frontiers | Frontiers in Ecology and Evolution

TYPE Original Research
PUBLISHED 16 October 2025
DOI 10.3389/fevo.2025.1676353

OPEN ACCESS

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RECEIVED 30 July 2025
ACCEPTED 26 September 2025
PUBLISHED 16 October 2025

CITATION
Jiang S, Yin J and Jiang Y (2025) Can National Forest Cities Construction promote Urban Sustainability and Resilience? Evidence from a quasi-natural experiment in China.
Front. Ecol. Evol. 13:1676353.
doi: 10.3389/fevo.2025.1676353

Can National Forest Cities Construction promote Urban Sustainability and Resilience? Evidence from a quasi-natural experiment in China

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With the rapid acceleration of global urbanization, Urban Sustainability and Resilience (USR) have emerged as pivotal issues in addressing resource scarcity, environmental degradation, and extreme climate challenges. Focusing on this context, this study investigates whether the National Forest Cities Construction (NFCC) policy promotes urban sustainability and resilience and examines how human capital (HC), artificial intelligence (AI) and government support (GS) mediate these effects. This study evaluates the impact of National Forest Cities Construction (NFCC) policies on USR using panel data from 300 Chinese cities from 2000 to 2023. Employing a multi-period Difference-in-Differences (DID) approach and constructing an entropy-weighted TOPSIS evaluation framework, we systematically assess the policy effects on urban economic, social, and environmental coordination and risk response capacities. Our findings reveal a significant positive impact of NFCC policies on overall USR, with pronounced heterogeneous effects observed across regions and city scales—most notably, policies exhibit the strongest effects in eastern regions and are particularly sensitive among small-to-medium-sized cities. Further mechanism analyses identify three intrinsic transmission pathways: Human Capital (HC), Artificial Intelligence (AI), and Government Support (GS). Although the HC channel initially displays a negative adjustment effect, the gradual accumulation of skilled talent significantly enhances its positive influence over time. In contrast, while the AI channel effectively promotes intelligent technology adoption, it negatively affects Urban Sustainability (US) yet positively contributes to Urban Resilience (UR). The GS channel significantly increases public financial investment and environmental governance; however, inefficiencies in resource allocation yield negative transmission effects on both US and UR. These empirical insights clarify the effectiveness of NFCC policies and their regional and scale-specific differences, offering practical recommendations for policy optimization and governance strategies. Ultimately, this study provides a robust theoretical and empirical foundation for advancing high-quality urban development characterized by integrated economic growth, environmental protection, and risk management.

KEYWORDS

National Forest Cities Construction, Urban Sustainability and Resilience, sustainability, quasi-natural experiment, multi-period DID mode

1 Introduction

The rapid progression of global urbanization has significantly boosted economic prosperity and social advancement; however, it has simultaneously intensified critical issues, including resource depletion, environmental degradation, and extreme climatic events (Cohen, 2006; Zhang, 2016). These challenges pose unprecedented threats to cities' capacity to maintain long-term Urban Sustainability (US) and Urban Resilience (UR). Consequently, achieving green growth and strengthening ecological resilience amid ongoing urban expansion has become a pressing issue for both researchers and policymakers (McCormick et al., 2013; Artmann et al., 2019; Elmqvist et al., 2019). US refers to balanced growth across economic, social, and environmental dimensions (Alberti, 1996). Its central objective involves harmonizing economic prosperity, environmental conservation, and social stability through efficient resource management, green technology adoption, and equitable social mechanisms (Klopp and Petretta, 2017). In contrast, UR emphasizes a city's capability to withstand disruptions, recover quickly, and adapt effectively to both internal and external shocks (Amirzadeh et al., 2022). The integration of US and UR requires cities to possess not only strong foundations for stable development but also flexibility in crisis response and recovery. This integration ensures continued urban vitality and resilience amid a dynamic external environment (Zhang and Li, 2018). Constructing cities characterized by high Urban Sustainability and Resilience (USR) thus necessitates achieving dynamic equilibrium among economic, environmental, and social factors, alongside continuously enhancing risk management and emergency response mechanisms. Such improvements are crucial for overall urban resilience and long-term sustainable growth. Recently, countries worldwide have actively pursued innovative urban development models (Cooke, 2011; Addanki and Venkataraman, 2017), within which policy innovation has become essential for promoting USR. In this context, China initiated the NFCC program in 2004. National Forest Cities Construction (NFCC) aims to develop exemplary cities with coordinated economic, ecological, and social growth through extensive urban greening, ecological restoration, and intelligent urban management practices (Wang C. et al., 2024). Beyond enhancing urban green coverage and environmental quality (Xu et al., 2020; Zhang et al., 2024), NFCC promotes structural adjustments and institutional innovations, targeting comprehensive improvements in US and UR (Xu and Song, 2024). However, existing research has predominantly focused on ecological and socioeconomic outcomes of NFCC (13(15, whereas systematic empirical analyses regarding the broader impacts of NFCC on USR—particularly its internal transmission mechanisms—remain limited. For example, Zhang and Zhong (2024) examined the direct impact and spatial spillover effects of NFCC on county-level economic growth, analyzing its impact mechanisms solely from labor and market dimensions without fully considering technological and governmental interventions (Zhang and Zhong, 2024). Xie et al. (2024) also analyzed NFCC's effects on public health, examining its impact pathways through reduced haze and altered resident behaviors (Xie et al., 2024). Hu et al. (2023) examined the impact of NFCC on smog emission reductions (Hu et al., 2023). Ai and Zhou (2023) analyzed NFCC's influence on economic growth, incorporating the mechanism effects of total factor productivity and human capital (Ai and Zhou, 2023). Xu et al. (2020) tested the impact of NFCC on urban air quality (Xu et al., 2020).

