCEPTED 15 April 2025
PUBLISHED 12 May 2025

CITATION
Lin X, Liao Y and Wang S (2025) Spatiotemporal analysis of decoupling urban expansion and carbon emissions in China: insights from different expansion and decoupling patterns. *Front. Environ. Sci.* 13:1579001. doi: 10.3389/fenvs.2025.1579001

COPYRIGHT
© 2025 Lin, Liao and Wang. This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY). The use, distribution or reproduction in other forums is permitted, provided the original author(s) and the copyright owner(s) are credited and that the original publication in this journal is cited, in accordance with accepted academic practice. No use, distribution or reproduction is permitted which does not comply with these terms.

Spatiotemporal analysis of decoupling urban expansion and carbon emissions in China: insights from different expansion and decoupling patterns

Xiangming Lin[1], Yuantao Liao[2,3,4] and Shaojian Wang[5]*

[1]Zhanjiang Planning, Survey and Design Institute Co., Ltd, Zhanjiang, China, [2]Guangzhou Urban Planning and Design Survey Research Institute Co., Ltd, Guangzhou, China, [3]ollaborative Innovation Center for Natural Resources Planning and Marine Technology of Guangzhou, Guangzhou, China, [4]Guangdong Enterprise Key Laboratory for Urban Sensing, Monitoring and Early Warning, Guangzhou, China, [5]School of Geography and Planning, Sun Yat-sen University, Guangzhou, China

As urbanization accelerates, decoupling urban development from environmental consumption, particularly carbon emissions, is crucial for sustainable growth and achieving carbon neutrality goals. This study introduces urban expansion intensity as a new perspective to analyze the decoupling between urban expansion and carbon emissions. Based on the Urban Expansion Disparity Index, 297 Chinese cities are classified. The Tapio model is used to examine the spatiotemporal variations in decoupling from 2007 to 2022, while the LMDI model identifies key factors influencing regional carbon emissions. Findings reveal: (1) a polarized decoupling pattern, dominated by weak and strong negative decoupling; (2) a strong link between urban expansion types and decoupling modes, with fast-expanding cities exhibiting weak/strong decoupling and growth linkage, while slow-expanding or shrinking cities show expansion-negative and strong negative decoupling; (3) expansion and affluence effects drive emissions, while technology mitigates them, with significant regional differences. This study provides theoretical insights into urban expansion and carbon decoupling dynamics, informing region-specific policy interventions.

KEYWORDS

carbon emissions, urban expansion, urban expansion disparity index, Tapio model, LMDI model

1 Introduction

Global warming has emerged as a critical environmental challenge, profoundly impacting human production and daily life worldwide. As the primary driver of climate change, carbon emissions have become a central focus in addressing the complex and evolving issues associated with global warming. Reducing carbon emissions is essential for achieving sustainable development at the regional level (Ballantyne et al., 2016). Cities, being the primary hubs of human social activities, are also the main sources of carbon emissions, stemming from industrial activities, energy consumption (Zhao et al., 2025), and residential usage (Fawzy et al., 2020). Research indicates that urban carbon emissions account for more than 85% of China's total emissions (Han et al., 2018), with key sectors such as industry and transportation being the predominant sources of energy use and

carbon output in urban areas (Ma et al., 2017). Moreover, the accelerating process of urbanization has led to changes in land use patterns (Wu et al., 2011), energy demand (Dong et al., 2020), industrial structure, and the mobility of population and technology, making urban carbon reduction increasingly complex. As a result, an increasing number of scholars have focused their research on the nonlinear relationship between urbanization and carbon emissions (Xu et al., 2018), as well as the impact of urbanization on carbon emission performance (Liu et al., 2018). Undoubtedly, promoting low-carbon development in cities has become a pressing and critical challenge that must be urgently addressed.

The concept of decoupling in environmental studies refers to the weakening or separation of the relationship between economic development, resource consumption, and environmental pressures (Chen et al., 2018). It is typically categorized into two types: resource decoupling, which focuses on reducing the link between economic growth and resource/energy use, and impact decoupling, which aims to mitigate the connection between economic development and environmental degradation (Wiedenhofer et al., 2020). Decoupling indicators, which enable the dynamic assessment and quantification of the relationship between economic activities and environmental impacts, have been widely applied in studies exploring the evolving interaction between environmental change and economic development in recent years (Ward et al., 2016; Jiang et al., 2022). In particular, as carbon reduction has become an urgent global climate challenge, decoupling models have been increasingly used to examine the relationship between economic growth and carbon emissions (Li et al., 2022), gradually evolving into a key theoretical framework for promoting green and low-carbon development.

Research on decoupling primarily focuses on several key areas. In terms of methodology, commonly used approaches include: the OECD model, proposed by the Organisation for Economic Co-operation and Development, which compares the growth rates of environmental pressure and economic development; the Tapio decoupling model, which offers a more detailed characterization of the interactions between economic growth and environmental impacts (Wu et al., 2018b; Wu et al., 2024); and integrated methods that combine decoupling analysis with decomposition techniques, such as the Logarithmic Mean Divisia Index (LMDI), to explore the underlying drivers of decoupling (Li et al., 2019). At the research scale, studies on decoupling have primarily focused on the national and provincial levels. At the national level, research has become increasingly comprehensive, including panel studies covering multiple countries (Shuai et al., 2019), comparative analyses of decoupling performance among countries within the same organization (such as the OECD) (Magazzino et al., 2023), comparisons between developed and developing countries regarding the decoupling of economic growth and carbon emissions (Wu et al., 2018), as well as case studies on typical countries such as the United States and China (Wang and Wang, 2019). At the provincial level, existing studies similarly encompass panel analyses across 30 provinces (Cohen et al., 2019), as well as investigations into the relationship between differentiated economic development and resource–environment dynamics in specific regions, such as the Yangtze River Economic Belt and the Central China Urban Agglomeration (Luo et al., 2021; Yuan et al., 2023). Case studies focusing on individual provinces, such as Jiangsu and Guangdong (Xu et al., 2021; Wang et al., 2017), have also been increasing, contributing to the development of a more comprehensive research framework. In terms of research content, current studies primarily focus on two areas: the decoupling between economic development and carbon emissions across different sectors, and the key factors influencing decoupling. For the former, research has increasingly concentrated on energy-intensive industries such as metal products, non-metallic manufacturing, construction, manufacturing, and transportation (Lin and Teng, 2022; Wang and Feng, 2019; Wu et al., 2018a; Ren and Hu, 2012; Li et al., 2023). For the latter, existing studies have demonstrated that both macro- and micro-level factors—including energy structure, industrial structure, technological progress, urbanization rate, and household income levels—play significant roles in shaping the decoupling process (Zhao et al., 2022; Hao et al., 2022).

However, we also identify certain limitations in existing studies on the decoupling of economic development and carbon emissions. First, in terms of spatial scale, most research has focused on large-scale analyses at the national, regional, or provincial levels or on decoupling studies of individual cities (Zheng et al., 2019; Li et al., 2019), while multi-city analyses at smaller scales remain insufficient. However, increasing evidence suggests that cities within the same province exhibit significant differences in development characteristics, economic growth responses, policy implementation, and environmental changes (Chen et al., 2019; Xie et al., 2025; Feng et al., 2025). These disparities underscore the necessity of conducting decoupling analyses at the urban scale, as city-level studies can more accurately capture the diversity of development trajectories and provide a stronger basis for targeted policy interventions. Second, regarding the selection of development indicators, existing decoupling studies predominantly define economic development in terms of GDP growth. While GDP serves as a quantitative measure of economic activity, it fails to directly reflect the associated environmental resource consumption. Moreover, economic growth is subject to an "optimal scale," implying that GDP alone cannot comprehensively capture the societal and environmental implications of decoupling, whether positive or negative (Herman, 2014; Vadén et al., 2020). To better elucidate the relationship between economic development and carbon emissions decoupling, researchers have increasingly incorporated additional variables, such as human wellbeing, into their analyses (Kallis et al., 2018). Thus, it is evident that beyond conventional indicators, incorporating additional economic development indicators closely linked to both the economy and the environment is crucial for accurately capturing the real societal and ecological impacts of decoupling. To address these gaps, this study takes cities as the fundamental research unit and employs urban construction land expansion intensity as a key variable to examine its decoupling relationship with carbon emissions. Urban construction land, defined as land within urban areas designated to meet the economic, social, and daily needs of residents, encompasses residential, industrial, commercial, public service facilities, transportation, municipal infrastructure, and green spaces (Lai et al., 2020). As a critical resource for urban development, the expansion of urban construction land significantly drives economic growth (Xie et al., 2018), making it a key explicit indicator of urbanization. However, it also represents a scarce

resource and a substantial "carbon source" (Peng et al., 2022). On one hand, changes in urban land expansion and utilization patterns directly influence carbon emissions (Sun et al., 2022); on the other hand, human activities on construction land generate indirect carbon emissions (Anser, 2019). From this analysis, it is evident that the expansion of urban construction land and sustainable development presents a paradoxical relationship. Achieving effective decoupling between urban expansion and carbon emissions is essential for reconciling carbon reduction goals with the pursuit of high-quality urban development. This underscores the need for innovative approaches to urban planning and resource management that balance growth with environmental sustainability.