Current studies have extensively discussed the concepts of US and UR (Roostaie et al., 2019; Zeng et al., 2022), proposing various multidimensional evaluation frameworks. However, most studies have primarily focused on evaluating the current state of urban environments or the outcomes of environmental quality improvements (Liu et al., 2017). There remains insufficient consideration of how national green-city construction policies contribute to guiding urban transformation. Furthermore, there is no consensus regarding the heterogeneous effects of these policies or the specific roles played by Human Capital (HC), Artificial Intelligence (AI), and Government Support (GS) as underlying transmission mechanisms. High-quality HC can significantly enhance a city's technological innovation capacity, optimize resource allocation, and accelerate green industrial development (Wang et al., 2022). However, systematic empirical evidence remains scarce on how NFCC policies may enhance local talent cultivation and technological accumulation, thereby promoting US and UR. Similarly, AI—representing a critical aspect of the ongoing technological revolution—is profoundly reshaping urban governance and industrial structures. Increasingly, intelligent technologies are recognized for their potential to optimize public services, improve administrative efficiency, and facilitate green transformation (Boyd and Holton, 2018). While some studies have explored AI's impact on urban environments and carbon emissions (Liu et al., 2022), limited research addresses how AI, propelled by green policies, serves as a vital factor in enhancing urban sustainability and resilience. GS is another critical factor, serving as essential institutional support for policy implementation through resource allocation, institutional innovations, and public investments (Wang et al., 2020). Previous research indicates positive impacts from governmental interventions on coordinated regional economic development and ecological improvements (Li et al., 2024). Nevertheless, comprehensive theoretical frameworks and empirical validations remain lacking on how GS—specifically governmental fiscal expenditures and policy interventions within the NFCC context—indirectly enhances US and UR through improvements in urban governance and infrastructure. Recent studies on related policies provide further context. Quasi–experimental analysis of the National Civilized City program shows that attaining the title increases per capita GDP by about 2.88%, with benefits varying across regions and administrative levels (Yang et al., 2025). Research on environmental regulation finds a significant 'U–shaped' relationship between regulatory intensity and the export–technology complexity of high–tech industries and highlights transmission channels via foreign direct investment, human capital and R&D (Yang et al., 2024a). Another study on urban digital construction reports that every 1% increase in digital–construction level raises GDP (Yang et al., 2024b). These findings underscore the diversity of urban policy impacts and motivate our examination of NFCC's effects on both sustainability and resilience.

Against this background, our research seeks to answer two key questions: (i) Does NFCC policy enhance urban sustainability and resilience? and (ii) Through which transmission mechanisms—human capital, artificial intelligence and government support—does this influence operate? Given these gaps, this study constructs a comprehensive evaluation index system for USR, incorporating 6 secondary and 22 tertiary indicators. We analyze the spatial distribution characteristics of NFCC, USR, US, and UR, using a dataset comprising 300 Chinese cities from 2000 to 2023. Employing a multi-period Difference-in-Differences (DID) model, we systematically examine the effects of NFCC on USR. Additionally, by introducing HC, AI, and GS as key mechanism variables, we aim to uncover the internal transmission pathways through which NFCC policies influence urban transformation. This approach provides novel theoretical insights and empirical evidence regarding how green urban policies drive comprehensive urban upgrades. This research moves beyond previous single-dimensional assessments of urban development by jointly investigating US and UR, enriching both sustainable development and urban resilience theories. Moreover, our detailed exploration of the transmission mechanisms—HC, AI, and GS—fills existing gaps in mechanism-oriented analyses, expanding the theoretical frameworks underlying sustainable and ecological urban construction. Ultimately, this study seeks to offer scientific and systematic theoretical guidance and practical recommendations for future urban governance, ecological restoration, and smart-city initiatives.

2 Literature review and theoretical hypotheses

NFCC, as a key component of China's green transformation strategy (Wang C. et al., 2024), has been promoted nationwide since 2004. Its core objective is to directly improve urban environmental quality and optimize spatial structure through large-scale urban greening, ecological restoration, and intelligent management (Zhang et al., 2024). Empirical evaluations of similar urban policies provide useful points of comparison. For instance, a quasi–experimental study of China's National Civilized City (NCC) program found that winning the NCC title increases per–capita GDP by about 2.88%, with benefits varying by region and city–administrative level (Yang et al., 2025). Research on environmental regulation in high–tech manufacturing documents a significant 'U–shaped' relationship between regulation intensity and the export–technology complexity of high–tech products, mediated by foreign direct investment, human capital and R&D investment (Yang et al., 2024a). Another study on urban digital construction shows that every 1% increase in digital–construction level raises city GDP (Yang et al., 2024b). These studies typically employ quasi–natural experiments or multi–period DID models and focus on specific economic or technological outcomes. By contrast, existing NFCC research has mainly evaluated ecological improvements and short–term socioeconomic benefits. Our work fills this gap by systematically assessing NFCC's effects on Urban Sustainability and Resilience (USR) and by modelling the internal transmission mechanisms of human capital, artificial intelligence and government support. Improved urban environments not only enhance residents' quality of life but also facilitate economic structural adjustment and better resource allocation, thereby promoting coordinated socio-economic and ecological development (Yun et al., 2024). Sustainable Development Theory (SDT) asserts that development must meet current needs without hindering future generations, guided by the principles of equity, sustainability, and commonality, and aiming for balanced, fair, efficient, and multidimensional growth (Holden et al., 2014). SDT provides a systematic framework for US by advocating balanced development across economic, social, and environmental dimensions while ensuring proper resource allocation and long-term ecological health. In contrast, RT emphasizes that systems must rapidly adapt, effectively defend, and quickly recover when faced with external shocks to maintain essential functions and stable operation (Pettersen and Schulman, 2019). Upgrading urban hardware and green infrastructure is regarded as a fundamental basis for fostering US, and under policy guidance, NFCC strengthens both UR and US through increased green coverage, improved environmental governance, and the adoption of ecological restoration technologies (Kaluarachchi, 2021).

Based on SDT, NFCC enhances urban ecosystem services through measures such as ecological restoration, air and water quality management, and urban greening (Roeland et al., 2019). Simultaneously, by improving urban landscapes and living environments, NFCC increases city attractiveness, which in turn supports economic structural optimization and the equitable distribution of social resources. A wealth of research indicates that environmental improvements often catalyze economic and social development, thus advancing US (Roseland, 2000; Naess, 2001). From the perspective of Resilience Theory (RT), NFCC's similar environmental improvement measures substantially bolster urban ecosystem services (Xu et al., 2024). Moreover, by enhancing urban aesthetics and livability, NFCC contributes to optimizing economic structures and redistributing social resources more equitably (Wang et al., 2024b). Empirical evidence also suggests a positive relationship between green urban construction and enhanced UR; policy implementation helps establish urban emergency plans, reinforces risk prevention mechanisms, and achieves efficient resource scheduling through intelligent systems.

Based on the above discussion, this paper proposes the following hypotheses:

H1: NFCC significantly promotes USR.

H2: NFCC significantly promotes US.

H3: NFCC significantly promotes UR.