Against the backdrop of accelerating urban expansion in China, the contradiction between rising carbon emissions and national emission reduction targets has created a "dual pressure," posing significant challenges for urban carbon control (Wang et al., 2024b). To address the research gap in decoupling studies from the perspective of "expansion intensity–carbon emissions" at the city level and to enrich the theoretical framework of low-carbon urban development, this study selects 297 cities in China as the sample area and classifies them based on their urban expansion speed using the Urban Expansion Disparity Index. Departing from conventional approaches, the study innovatively replaces the traditional GDP indicator, commonly employed in decoupling research, with the urban land expansion intensity indicator. By applying the Tapio decoupling model, the study investigates the spatiotemporal dynamics of the decoupling relationship between urban expansion intensity and carbon emissions across different city types from 2007 to 2022. Furthermore, an LMDI (Logarithmic Mean Divisia Index) model is developed to analyze the influence of urban construction land expansion, affluence, and technological effects on carbon emissions in various city types. This approach aims to identify key leverage points for implementing effective carbon reduction strategies, providing a nuanced understanding of the interplay between urban growth and environmental sustainability.

2 Materials and methods

2.1 Urban expansion indicator construction

Urban expansion typically refers to the outward growth and development of cities, most visibly manifested by the increase in the area of urban built-up land (Zhang and Han, 2024). To facilitate a more detailed analysis of the temporal patterns and spatial disparities in urban expansion, this study employs two key indicators: urban expansion intensity and the urban disparity change index. The specific formulas for these indicators are as follows.

2.1.1 Urban expansion intensity

Urban expansion intensity (***UI***) refers to the rate of increase in urban built-up land area over a specific period. It is commonly used to compare the expansion levels of different cities or the same city across different periods (Yang et al., 2023). In this study, it is defined as the ratio of the average annual growth in urban built-up land area to the initial land area, as shown in Equations 1:

$$UI = \frac{Area^{t2} - Area^{t1}}{Area^{t1} \times \Delta T} \times 100\% \quad (1)$$

In the equation, UI represents the urban expansion intensity across different cities, reflecting the level of urban built-up land expansion during the urbanization process. Area refers to the urban built-up land area during the given period, t1 and t2 represent different years, with the years 2007, 2010, 2013, 2016, 2019, and 2022 being considered in this study. T denotes the time gap between the panel years.

TABLE 1 Classification of urban expansion types.

Type	UEDI
High-speed Expansion	UEDI ≥ 2
Rapid Expansion	1.2 ≤ UEDI ≤ 2
Moderate Expansion	0.8 ≤ UEDI ≤ 1.2
Slow Expansion	0.4 ≤ UEDI ≤ 0.8
Ultra-slow Expansion	0 ≤ UEDI ≤ 0.4
Negative Expansion	UEDI ≤ 0

2.1.2 Urban expansion disparity index

The Urban Expansion Disparity Index (UEDI) is defined as the ratio between the urban expansion rate of a specific sample area and the overall urban expansion rate of the study region. This index quantitatively characterizes the spatial heterogeneity in urban expansion intensity among different cities during the same temporal period. The mathematical formulation of UEDI is expressed in Equations 2:

$$UEDI = \frac{(Area_i^{t2} - Area_i^{t1}) \times Area^{t1}}{(Area^{t2} - Area^{t1}) \times Area_i^{t1}} \quad (2)$$

According to relevant literature (Liu et al., 2016), urban expansion levels can be classified into six categories: High-speed expansion (HE), Rapid expansion (RE), Moderate expansion (ME), Slow expansion (SE), Ultra-slow expansion (USE), and Negative expansion (NE). The specific classification criteria are provided in Table 1.

2.2 Decoupling analysis method

Decoupling refers to the process of reducing or eliminating the link between economic growth and resource consumption or environmental degradation. In other words, it signifies a situation where economic growth is no longer constrained by environmental and resource limitations, making decoupling a key indicator for assessing sustainable development. This concept is widely employed in studies examining the relationship between economic benefits and environmental costs (Xin et al., 2021). Common methods for decoupling analysis include the OECD approach and the Tapio decoupling model. Among these, the Tapio model offers an advantage by capturing the dynamic characteristics of variable changes, rather than providing mere static descriptions. Moreover, it is particularly effective in capturing complex nonlinear relationships,

TABLE 2 Decoupling diversion.

Status		Carbon emission	Land expansion	Tapio value
Decoupling	Declining Decoupling	<0	<0	DI > 1.2
	Strong Decoupling	<0	>0	DI < 0
	Weak Decoupling	>0	>0	0<DI < 0.8
Linkage	Growth Linkage	>0	>0	0.8<DI < 1.2
	Declining Linkage	<0	<0	0.8<DI < 1.2
Negative Decoupling	Expanding Negative Decoupling	>0	>0	DI > 1.2
	Strong Negative Decoupling	>0	<0	DI < 0
	Weak Negative Decoupling	<0	<0	0<DI < 0.8

making it applicable in a broader range of scenarios (Hou et al., 2023). Given that urban construction land serves as an intuitive reflection of functional area changes—such as residential, industrial, and commercial zones, which are primary sites of economic activity and carbon emissions—this study substitutes the conventional economic change indicator in the Tapio model with urban expansion intensity. This approach aims to explore the decoupling relationship between urban expansion intensity and carbon emissions. The formula is as follows in Equations 3 (Tapio, 2005):

$$DI = \frac{(CE_t - CE_{t-1})/CE_{t-1}}{(Area_t - Area_{t-1})/Area_{t-1}} = \frac{E_{\Delta t}}{UI_{\Delta t}} \tag{3}$$

Here, DI represents the decoupling index, with specific classifications shown in Table 2. $E_{\Delta t}$ denotes the rate of change in emissions over the study interval (measured every 3 years), $UI_{\Delta t}$ while represents the rate of change in urban construction land intensity during the same interval.

2.3 LMDI decomposition analysis

The Kaya identity is a structural decomposition framework for analyzing changes in carbon emissions, derived from the IPAT model (Wang et al., 2005). Building on this analysis, this study uses the Kaya identity to decompose the factors influencing carbon emissions into scale effect (P), affluence effect (A), and technology effect (T). The specific decomposition formula is as follows in Equations 4:

$$CE = Area \times \frac{GDP}{Area} \times \frac{CE}{GDP} = P \times A \times T \tag{4}$$

Here, A represents the secondary industry GDP generated per unit of urban construction land, reflecting the economic efficiency of urban expansion. The secondary industry GDP is selected to represent economic development because, compared to total GDP, it has a stronger and more representative correlation with urban land expansion and carbon emissions. T denotes the carbon emissions per unit of GDP, indicating the technological effect of carbon reduction across different cities. The LMDI additive decomposition is a method based on logarithmic mean weights, used to disaggregate total changes into the additive contributions of multiple driving factors (Xin et al., 2023). Building on the Kaya identity, it further refines the scale effect, affluence effect, and technology effect to quantify their specific contributions to changes in carbon emissions. The detailed formula is as follows in Equations 5:

$$\begin{cases} \Delta CE_{\Delta t} = CE^t - CE^0 = \Delta CE_P^t + \Delta CE_A^t + \Delta CE_T^t \\ \Delta CE_P^t = \sum \theta \ln \dfrac{P^t}{P^0} \\ \Delta CE_A^t = \sum \theta \ln \dfrac{A^t}{A^0} \\ \Delta CE_T^t = \sum \theta \ln \dfrac{T^t}{T^0} \\ \theta = \dfrac{CE^t - CE^0}{\ln CE^t - \ln CE^0} \end{cases} \tag{5}$$

Here, θ represents the logarithmic mean weight, and 0-t denotes the time interval.

2.4 Data resources

The data utilized in this study can be categorized into two primary types. The first type comprises city-level carbon emission data, sourced from the Emissions Database for Global Atmospheric Research (EDGAR v8.0) (Crippa et al., 2023). The second type includes data on urban built-up areas and industrial GDP, obtained from various statistical resources, including the China Statistical Yearbook, China City Statistical Yearbook, and China Urban Construction Statistical Yearbook. Based on data availability and completeness, a total of 297 cities were selected for the analysis. The study focuses on the years 2007, 2010, 2013, 2016, 2019, and 2022 to investigate the decoupling relationship between urban expansion and carbon emissions. Missing data points were addressed using interpolation methods to ensure the robustness of the dataset.

3 Results

3.1 Urban expansion and carbon emission changes

Table 3 and Figure 1 illustrate the changes in urban expansion intensity and the distribution of expansion disparity indices

TABLE 3 The number of cities corresponding to changes in urban expansion intensity during the study period.

Period	≤0	0-5	5-10	10-20	20-30	30-40	40-50	≥50
2007-2010	18	136	62	56	10	5	2	8
2010-2013	40	142	59	45	5	3	1	0
2013-2016	35	141	60	41	10	3	1	3
2016-2019	36	172	51	27	7	1	0	2
2019-2022	53	179	39	18	2	3	2	1