From the perspectives of SDT and RT, NFCC improves not only urban environmental quality and public service levels (Xie et al., 2023) but also urban living and working conditions, thereby attracting and retaining high-quality talent to promote HC development (Chen et al., 2021). SDT emphasizes balanced development across economic, social, and environmental dimensions, while HC—representing a concentration of knowledge, skills, and innovative capacity (Zheng and Du, 2020)—serves as a key endogenous driver for such balanced growth. From the perspective of human capital theory, investments in education, health and high–quality living environments enhance labor productivity and innovation capacity (Ibrahim, 2023). Cities endowed with abundant green spaces and cultural amenities tend to attract a 'creative class' of highly skilled workers whose presence fosters technological innovation, social cohesion and environmentally conscious consumption (Wu et al., 2024). These dynamics explain why NFCC's improvements in urban ecological quality and public amenities can strengthen the economic, social and environmental dimensions of urban sustainability and resilience (Xu and Song, 2024). By improving ecological conditions and living environments, NFCC enhances a city's ability to attract and retain top talent, thus significantly promoting HC development (Xu et al., 2024). With enhanced HC, a city gains greater capacities for technological innovation and resource integration (Sun, 2022). This progress not only optimizes industrial structure, management efficiency, and public service quality to achieve coordinated socio-economic and environmental development but also enhances the city's ability to rapidly adapt to and manage external shocks such as natural disasters, economic fluctuations, or social unrest (Meng et al., 2021). Therefore, by leveraging the HC channel, NFCC simultaneously promotes US and UR. Based on this mechanism, the following hypotheses are posited: H4: NFCC significantly promotes HC development.

H5: NFCC promotes USR via the HC channel.

H6: NFCC promotes US via the HC channel.

H7: NFCC promotes UR via the HC channel.

NFCC not only drives urban development directly through improvements in environmental quality and resource allocation but also plays a crucial role in advancing digital transformation and technological innovation. In promoting green transformation and ecological governance, NFCC enhances infrastructure and urban management, creating favorable conditions for the deployment of digital platforms and intelligent systems (Sanesi et al., 2017). This environment, in turn, supports the development of AI by providing essential technical backing and market conditions. Through rapid adoption and application, AI endows urban governance with real-time data collection, precise monitoring, and intelligent decision-making capabilities (Yigitcanlar et al., 2021). According to SDT, achieving US requires balanced development across economic, social, and environmental dimensions, and AI facilitates this balance by optimizing resource allocation, boosting management efficiency, and fostering service innovation (Son et al., 2023). In addition, digital–transformation theory posits that intelligent technologies empower cities to integrate heterogeneous data sources, enabling predictive analytics for resource demand, pollution control and public–health surveillance (Wang et al., 2024a). These capabilities not only improve operational efficiency but also expand citizens' access to public services, contributing to social inclusiveness and environmental sustainability (Yu et al., 2023). However, AI deployments also consume large amounts of electricity and cooling water; proliferating AI data centers produce electronic waste and 'use massive amounts of electricity, spurring the emission of planet–warming greenhouse gases (Richards et al., 2023). Therefore, greening AI is essential for ensuring its net positive contribution. Moreover, from an RT perspective, when facing external shocks such as natural disasters, economic fluctuations, or social crises, cities rely on effective risk-warning and emergency response mechanisms (Seeliger and Turok, 2013)—a function for which AI is indispensable (Son et al., 2023). Intelligent monitoring and data analytics enable swift responses and effective coordination, thereby enhancing a city's ability to prevent and manage emergencies (Alahakoon et al., 2023), which ultimately bolsters overall UR. Consequently, by promoting the widespread adoption of AI, NFCC directly advances intelligent urban management and, through its technological impetus, further drives coordinated development across multiple dimensions while strengthening a city's adaptability and recovery capacity. On this basis, the following hypotheses are formulated:H8: NFCC significantly promotes AI development.

H9: NFCC promotes USR via the AI channel.

H10: NFCC promotes US via the AI channel.

H11: NFCC promotes UR via the AI channel.

In addition to serving as a green policy that directly improves urban environmental quality and resource allocation, NFCC also triggers a series of institutional changes at the governmental level, thereby providing policy and financial support for urban green transformation. Specifically, SDT stresses that balanced development across economic, social, and environmental dimensions requires

effective GS, which acts as a vital institutional guarantee (Yang et al., 2013). Public–administration and meta–governance theories emphasize that cross–sectoral collaboration and coherent policy instruments are crucial for aligning economic, social and environmental goals (Christopoulos et al., 2016). Through legislation, fiscal transfers and targeted subsidies, government support can steer markets and communities toward sustainable behaviors, mobilize social capital and coordinate multiple stakeholders, thereby building institutional resilience and enhancing a city's capacity to withstand shocks (de Oliveira et al., 2013). In parallel, RT maintains that a city's capacity to respond to sudden shocks depends not only on physical infrastructure but also on robust policies, funding, and management systems (Dzigbede et al., 2020). Within this framework, by refining policy systems and increasing fiscal investments, NFCC can directly enhance GS, thereby providing the essential public services, green infrastructure, and environmental governance resources needed to underpin US and UR (Zhang and Zhong, 2024). Moreover, as GS strengthens, its role in optimizing public resource allocation, fostering interdepartmental coordination, and guiding social capital participation becomes increasingly critical (Christopoulos et al., 2012). These effects collectively promote coordinated development across economic, social, and environmental dimensions and help establish efficient risk-warning and emergency response systems, enhancing a city's capacity for rapid recovery and adaptation to external shocks (Sun et al., 2024). Thus, through the GS channel, NFCC not only directly promotes improvements in US and UR but also achieves synergistic enhancements in overall urban sustainability and resilience. Based on this transmission mechanism, the following hypotheses are posited:
H12: NFCC significantly promotes GS.

H13: NFCC promotes USR via the GS channel.

H14: NFCC promotes US via the GS channel.

H15: NFCC promotes UR via the GS channel.

Based on this, the following theoretical mechanism framework is constructed (Figure 1).

3 Research design

3.1 Variable description

3.1.1 Dependent variables

(1) Urban Sustainability and Resilience. Based on the studies of Buzási et al. (2022) and the evaluation method of Delgado-Ramos et al (Delgado-Ramos and Guibrunet, 2017), and considering cities' economic and social characteristics, the USR indicator is decomposed into two sub-dimensions: US and UR. Together, they support an integrated evaluation system measured by 6