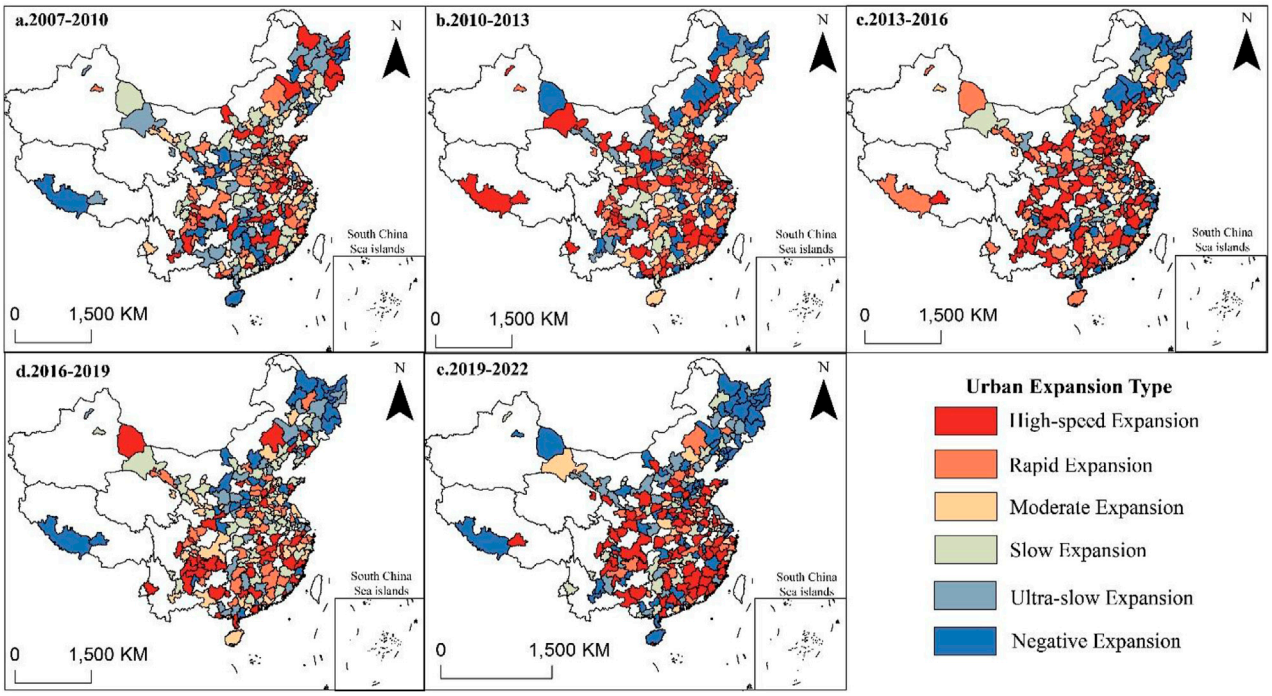


FIGURE 1
Urban expansion types, 2007–2022.

among the sample cities over the study period. Overall, urban land use in China has continuously expanded, though at a relatively low intensity, predominantly within the range of 0–5. Over time, urban expansion intensity has shown a steady decline. For example, cities with an intensity range of 20–30 decreased from 10 during 2007–2010 to just two during 2019–2022. Notably, the number of cities with an expansion intensity below five has increased since 2013, a trend that can be attributed to policies promoting efficient and intensive land use, ecological civilization initiatives, and the implementation of ecological redlines (Nuissl and Siedentop, 2021; Yang and Xie, 2021). Concurrently, there has been a rise in the number of cities experiencing negative expansion. From the perspective of expansion disparity indices, urban expansion has exhibited an overall increasing trend, accompanied by growing polarization. High-speed expansion and slow or negative expansion have emerged as the dominant patterns. During 2019–2022, the number of cities with high-speed expansion reached 98, accounting for 33.0% of all expansion types. In contrast, the number of cities with ultra-low-speed or declining expansion ranged between 50 and 60. This polarization is likely the result of the uneven pace of urban development during periods of rapid urbanization and industrialization. While some cities have faced constraints due to policies or resource limitations, others have experienced significantly higher expansion intensity than most regions. Spatially, areas of high-speed urban expansion have gradually shifted from central regions to southeastern coastal areas, while low-speed expansion zones are predominantly located in northeastern regions. This spatial pattern is consistent with China's development strategies and the current state of economic and urbanization progress.

Figure 2 illustrates the changes in carbon emissions across cities over the study period. From a temporal perspective, between 2007 and 2013, carbon emissions in most cities exhibited a rapid

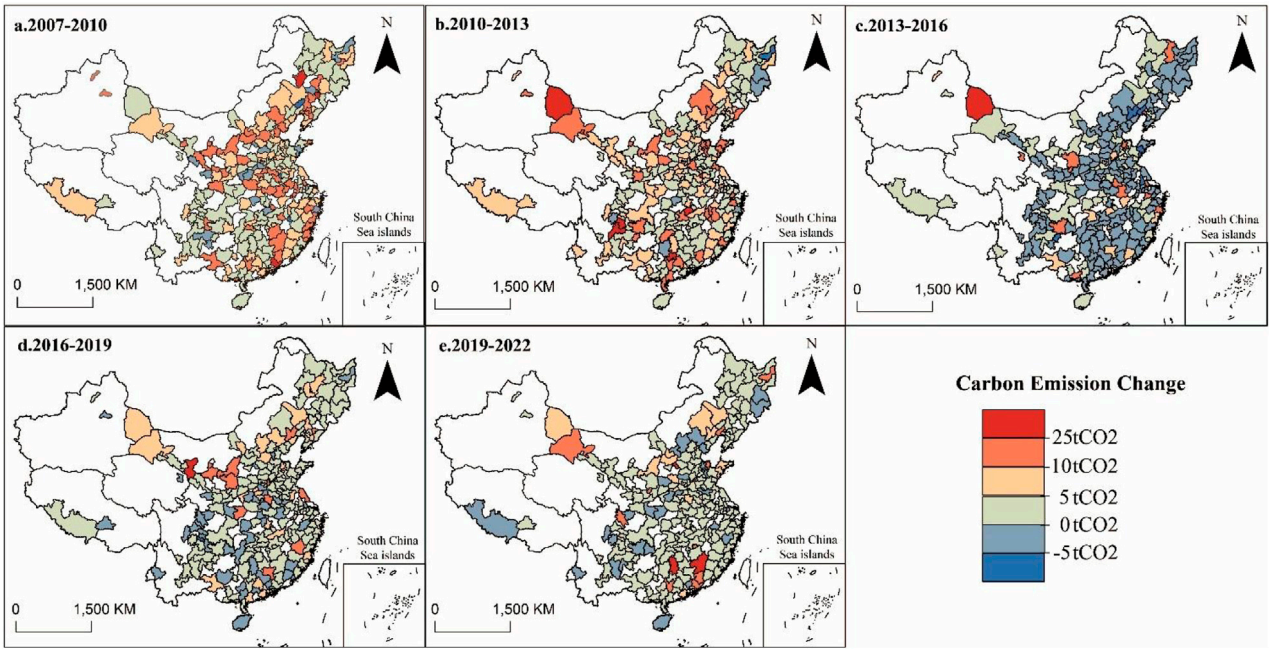


FIGURE 2
Carbon emission distribution, 2007–2022.

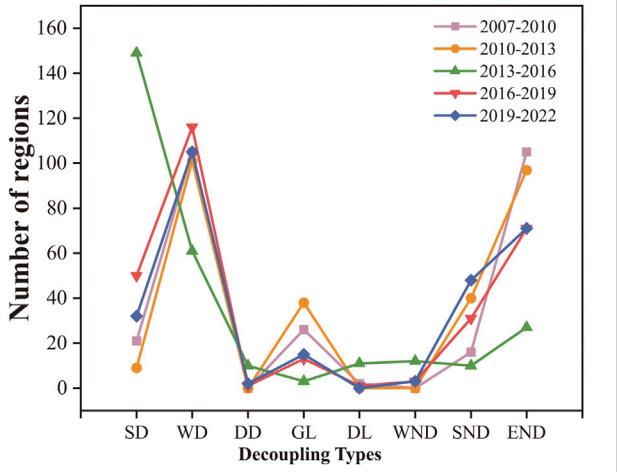


FIGURE 3
Decoupling changes of China's cities, 2007–2022.

growth trend, with increases ranging from 10 to 25 t. During the 2013–2016 period, carbon emissions decreased in the majority of cities, with a year-on-year reduction of approximately 0–5 t. From 2016 to 2022, carbon emissions rebounded, although the increase was modest, with a growth range of 0–5 t. Spatially, inland and northeastern regions experienced relatively higher carbon emission increases, with growth concentrated in resource-intensive or industrial cities such as Huanggang, Xianning, and Yanan. Furthermore, this analysis reveals a general trend: the pattern of changes in urban expansion intensity closely mirrors the trends in carbon emission fluctuations across cities.

3.2 Urban expansion and decoupling of carbon emissions

3.2.1 Types of urban decoupling

Figure 3 illustrates the distribution of decoupling types among the sample cities during the study period. In summary, weak decoupling (WD), strong negative decoupling (SND), and expanding negative decoupling are the most prevalent decoupling relationships between urban expansion and carbon emissions in China. Over the study period, the number of cities exhibiting WD remained around 100, while those with SND fluctuated around 74. Strong decoupling (SD) and growth linkage (GL) were also relatively common decoupling types, with the number of cities categorized under SD peaking at 149 during the 2013–2016 period but remaining below 50 in other years. The number of cities with SND remained relatively stable, hovering around 40 throughout the study. On the other hand, declining decoupling (DD), declining linkage (DL), and weak negative decoupling (WND) were less frequent, with some years showing no cities in these categories. Overall, the structure of decoupling types in Chinese cities has remained relatively stable over the past 15 years, though a clear polarization is evident. On one hand, while urban expansion intensity and carbon emissions continue to rise, most regions are gradually reducing the negative by-products of carbon emissions, with initial successes in low-carbon urban development. On the other hand, a significant number of cities still face rising carbon emissions, despite a decrease in urban construction land, which highlights persistent issues related to inefficient land use and energy-intensive industrial structures.

Figure 4 illustrates the spatial distribution of the decoupling dynamics between urban expansion intensity and carbon emissions. It is evident that cities characterized by expanding negative

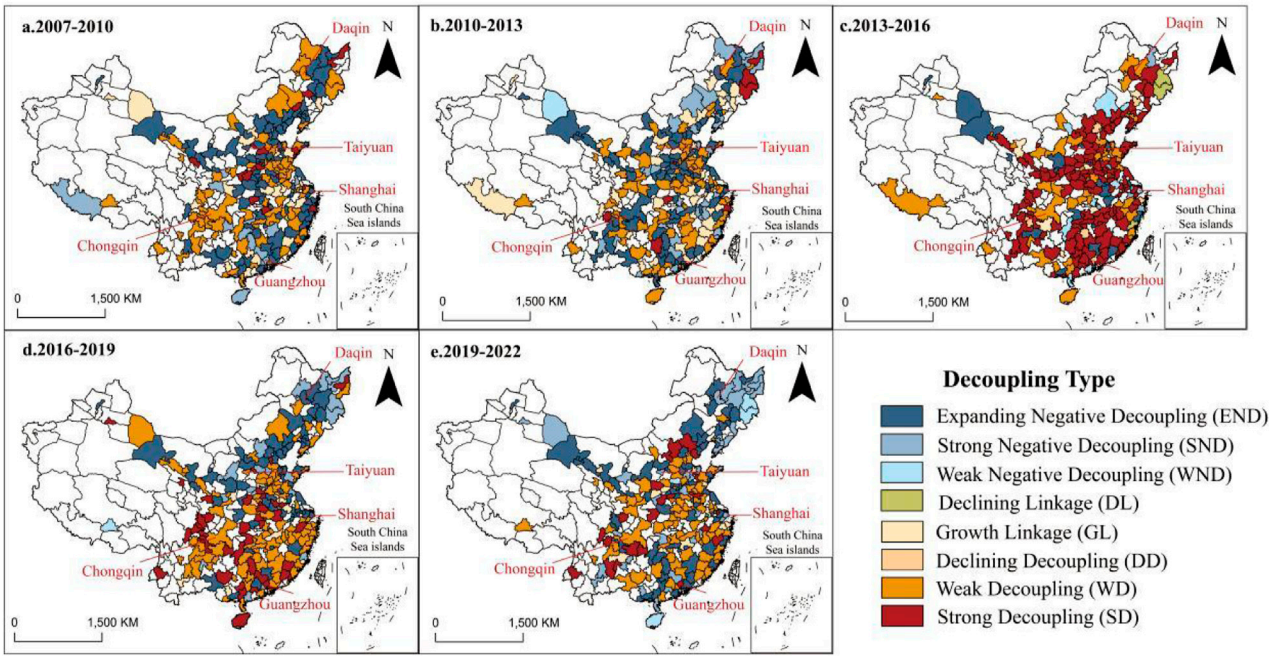


FIGURE 4
Spatial distribution of decoupling types of China's cities, 2007–2022.

decoupling (END) and strong negative decoupling (SND) are primarily concentrated in the northeastern region and certain economically fast-growing cities in central China. In contrast, weak decoupling (WD) and strong decoupling (SD) cities are predominantly located in the southeastern coastal areas, with this spatial pattern becoming increasingly pronounced over time. Overall, the spatial distribution of decoupling characteristics is closely related to factors such as the level of economic development, industrial structure, and technological progress. Different urban development patterns lead to varying intensities and functional demands for construction land, resulting in distinct decoupling states. Generally, regions with advanced economies, significant industrial upgrading, and strong innovation capabilities exhibit better decoupling performance. In contrast, areas with a single economic structure, reliance on high-carbon industries, and a lack of green technology adoption tend to experience weaker decoupling. Moreover, policy orientation also plays a crucial role in the decoupling between construction land use and carbon emissions. For instance, early policies like the Western Development Strategy and the Northeast Industrial Revitalization Plan increased construction land use intensity and carbon emissions. On the other hand, the implementation of the "Zero-Waste City" policy has promoted resource-efficient development (Qian et al., 2025), accelerated the green transition of enterprises and localities, and directly reduced urban carbon emissions.

At the city level, specific patterns further emerge, SND cities are concentrated in areas where traditional industries dominate and economic transformation is still in its early stages. Examples include Taiyuan and Jincheng in Shanxi, and Daqing and Jiamusi in Heilongjiang. Despite the slowdown in urban expansion due to factors such as land use policies, fiscal constraints, or population loss (Huo and Huang, 2023), these cities' economic structures remain heavily dependent on high-carbon industries, such as coal and steel. The persistence of inefficient energy systems and outdated industrial practices places these cities in the SND stage. On the other hand, END cities are typically found in rapidly developing regions, such as Shenzhen and Chongqing. While urbanization continues to generate high demand for construction land, these cities, despite implementing some low-carbon policies and efforts to transition toward service-oriented and high-tech industries, still heavily rely on manufacturing and construction sectors. As a result, the growth rate of carbon emissions exceeds that of urban expansion, with limited benefits from energy structure optimization. In contrast, WD and SD cities are predominantly concentrated in Beijing and the Yangtze River Delta region, including cities like Shanghai, Suzhou, and Hangzhou. In these areas, heavy industries have been optimized or relocated to surrounding regions, while the development of e-commerce, internet-based technologies, and other high-tech service industries has matured (Wang et al., 2022). The application of low-carbon technologies further supports this transition, resulting in slower urban expansion and a clear decoupling from the negative impacts of carbon emissions.

3.2.2 Decoupling analysis by urban expansion types

Figure 5 illustrates the decoupling status of carbon emissions across different urban expansion types, revealing a significant correspondence between the two, with only minor changes over time. Overall, cities with rapid expansion predominantly exhibit weak decoupling (WD) and growth linkage (GL), where the growth rate of carbon emissions is either comparable to or slightly lower than the rate of urban expansion. Over time, these cities tend to transition toward strong decoupling (SD), an increasingly desirable state. In contrast, cities with slower or stagnant expansion mainly experience expanding negative decoupling (END), characterized by

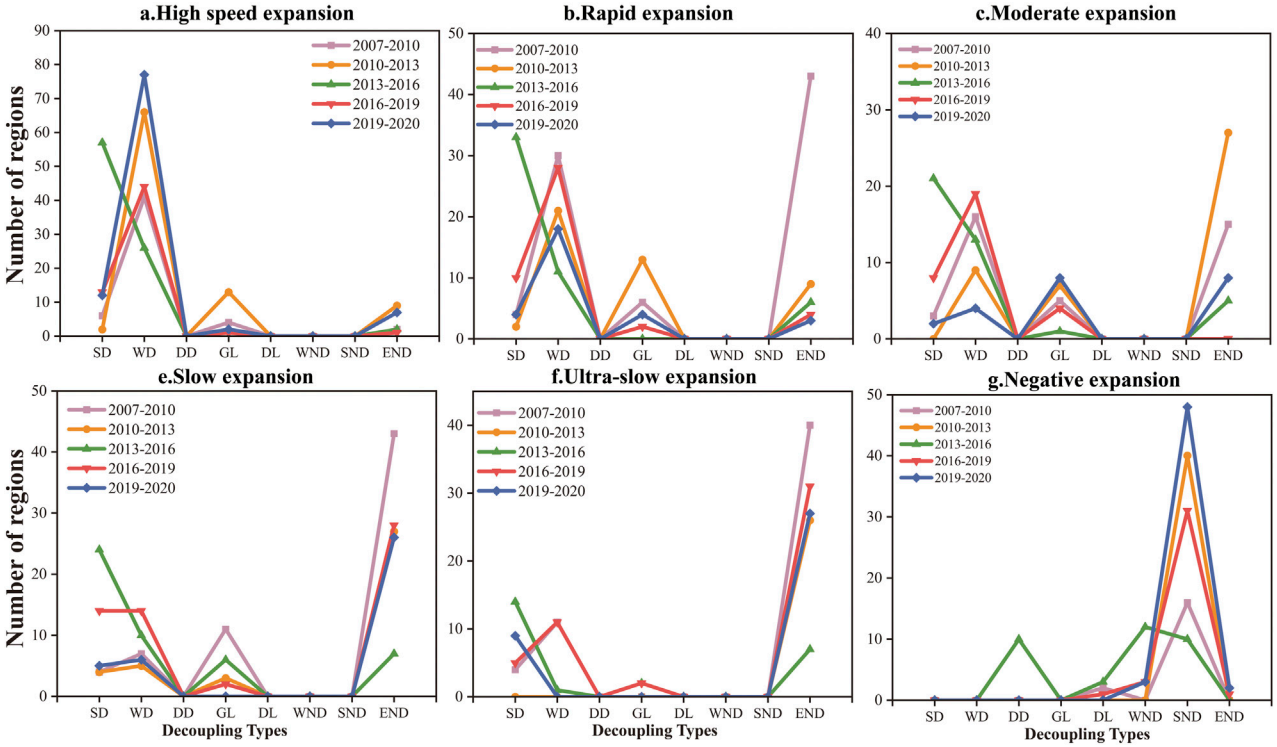


FIGURE 5
Sub-expansion type decoupling condition of China's cities, 2007–2022. **(a)** High speed expansion. **(b)** Rapid expansion. **(c)** Moderate expansion. **(d)** Slow expansion. **(e)** Ultra-slow expansion. **(f)** Negative expansion.

a highly unbalanced development pattern where carbon emissions rise significantly faster than urban land expansion. Examining the cities corresponding to these expansion types, it becomes evident that the rate of urban land expansion reflects, to some extent, the vitality of urban development, particularly in terms of industrial and economic growth. Cities with faster expansion generally exhibit greater economic diversification, continuous industrial upgrading, and improved energy efficiency, facilitating a transition from high-carbon, resource-intensive growth to a more low-carbon and efficient development model. Consequently, land-use efficiency and environmental benefits steadily improve. Conversely, cities with slower expansion—or even contraction—often face geographical constraints, resource limitations, or funding shortages that hinder their development. These cities tend to have a single economic structure and remain heavily reliant on traditional high-carbon industries, lacking new growth drivers. As a result, urban land use remains inefficient, and progress toward green development is significantly lagging.