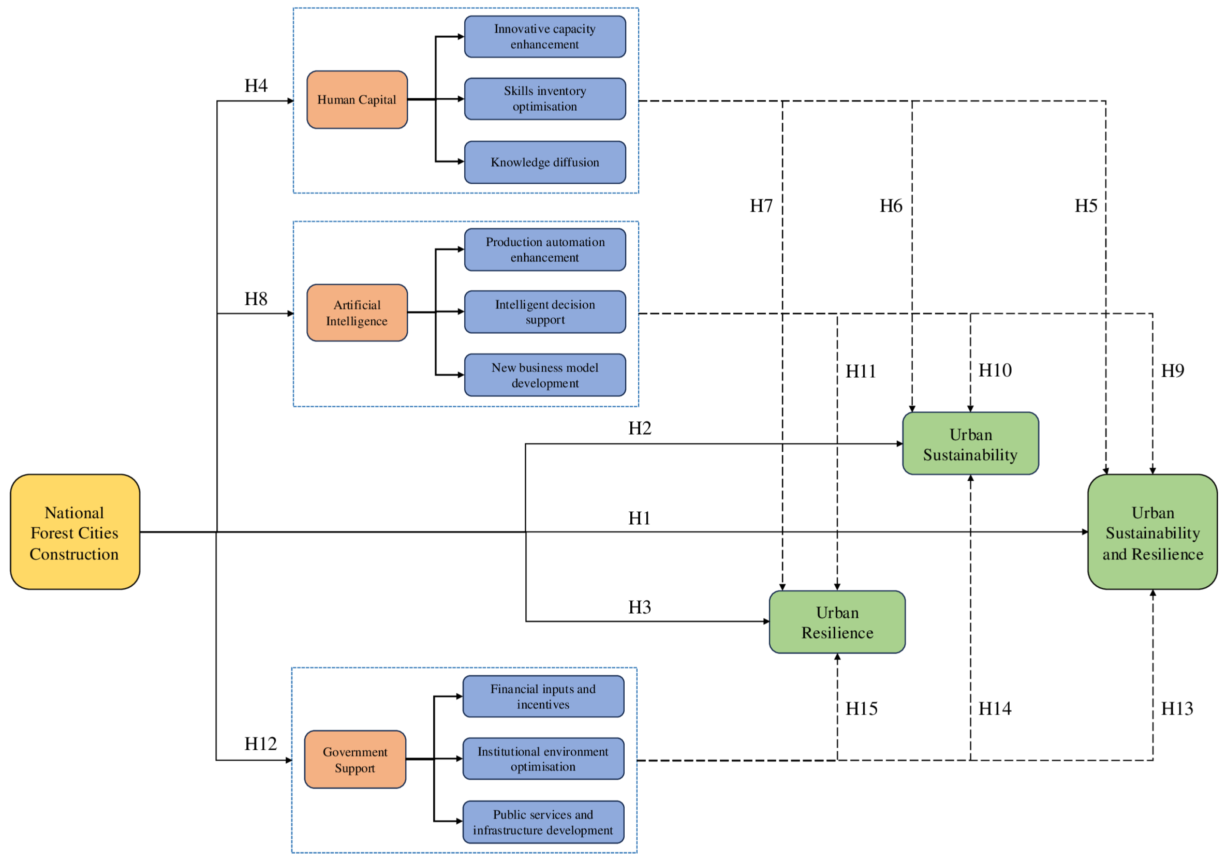

FIGURE 1
Theoretical mechanism diagram.

secondary indicators and 22 tertiary indicators (see Table 1). Following the method of Xu et al (Xu et al., 2022), we construct an entropy-weighted TOPSIS model and calculate the USR values for 300 Chinese prefecture-level cities using the collected data (see Appendix A).

(2) Urban Sustainability. The US indicator is decomposed into three sub-dimensions—economic development, social development, and ecological development—using 10 tertiary indicators. The entropy-weighted TOPSIS model of Xu et al. (2022) is employed to compute the US values for the sample cities (see Appendix A).

(3) Urban Resilience. The UR indicator is decomposed into three sub-dimensions: risk resistance, adaptive adjustment, and recovery growth, measured via 12 tertiary indicators. Following the method of Xu et al (Dang et al., 2025), an entropy-weighted TOPSIS model is constructed to calculate the UR values for the 300 prefecture-level cities (see Appendix A).

3.1.2 Core independent variable

The core independent variable is the interaction term between a city dummy for NFCC policy implementation and a time dummy variable. Cities recognized for NFCC are assigned a value of 1

TABLE 1 Urban Sustainability and Resilience evaluation indicator system.

Primary indicator	Secondary indicator	Tertiary indicator	Indicator description	Unit
Urban Sustainability	Economic Development	Development Level	Per capita GDP	yuan/person
		Development Efficiency	Ratio of local fiscal revenue to total fixed asset investment	%
		Economic Openness	Ratio of total imports and exports to local GDP	%
	Social Development	Educational Attainment	Number of full-time faculty in ordinary higher education institutions	persons
		Social Distribution	Number of employees in private and self-employed sectors in urban areas	persons
		Social Vitality	Total retail sales of consumer goods	10,000 yuan
	Ecological Development	Air Quality	PM2.5 concentration	μg/m³
		Water Environment Efficiency	Ratio of compliant industrial wastewater discharge to total industrial wastewater	%
		Land Use Efficiency	Cultivated land area per capita	mu
		Solid Waste Utilization	Comprehensive utilization rate of industrial solid waste	%
Urban Resilience	Risk Resistance	Life Security	Total grain output	10,000 tons
		Income Level	Average wage of on-post employees	yuan
		Employment Pressure	Number of registered unemployed persons in urban areas	persons
		Financial Risk	Loan-to-deposit ratio at year-end	%
	Adaptive Adjustment	Investment Scale	Total fixed asset investment	10,000 yuan
		Fiscal Self-Sufficiency	Ratio of local fiscal revenue to expenditure	%
		Savings Level	Balance of household savings at year-end	10,000 yuan
		Social Security	Number of hospital beds in hospitals and health centers	beds
	Recovery Growth	Science & Technology Input	Proportion of science & technology expenditure in fiscal expenditure	%
		Education Investment	Proportion of education expenditure in fiscal expenditure	%
		Innovation Output	Number of granted patents	items
		Industrial Structure	Ratio of value-added in tertiary industry to that in secondary industry	%

(treatment group), while non-recognized cities are assigned 0 (control group). For treated cities, the dummy takes the value of 1 from the year of recognition onward and 0 before recognition. For control cities, the time dummy remains 0 in all years.

3.1.3 Control variables

Following Dang, Wang, Tu, and Yuan et al (Yuan et al., 2022; Dang et al., 2025), this study selects four control variables: Population Density (pd): Measured by the number of permanent residents per square kilometer; Openness (doow): Captured by the number of foreign-invested enterprises in the region; Internet Development (nd): Measured using the number of international internet users; Infrastructure (inf): Represented by railway passenger volume.