A detailed analysis of specific cities reveals: WD cities are predominantly located in moderately developed cities in central and southern China, including Zhengzhou, Chengdu, Wuxi, and Ningbo. Despite their strong demand for construction land, these cities have increasingly adopted efficient and intensive land-use practices, transitioned to cleaner energy sources, and shifted their industrial structures toward low-carbon sectors, such as services. Taking Chengdu as an example, the city experienced rapid urban expansion from 2007 to 2022, with construction land increasing by 34.31 square kilometers. However, carbon emission growth gradually slowed, rising by 3.14 tCO2 from 2007 to 2010 but only by 1.45 tCO2 between 2019 and 2022. Notably, from 2013 to 2019, carbon emissions even showed a negative growth trend. This deceleration is closely linked to the upgrading of Chengdu's automotive and equipment manufacturing industries, as well as the gradual refinement of green spatial optimization strategies, such as the "Eastward Expansion, Central Optimization" initiative. Compared to cities with other expansion types, these WD cities represent an ideal model of economic and environmental synergy. However, they still have significant room for improvement before achieving SD scenarios. For cities with slow or ultra-slow expansion, expanding negative decoupling (END) is the dominant decoupling type. These cities, often located in central and northeastern regions such as Tangshan, Lanzhou, and Jilin, are typically industrial hubs facing a conflict between high land demand and resource constraints. The failure of these cities' industrial structures to transition to low-carbon models, combined with persistent energy demand, has resulted in unchecked growth of carbon emissions, leading to land-use overload (Bao et al., 2022). Taking Jilin City as an example, from 2007 to 2022, the expansion of urban construction land was minimal, increasing by only 13.38 square kilometers, with just 1.20 square kilometers added between 2016 and 2022. However, carbon emissions surged significantly, rising by 12.60 tCO2. Throughout the study period, Jilin City's economic development remained heavily dominated by industrial sectors. Despite the gradual implementation of farmland balance and land reclamation policies, the rapid growth of traditional industries such as chemicals, automotive

10.3389/fenvs.2025.1579001

TABLE 4 Analysis of effects by decoupling type.

Period	Decoupling types	Urban expansion effect	Affluence effect	Technological effect
2007-2010	GL	15.49	30.30	−30.34
	WD	120.11	86.21	−172.46
	SD	14.36	27.41	−46.25
	SND	−5.95	34.55	−20.57
	END	32.81	148.86	−100.36
	DL	−0.97	4.05	−4.13
	Total	175.85	331.38	−374.11
2010-2013	GL	17.77	37.29	−37.56
	WD	71.96	58.67	−103.28
	SD	3.62	7.39	−12.23
	SND	−21.05	70.85	−29.20
	END	24.90	112.71	−67.81
	Total	97.2	286.91	−250.08
2013-2016	GL	3.25	1.90	−2.00
	WD	32.66	−12.90	−11.92
	WND	−14.83	17.28	−4.04
	SD	88.74	−48.91	−73.78
	SND	−3.72	4.19	3.77
	END	6.84	3.23	11.51
	DD	−0.79	−4.89	2.83
	DL	−0.78	2.54	−2.52
	Total	111.37	−37.56	−76.15
2016-2019	GL	4.01	4.51	−4.52
	WD	63.81	−22.43	−25.21
	WND	−1.33	2.86	−1.61
	SD	15.72	7.27	−26.62
	SND	−20.57	32.93	−2.59
	END	12.87	−18.33	43.72
	DD	−0.01	0.37	−0.39
	DL	−0.04	0.24	−0.24
	Total	74.46	7.42	−17.46
2019-2022	GL	3.25	1.95	−2.12
	WD	70.08	−24.37	−28.25
	WND	−0.72	1.14	−0.56
	SD	6.07	6.16	−16.82
	SND	−27.94	35.22	3.87
	END	7.64	9.50	11.60
	DD	−0.47	0.78	−1.79
	Total	57.91	30.38	−34.07

manufacturing, and metallurgy continued to generate substantial carbon emissions, resulting in a poor decoupling performance. In cities exhibiting negative expansion, strong negative decoupling (SND) emerges as the primary decoupling type. Such cities are predominantly located in northeastern provinces like Yichun and Harbin. In these regions, land contraction is accompanied by rising carbon emissions, driven by inefficient, energy-intensive development models dominated by heavy industries. This high-energy, low-efficiency development warrants urgent attention (Wang et al., 2020; Zeng et al., 2022). Taking Yichun City as an example, from 2007 to 2022, urban construction land contracted by 13.03 square kilometers. However, carbon emissions continued to rise, increasing by 26.37 tCO2. This trend is likely driven by the city's status as a resource-declining economy, where the forestry and mining industries—once the backbone of local development—have steadily declined. As a result, land demand has decreased, and some industrial areas, due to inefficient utilization and business closures, have been left idle, prompting the government to reclaim and repurpose them. It is important to note that these classifications represent the predominant decoupling types for each urban expansion category, though exceptions do exist. For example, cities like Beijing and Shanghai, despite ongoing industrial transformation and widespread adoption of low-carbon policies, face challenges such as population influx and saturated land use. These factors have led to decoupling statuses like END. To address these challenges, strategies such as enclave development and cross-regional collaboration policies have gained increasing prominence and are being actively implemented in recent years.

3.3 Decomposition effect analysis

Based on the LMDI decomposition results, the effects of land expansion, affluence, and technological progress on changes in carbon emission intensity are analyzed across different decoupling and urban land expansion types. Table 4 presents the specific effects of these three factors on cities with varying decoupling types. Overall, both the land expansion effect and the affluence effect contribute positively to carbon emissions, thereby driving increases in emission levels. However, the influence of these effects weakens over time. Specifically, the total land expansion effect decreased from 175.85 in the 2007–2010 period to 57.91 in 2019–2022, while the affluence effect declined from 331.38 to 30.38 over the same period. This trend can be attributed to the fact that urban land expansion often entails the proliferation of energy-intensive and high-carbon activities, such as infrastructure development and industrial transportation, while economic growth leads to higher income levels and increased consumption, both of which contribute to greater carbon emissions. However, as industrial structures evolve and low-carbon awareness increases, the magnitude of these promoting effects gradually diminishes (Sun and Huang, 2020; Zhang et al., 2017). In contrast, the technological effect consistently exerts a negative inhibitory impact on carbon emissions, contributing to a reduction in emissions throughout the study period. Technological advancements, particularly those related to efficiency improvements and the adoption of clean energy technologies, have proven to be effective mechanisms for mitigating carbon emissions (Xie et al., 2021).

The effects of the three factors—land expansion, affluence, and technological progress—differ across specific decoupling types. For instance, in the 2019–2022 analysis, regions characterized by SD, WD, and GL decoupling types are typically in a transitional phase, shifting from traditional low-value-added industries to emerging high-value-added sectors. This structural transformation is often accompanied by substantial economic growth, which in turn diminishes or even reverses the positive impact of the affluence effect on carbon emissions. Conversely, regions with SND, WND, and DD decoupling types tend to experience a suppressive effect on carbon emissions due to urban decline. In these areas, urban land use is generally contracting, and any expansion typically focuses on redeveloping existing urban areas, such as creative industry parks, which are less associated with high-carbon activities. As a result, the influence of land expansion on carbon emissions is reduced (Liu et al., 2023). Finally, in regions exhibiting SND and END decoupling types, technological advancements contribute to increased carbon emissions. These regions continue to heavily rely on high-carbon industries for economic growth, and while technological improvements may enhance the production efficiency of these industries, they do not substantially alter the underlying energy structure or industry characteristics. Consequently, the application of such technologies still results in significant carbon emissions.

4 Discussion

In the context of rapid urbanization, urban expansion stands as one of the most significant socio-economic phenomena. Urban land functions as the primary spatial platform for infrastructure, industries, and human activities. The process of urban expansion reflects the dynamic interaction between economic development and resource-environmental factors. Investigating the relationship between urban expansion and carbon emissions offers valuable insights into land-use efficiency, clarifies the link between urbanization and green, low-carbon development, and provides a crucial theoretical foundation for achieving carbon neutrality within the context of urban development (Wang et al., 2024a). Therefore, this study classifies 297 sample cities into distinct urban expansion types using the Urban Expansion Disparity Index. It then examines the spatiotemporal evolution of the decoupling relationship between urban expansion intensity and carbon emissions from 2007 to 2022 using the Tapio decoupling index. Finally, the study explores the differentiated contributions of urban expansion, affluence, and technological effects to carbon emissions through LMDI structural decomposition.

The study demonstrates that the decoupling between urban expansion and carbon emissions in China has remained relatively stable over time, gradually progressing towards the ideal scenario of "urban expansion increasingly decoupling from the negative externalities of carbon emissions." However, significant room for improvement remains. Spatially, there is a pronounced polarization in the decoupling outcomes, with weak decoupling (WD) and strong negative decoupling (SND) emerging as the two dominant and contrasting decoupling types across Chinese cities. A closer analysis by city type reveals that cities exhibiting improved decoupling trends tend to be characterized by dynamic urban vitality, successful industrial restructuring, and robust economic

transformation. The Yangtze River Delta region stands out as a key cluster of such cities. In contrast, cities with deteriorating decoupling trends, often experience what is referred to as "Hegangzation" (a term describing the economic stagnation, population outflow, and urban decline faced by resource-dependent cities like Hegang in Heilongjiang Province) (Huang et al., 2024), face persistent challenges such as entrenched development patterns and stalled industrial transitions. These cities are predominantly located in the northeastern provinces and certain parts of central and western China. The emergence of different decoupling types is closely linked to regional development policies, economic structures, and local vitality. The unequal decoupling patterns highlight the role of rapid urbanization in exacerbating regional disparities and polarization in urban development (Hu et al., 2024). To achieve comprehensive decoupling between urban expansion and carbon emissions, it is crucial to prioritize coordinated development across urban areas.

Analyzing the relationship between urban expansion types and carbon emission decoupling types reveals a significant and relatively stable correspondence. In general, cities experiencing rapid expansion are predominantly associated with weak decoupling (WD) and growth linkage (GL) decoupling types. These cities, typically at an upper-middle stage of development, continue to exhibit strong demand for land. However, the direction of their development—whether toward WD or GL—largely depends on factors such as the intensity of land use (extensive vs intensive) and the nature of their industrial structure (high-carbon vs energy-efficient). Cities characterized by slow expansion are mainly linked to expansion-negative decoupling (END). These cities often grapple with the contradiction of high land demand and limited available resources. Their development remains heavily reliant on energy-intensive industries, positioning them as both major sources of environmental pollution and key targets for low-carbon governance efforts. Conversely, cities in decline predominantly exhibit stagnation-negative decoupling (SND). Under the combined pressures of population loss and resource depletion, these cities are marked by inefficient and energy-intensive development patterns. To address these challenges, it is crucial for these cities to cultivate new growth drivers and undergo structural transformation.

The effect analysis results indicate that, overall, both urban land expansion and affluence contribute to increased carbon emissions, while technological effects play a suppressive role. This suggests that China's current economic development remains heavily dependent on resource consumption, although technological innovation can help mitigate carbon emissions to some extent. However, the impact of these effects varies across different decoupling types, reflecting regional disparities in development stages. In regions undergoing industrial restructuring towards low-carbon, high-value-added sectors, the contribution of the affluence effect to carbon emissions significantly weakens, and may even become suppressive. Conversely, in regions where industrial structures continue to rely heavily on energy-intensive industries, both affluence and technological effects contribute substantially to carbon emissions. In shrinking cities, which suffer from a lack of economic vitality, the relationship between urban land expansion and carbon emissions is weaker, and the expansion effect has a minimal impact on driving emissions.

5 Conclusions and policy implications

This study analyzes 297 Chinese cities, classifying them by urban expansion intensity using the Urban Expansion Disparity Index. The Tapio decoupling model is employed to investigate the spatiotemporal evolution of decoupling relationships between urban expansion and carbon emissions from 2007 to 2022. Additionally, the LMDI model is applied to assess the impacts of land expansion, affluence, and technological factors on the carbon intensity of cities across different decoupling types. The results reveal a pronounced polarization in the decoupling states of urban expansion intensity and carbon emissions in China, with Weak Decoupling (WD) and Strong Negative Decoupling (SND) being the dominant types. From an urban typology perspective, there is a clear correspondence between urban expansion types and decoupling outcomes: rapidly expanding cities are predominantly categorized as WD and Growth Linkage (GL) types, slowly expanding cities are mainly classified as Expansion-Negative Decoupling (END) types, while declining cities are primarily characterized by SND. Furthermore, in the context of China's current development stage, urban expansion and affluence significantly contribute to increased carbon emissions, while technological advancements effectively mitigate them. Compared to previous studies, this research innovatively adopts urban construction land expansion intensity as an indicator of economic development, addressing the limitations of GDP, which fails to capture the environmental resource consumption associated with economic growth and, consequently, cannot fully reflect the social and environmental impacts of the decoupling process between urban development and carbon emissions. By systematically analyzing the decoupling relationship between urban expansion and carbon emissions across different city types, this study provides a comprehensive examination of the underlying mechanisms linking urban development and environmental sustainability. From a land-use perspective, it establishes a solid theoretical foundation for formulating differentiated carbon reduction policies tailored to cities with varying urban expansion patterns, thereby contributing to a synergistic balance between new urbanization and low-carbon sustainable development across diverse urban contexts.

Based on these findings, several policy recommendations are proposed to address the identified challenges and leverage the potential of low-carbon urban development.

Firstly, from a regional development perspective, addressing the unequal patterns of urban expansion and carbon emission decoupling necessitates the establishment of a collaboration-oriented regional strategy to reduce interregional disparities. On the one hand, the government should prioritize policy support for the northeastern provinces and certain underdeveloped central regions. This can be achieved through specific measures such as encouraging the development of the non-public economy, implementing policies to promote border-area openness in the northeast, and enhancing infrastructure and transportation networks in key development zones, remote and underprivileged areas, and other less-developed regions. These efforts aim to accelerate industrial restructuring, expand external openness, and foster new growth drivers, ultimately reversing urban decline and revitalizing regional development. On the other hand, further advancing urban cluster integration should be accompanied by targeted support for less-developed areas through policies such as paired assistance and cooperative partnerships.

These initiatives should facilitate resource and technology sharing while ensuring that potential risks, such as carbon leakage during industrial relocation, are effectively managed. This strategy aims to harness urban growth dynamics to drive high-quality regional development, achieving both sustainable progress and balanced regional equity.

Secondly, improving the current decoupling status through industrial restructuring and land-use optimization remains a crucial pathway for achieving low-carbon development. To this end, tailored carbon reduction policies should be implemented based on the specific developmental characteristics of different urban expansion types. For rapidly expanding cities, efforts should focus on promoting the rapid development of low-carbon, high-value-added industries, advancing smart city initiatives, and expanding renewable energy adoption to reduce carbon emissions. Additionally, optimizing land-use efficiency is essential—implementing a compact urban development model, restructuring land-use patterns, curbing inefficient urban sprawl, and encouraging high-density, low-carbon communities can significantly mitigate the high carbon footprint associated with extensive urban expansion. For slowly expanding cities, priority should be given to accelerating the low-carbon transition of energy-intensive industries. This can be achieved by encouraging enterprises to adopt cleaner production technologies, improving energy efficiency (Sun et al., 2024), and exploring digitalization and smart manufacturing pathways to reduce their carbon footprint. Simultaneously, in terms of land use, optimizing land-use planning, revitalizing underutilized land, and promoting the renewal and redevelopment of old industrial areas can enhance both economic and ecological benefits. For declining cities, the key lies in fostering emerging industries and stimulating new growth drivers. This can be achieved by attracting external investment and introducing advanced technology industries to transform the urban development model, addressing both economic stagnation and environmental degradation. Additionally, land reclamation and ecological restoration measures should be implemented, alongside strategic urban zoning to prevent unregulated expansion that could harm the environment. Promoting green agriculture and eco-tourism can further enhance the comprehensive value of land, supporting sustainable development.

Finally, harnessing the emission-reduction potential of technological innovation is a vital pathway for achieving synergy between urban development and carbon reduction (Liang et al., 2024). Efforts should focus on advancing the research, development, and deployment of low-carbon technologies through increased financial investment and targeted policy support. Accelerating the adoption of these technologies across diverse cities and industries is essential, particularly in energy-intensive cities and traditional industrial sectors. Such measures will provide the necessary technological foundation to facilitate the decoupling of urban expansion from carbon emissions, driving progress toward sustainable urban development.

However, this study has several limitations. First, the reliance on local statistical yearbook data for urban construction land may introduce discrepancies between reported data and actual land use. These discrepancies arise from variations in statistical standards and data accuracy across different regions and years. Second, the selection of sample areas is constrained by data availability, leading to incomplete coverage of urban areas nationwide. This limitation is particularly evident in the underrepresentation of cities in northwestern provinces, such as Tibet, Xinjiang, and Qinghai, which may result in regional gaps in the analysis. Finally, this study provides a relatively simplified analysis of the mechanisms influencing the decoupling relationship between urban expansion and carbon emissions. It primarily considers internal factors such as affluence effects, technological effects, and emission intensity effects, while overlooking potential external influences, such as policy interventions, on the decoupling process. Future research should employ more sophisticated models, such as the PSM-DID approach (Wang et al., 2024), to further investigate the underlying mechanisms shaping the relationship between urban expansion and carbon emissions, thereby offering a more comprehensive theoretical foundation for carbon reduction policies.

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

XL: Resources, Software, Writing – original draft. YL: Writing – original draft. SW: Conceptualization, Supervision, Writing – original draft.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This work was supported by Collaborative Innovation Center for Natural Resources Planning and Marine Technology of Guangzhou (Nos. 2023B04J0301 and 2023B04J0046).

Acknowledgments

Last but not least, many thanks for the support of Academic Specialty Group for Urban Sensing in Chinese Society of Urban Planning.

Conflict of interest

Author XL was employed by Survey and Design Institute Co., Ltd. Author YL was employed by Guangzhou Urban Planning & Design Survey Research Institute Co., Ltd.

The remaining author declares 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 author(s) declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Anser, M. K. (2019). Impact of energy consumption and human activities on carbon emissions in Pakistan: application of STIRPAT model. *Environ. Sci. Pollut. Res.* 26 (13), 13453–13463. doi:10.1007/s11356-019-04859-y

Ballantyne, A. G., Wibeck, V., and Neset, T.-S. (2016). Images of climate change – a pilot study of young people's perceptions of ICT-based climate visualization. *Clim. Change* 134, 73–85. doi:10.1007/s10584-015-1533-9

Bao, C., Wang, H., and Sun, S. (2022). Comprehensive simulation of resources and environment carrying capacity for urban agglomeration: a system dynamics approach. *Ecol. Indic.* 138, 108874. doi:10.1016/j.ecolind.2022.108874

Chen, J., Wang, P., Cui, L., Huang, S., and Song, M. (2018). Decomposition and decoupling analysis of CO2 emissions in OECD. *Appl. Energy* 231, 937–950. doi:10.1016/j.apenergy.2018.09.179

Chen, L., Xu, L., and Yang, Z. (2019). Inequality of industrial carbon emissions of the urban agglomeration and its peripheral cities: a case in the pearl River Delta, China. *Renew. Sustain. Energy Rev.* 109, 438–447. doi:10.1016/j.rser.2019.04.010

Crippa, M., Guizzardi, D., Pagani, F., and Pisoni, E. (2023). *GHG Emissions at sub-national level.* European Commission, Joint Research Centre (JRC). Available online at: http://data.europa.eu/89h/d67eeda8-c03e-4421-95d0-0adc460b9658

Dong, B., Ma, X., Zhang, Z., Zhang, H., Chen, R., Song, Y., et al. (2020). Carbon emissions, the industrial structure and economic growth: evidence from heterogeneous industries in China. *Environ. Pollut.* 262, 114322. doi:10.1016/j.envpol.2020.114322

Fawzy, S., Osman, A. I., Doran, J., and Rooney, D. W. (2020). Strategies for mitigation of climate change: a review. *Environ. Chem. Lett.* 18 (6), 2069–2094. doi:10.1007/s10311-020-01059-w

Feng, W., Guo, B., and Yu, Y. (2025). The impact of green finance reform on industrial water pollution: evidence from innovation pilot zones in China. *Water Econ. Policy, March*, 2440010. doi:10.1142/S2382624X24400101

Han, F., Xie, R., Lu, Y., Fang, J., and Liu, Y (2018). The effects of urban agglomeration economies on carbon emissions: evidence from Chinese cities. *J. Clean. Prod.* 172, 1096–1110. doi:10.1016/j.jclepro.2017.09.273

Hao, J., Gao, F., Fang, X., Nong, X., Zhang, Y., and Hong, F. (2022). Multi-factor decomposition and multi-scenario prediction decoupling analysis of China's carbon emission under dual carbon goal. *Sci. Total Environ.* 841, 156788. doi:10.1016/j.scitotenv.2022.156788

Herman, E. D. (2014). *From uneconomic growth to a steady-state economy*. Cheltenham; Edward Elgar Publishing.

Hou, L., Wang, Y., Hu, L., Wang, Y., Li, Y., and Zheng, Y. (2023). Economic growth and carbon emissions analysis based on tapio-ekc coupled integration and scenario simulation: a case study of China's transportation industry. *Environ. Dev. Sustain.* 26 (7), 18855–18881. doi:10.1007/s10668-023-03418-3

Hu, Y., Connor, D. S., Stuhlmacher, M., Peng, J., and Turner Ii, B. L. (2024). More urbanization, more polarization: evidence from two decades of urban expansion in China. *Npj Urban Sustain.* 4 (1), 33. doi:10.1038/s42949-024-00170-z

Huang, S., Lyu, Y., Shi, H., and Wu, C. (2024). Spatiotemporal analysis of the coupling relationship between urban infrastructure and land utilization in a shrinking city: a case study of Hegang, northeast China. *Land* 13 (11), 1904. doi:10.3390/land13111904

Huo, J., and Huang, S. (2023). Spatio-temporal characteristics and influencing factors of urban shrinkage in county level of Heilongjiang province, northeast China. *Heliyon* 9 (11), e21436. doi:10.1016/j.heliyon.2023.e21436

Jiang, Y., Tian, S., Xu, Z., Gao, L., Xiao, L., Chen, S., et al. (2022). Decoupling environmental impact from economic growth to achieve sustainable development goals in China. *J. Environ. Manag.* 312, 114978. doi:10.1016/j.jenvman.2022.114978

Kallis, G., Kostakis, V., Lange, S., Muraca, B., Paulson, S., and Schmelzer, M. (2018). Research on degrowth. *Annu. Rev. Environ. Resour.* 43 (1), 291–316. doi:10.1146/annurev-environ-102017-025941

Lai, Y., Chen, K, Zhang, J., and Liu, F. (2020). Transformation of industrial land in urban renewal in shenzhen, China. *Land* 9 (10), 371. doi:10.3390/land9100371

Li, J., Chen, Y., Li, Z., and Huang, X. (2019). Low-carbon economic development in central asia based on LMDI decomposition and comparative decoupling analyses. *J. Arid Land* 11 (4), 513–524. doi:10.1007/s40333-019-0063-0

Li, J., Huang, G., Li, Y., Liu, L., and Zheng, B. (2022). Decoupling degrees of China's economic growth from three-perspective carbon emissions. *J. Clean. Prod.* 368, 133209. doi:10.1016/j.jclepro.2022.133209

Li, X.-Y., Chen, T., and Chen, B. (2023). Research on the influencing factors and decoupling state of carbon emissions in China's transportation industry. *Sustainability* 15 (15), 11871. doi:10.3390/su151511871

Li, Y.-N, Cai, M., Wu, K., and Wei, J. (2019). Decoupling analysis of carbon emission from construction land in Shanghai. *J. Clean. Prod.* 210, 25–34. doi:10.1016/j.jclepro.2018.10.249

Liang, J., Wang, S., Liao, Y., and Feng, K. (2024). Carbon Emissions embodied in investment: assessing emissions reduction responsibility through multi-regional input-output analysis. *Appl. Energy.* 358, 122558. doi:10.1016/j.apenergy.2023.122558

Lin, B., and Teng, Y. (2022). Decoupling of economic and carbon emission linkages: evidence from manufacturing industry chains. *J. Environ. Manag.* 322, 116081. doi:10.1016/j.jenvman.2022.116081

Liu, B., Chen, T., Li, Y., Song, H., and Ma, Z. (2018). Research on the effects of urbanization on carbon emissions efficiency of urban agglomerations in China. *J. Clean. Prod.* 197, 1374–1381. doi:10.1016/j.jclepro.2018.06.295

Liu, F., Zhang, Z., Shi, L., Zhao, X., Xu, J., Yi, L., et al. (2016). Urban expansion in China and its spatial-temporal differences over the past four decades. *J. Geogr. Sci.* 26, 1477–1496. doi:10.1007/s11442-016-1339-3

Luo, H., Li, L, Lei, Y., Wu, S., Yan, D., Fu, X., et al. (2021). Decoupling analysis between economic growth and resources environment in central plains urban agglomeration. *Sci. Total Environ.* 752, 142284. doi:10.1016/j.scitotenv.2020.142284

Ma, M., Yan, R., Du, Y., Ma, X., Cai, W., and Xu, P. (2017). A methodology to assess China's building energy savings at the national level: an IPAT–LMDI model approach. *J. Clean. Prod.* 143, 784–793. doi:10.1016/j.jclepro.2016.12.046

Magazzino, C., Pakrooh, P., and Abedin, M. Z. (2023). A decomposition and decoupling analysis for carbon dioxide emissions: evidence from OECD countries. *Environ. Dev. Sustain.* 26 (11), 28539–28566. doi:10.1007/s10668-023-03824-7

Nuissl, H., and Siedentop, S. (2021). "Urbanisation and land use change," in *Sustainable land management in a European context. Human-environment interactions.* Editors T. Weith, T. Barkmann, N. Gaasch, S. Rogga, C. Strauß, and J. Zscheischler (Cham: Springer International Publishing), 8, 75–99. doi:10.1007/978-3-030-50841-8_5

Peng, J., Zheng, Y., and Liu, C. (2022). The impact of urban construction land use change on carbon emissions: evidence from the China land market in 2000–2019. *Land* 11 (9), 1440. doi:10.3390/land11091440

Qian, Y., Jiang, J., Guo, B., and Hu, F. (2025). The impact of 'zero-waste city' pilot policy on corporate green transformation: a causal inference based on double machine learning. *Front. Environ. Sci.* 13, 1564418. doi:10.3389/fenvs.2025.1564418

Ren, S., and Hu, Z. (2012). Effects of decoupling of carbon dioxide emission by Chinese nonferrous metals industry. *Energy Policy* 43, 407–414. doi:10.1016/j.enpol.2012.01.021

Shuai, C., Chen, X, Wu, Y., Zhang, Y, and Tan, Y. (2019). A three-step strategy for decoupling economic growth from carbon emission: empirical evidences from 133 countries. *Sci. Total Environ.* 646, 524–543. doi:10.1016/j.scitotenv.2018.07.045

Sun, C., Zhang, Y., Ma, W., Wu, R., and Wang, S. (2022). The impacts of urban form on carbon emissions: a comprehensive review. *Land* 11 (9), 1430. doi:10.3390/land11091430

Sun, W., and Huang, C. (2020). How does urbanization affect carbon emission efficiency? Evidence from China. *J. Clean. Prod.* 272, 122828. doi:10.1016/j.jclepro.2020.122828

Sun, Y., Wen, G., Dai, H., Feng, Y., Azaele, S., Lin, W., and Zho, F. (2024). Quantifying the resilience of coal energy supply in china toward carbon neutrality. *Research,* 7 0398. doi:10.34133/research.0398

Tapio, P. (2005). Towards a theory of decoupling: degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transp. Policy* 12 (2), 137–151. doi:10.1016/j.tranpol.2005.01.001

Vadén, T., Lähde, V., Majava, A., Järvensivu, P., Toivanen, T., Hakala, E., et al. (2020). Decoupling for ecological sustainability: a categorisation and review of research literature. *Environ. Sci. and Policy* 112, 236–244. doi:10.1016/j.envsci.2020.06.016

Wang, C., Chen, J., and Zou, J (2005). Decomposition of energy-related CO2 emission in China: 1957–2000. *Energy* 30 (1), 73–83. doi:10.1016/j.energy.2004.04.002

Wang, H., Wang, Y., Fan, C., Wang, X., Yao, W., Zhang, Z., et al. (2020). Material consumption and carbon emissions associated with the infrastructure construction of 34 cities in northeast China. *Complexity* 2020, 1–20. doi:10.1155/2020/4364912

Wang, J., Dong, X., and Dong, K. (2022). How does ICT agglomeration affect carbon emissions? The case of Yangtze River Delta urban agglomeration in China. *Energy Econ.* 111, 106107. doi:10.1016/j.eneco.2022.106107

Wang, M., and Feng, C. (2019). Decoupling economic growth from carbon dioxide emissions in China's metal industrial sectors: a technological and efficiency perspective. *Sci. Total Environ.* 691, 1173–1181. doi:10.1016/j.scitotenv.2019.07.190

Wang, M., Wang, Y., Yang, Z., and Guo, B. (2024). Does energy-consuming rights trading policy achieve urban pollution and carbon reduction? A quasi-natural experiment from China. *Front. Environ. Sci.* 12, 1430031. doi:10.3389/fenvs.2024.1430031

Wang, S., Chen, X., Xie, R., Liu, K., Wang, J., Liu, X., et al. (2024a). Demand-side insights for steering human appropriation of net primary productivity within planetary boundaries. *One Earth* 7 650–662. doi:10.1016/j.oneear.2024.02.010

Wang, S., Zhou, S., Wu, R., Feng, K., and Hubacek, K. (2024b). Interregional flows of embodied carbon storage associated with land-use change in China. *Ann. Am. Assoc. Geogr.* 114 1526–1545. doi:10.1080/24694452.2024.2356849

Wang, Q., and Wang, S. (2019). Decoupling economic growth from carbon emissions growth in the United States: the role of research and development. *J. Clean. Prod.* 234, 702–713. doi:10.1016/j.jclepro.2019.06.174

Wang, Y., Xie, T., and Yang, S. (2017). Carbon emission and its decoupling research of transportation in Jiangsu province. *J. Clean. Prod.* 142, 907–914. doi:10.1016/j.jclepro.2016.09.052

Ward, J. D., Sutton, P. C., Werner, A. D., Costanza, R., Mohr, S. H., and Craig, T. S. (2016). Is decoupling GDP growth from environmental impact possible? *PLoS One* 11 (10), e0164733. doi:10.1371/journal.pone.0164733

Wiedenhofer, D., Virág, D., Kalt, G., Plank, B., Streeck, J., Pichler, M., et al. (2020). A systematic review of the evidence on decoupling of GDP, resource use and GHG emissions, Part I: bibliometric and conceptual mapping. *Environ. Res. Lett.* 15 (6), 063002. doi:10.1088/1748-9326/ab8429

Wu, Y, Chau, K. W., Lu, W., Shen, L., Shuai, C., and Chen, J. (2018a). Decoupling relationship between economic output and carbon emission in the Chinese construction industry. *Environ. Impact Assess. Rev.* 71, 60–69. doi:10.1016/j.eiar.2018.04.001

Wu, Y., Luo, Z., and Wu, Z. (2024). Exploring the relationship between urbanization and vegetation ecological quality changes in the Guangdong–Hong Kong–Macao greater bay area. *Land* 13 (8), 1246. doi:10.3390/land13081246

Wu, Y., Zhang, X., and Shen, L. (2011). The impact of urbanization policy on land use change: a scenario analysis. *Cities* 28 (2), 147–159. doi:10.1016/j.cities.2010.11.002

Wu, Y, Zhu, Q., and Zhu, B. (2018b). Decoupling analysis of world economic growth and CO2 emissions: a study comparing developed and developing countries. *J. Clean. Prod.* 190, 94–103. doi:10.1016/j.jclepro.2018.04.139

Xie, H., Zhu, Z., Wang, B., Liu, G., and Zhai, Q. (2018). Does the expansion of urban construction land promote regional economic growth in China? Evidence from 108 cities in the Yangtze River Economic Belt. *Sustainability* 10 (11), 4073. doi:10.3390/su10114073

Xie, X., Wang, J., and Liu, M. (2025). Regional disparities and driving factors of residential carbon emissions: an empirical analysis based on samples from 270 cities in China. *Land* 14 (3), 510. doi:10.3390/land14030510

Xie, Z., Wu, R., and Wang, S. (2021). How technological progress affects the carbon emission efficiency? Evidence from national panel quantile regression. *J. Clean. Prod.* 307, 127133. doi:10.1016/j.jclepro.2021.127133

Xin, L., Jia, J., Hu, W., Zeng, H., Chen, C., and Wu, B (2021). Decomposition and decoupling analysis of CO2 emissions based on LMDI and two-dimensional decoupling model in gansu province, China. *Int. J. Environ. Res. Public Health* 18 (11), 6013. doi:10.3390/ijerph18116013

Xin, M., Guo, H., Li, S., and Chen, L. (2023). Can China achieve ecological sustainability? An LMDI analysis of ecological footprint and economic development decoupling. *Ecol. Indic.* 151, 110313. doi:10.1016/j.ecolind.2023.110313

Xu, Q., Dong, Y.-X, and Yang, R. (2018). Urbanization impact on carbon emissions in the pearl River Delta region: kuznets curve relationships. *J. Clean. Prod.* 180, 514–523. doi:10.1016/j.jclepro.2018.01.194

Xu, W., Xie, Y., Xia, D., Ji, L., and Huang, G. (2021). A multi-sectoral decomposition and decoupling analysis of carbon emissions in Guangdong province, China. *J. Environ. Manag.* 298, 113485. doi:10.1016/j.jenvman.2021.113485

Yang, H., Ma, J., Jiao, X., Shang, G., and Yan, H. (2023). Characteristics and driving mechanism of urban construction land expansion along with rapid urbanization and carbon neutrality in Beijing, China. *Land* 12 (7), 1388. doi:10.3390/land12071388

Yang, M., and Xie, Y. (2021). Spatial pattern change and ecosystem service value dynamics of ecological and non-ecological redline areas in nanjing, China. *Int. J. Environ. Res. Public Health* 18 (8), 4224. doi:10.3390/ijerph18084224

Yuan, L., Li, R., Wu, X., He, W., Kong, Y., Ramsey, T. S., et al. (2023). Decoupling of economic growth and resources-environmental pressure in the Yangtze River Economic Belt, China. *Ecol. Indic.* 153, 110399. doi:10.1016/j.ecolind.2023.110399

Zeng, T., Jin, H., Geng, Z., Kang, Z., and Zhang, Z. (2022). The effect of urban shrinkage on carbon dioxide emissions efficiency in northeast China. *Int. J. Environ. Res. Public Health* 19 (9), 5772. doi:10.3390/ijerph19095772

Zhang, N., Yu, K., and Chen, Z. (2017). How does urbanization affect carbon dioxide emissions? A cross-country panel data analysis. *Energy Policy* 107, 678–687. doi:10.1016/j.enpol.2017.03.072

Zhang, X., and Han, H. (2024). Characteristics and factors influencing the expansion of urban construction land in China. *Sci. Rep.* 14 (1), 16040. doi:10.1038/s41598-024-67015-8

Zhao, X., Jiang, M., and Zhang, W. (2022). Decoupling between economic development and carbon emissions and its driving factors: evidence from China. *Int. J. Environ. Res. Public Health* 19 (5), 2893. doi:10.3390/ijerph19052893

Zhao, Y, Ma, J., Li, Y., Cheng, K., Zhang, M., Liu, Z., and Yang, F. (2025). Carbon emission based predictions of anthropogenic impacts on groundwater storage at typical basins in 2050. *Sci. Partner J.* 2025 0680. doi:10.34133/research.0680

Zheng, X., Wang, R., and Qi, H. (2019). A city-scale decomposition and decoupling analysis of carbon dioxide emissions: a case study of China. *J. Clean. Prod.* 238, 117824. doi:10.1016/j.jclepro.2019.117824

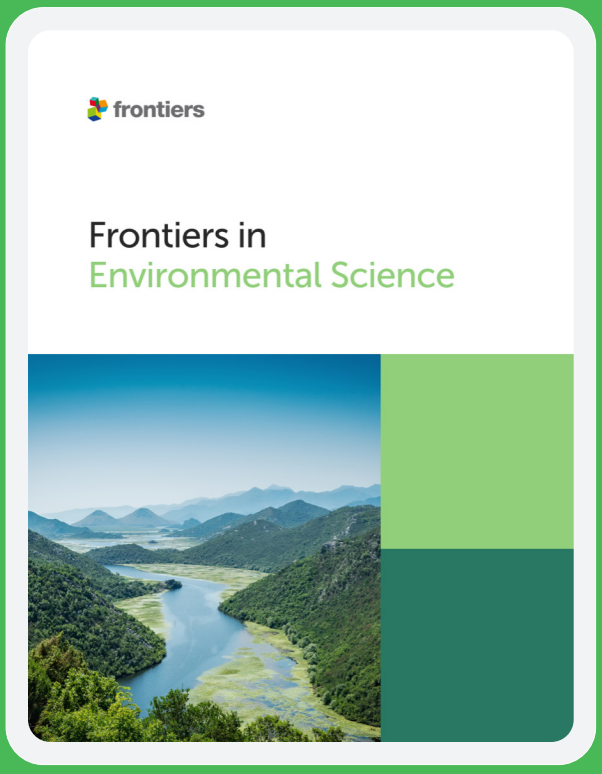
Frontiers in Environmental Science

Explores the anthropogenic impact on our natural world

An innovative journal that advances knowledge of the natural world and its intersections with human society. It supports the formulation of policies that lead to a more inhabitable and sustainable world.

Discover the latest Research Topics

See more →



Frontiers

Avenue du Tribunal-Fédéral 34
1005 Lausanne, Switzerland
frontiersin.org

Contact us

+41 (0)21 510 17 00
frontiersin.org/about/contact