3.1.4 Mechanism variables

To further investigate the transmission mechanism underlying NFCC's effect on USR, three mechanism variables are introduced: HC: Measured as the ratio of undergraduate and college students to the total population at year-end, reflecting the region's stock of high-quality talent and its potential for technological innovation; AI: Measured by the density of robot installations, indicating the prevalence of advanced automation technology and the level of technological innovation; GS: Measured by the ratio of general government expenditures to regional GDP, representing the intensity of government public investment and policy support. These three mechanism variables jointly form the channels through which NFCC policies, by improving HC, promoting AI development, and strengthening GS, indirectly enhance USR. Detailed definitions for all variables are provided in Table 2.

3.2 Data sources

The study uses panel data for 300 prefecture-level cities in China over the period 2000–2023. Data sources include the China City Statistical Yearbook, various provincial and municipal statistical yearbooks, the CNRDS – China National Research Data Service platform, and the EPS Global Data Statistical Platform. Specifically, the indicators within the urban sustainability and resilience evaluation framework for the dependent variable were cross-validated using data from the China Urban Statistical Yearbook, provincial and municipal statistical yearbooks, and the EPS Global Data Platform. The explanatory variable, national forest city construction data, is derived from the date cities were designated as national forest cities, as published on government websites. The control variables and mechanism variables—human capital and government intervention—are also sourced from the China Urban Statistical Yearbook, provincial and municipal statistical yearbooks, and cross-validated using the EPS Global Data Platform. The mechanism variable, artificial intelligence, is sourced from CNRDS—the China Research Data Service platform. To ensure sample consistency, prefecture-level cities that include counties or district-level municipalities recognized for NFCC but not entirely recognized are excluded. Only prefecture-level data are used. For regions in Tibet with missing data, linear interpolation and median substitution methods are applied to fill the gaps. Missing observations represented less than 3% of the sample; for gaps of up to two consecutive years we applied linear interpolation, while longer gaps were filled with the median value of the corresponding province and year. These quality–control measures enhance the robustness of our results. Data processing is performed using STATA17, and map visualizations are produced via ArcGIS10.8.Model Selection and Construction.

TABLE 2 Variable descriptions.

Classification	Declaration	Symbol	Definition
Dependent Variable	Urban Sustainability and Resilience	*usr*	Calculated using the entropy-weighted TOPSIS method
	Urban Sustainability	*us*	Calculated using the entropy-weighted TOPSIS method
	Urban Resilience	*ur*	Calculated using the entropy-weighted TOPSIS method
Independent Variable	National Forest Cities Construction	*nfcc*	Interaction term between the policy implementation dummy and time dummy
Control Variable	Population Density	*pd*	Number of permanent residents per square kilometer
	Degree of Openness	*doow*	Measured by the number of foreign-invested enterprises in each region
	Network Development	*nd*	Measured by the number of international internet users in each region
	Infrastructure	*inf*	Measured by railway passenger volume in each region
Mechanism Variable	Human Capital	*hc*	Ratio of undergraduate and junior college students to the total population
	Artificial Intelligence	*ai*	Robot installation density
	Government Support	*gs*	Ratio of general government expenditure to regional GDP

The empirical analysis is based on a multi-period Difference-in-Differences (DID) model, employing the NFCC policy as a quasi-natural experiment to examine its impact on USR. The baseline model is specified as follows:

$$usr_{it} = \alpha_0 + \alpha_1 nfcc_{it} + \alpha_2 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{1}$$

$$us_{it} = \varsigma_0 + \varsigma_1 nfcc_{it} + \varsigma_2 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{2}$$

$$ur_{it} = \tau_0 + \tau_1 nfcc_{it} + \tau_2 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{3}$$

Where usr_{it}, us_{it}, and ur_{it} denote the measures of USR, US, and UR for city i in year t; $nfcc_{it}$ is the interaction term for NFCC policy implementation; $Control_{it}$ represents the vector of control variables; μ_i and φ_t denote city and time fixed effects respectively; and ε_{it} is the error term (Equations 1–3).

Furthermore, to explore the underlying transmission mechanisms, additional regression models are constructed by incorporating HC, AI, and GS as mechanism variables. These models examine the direct impact of NFCC on each mechanism variable and the mediating effect of these variables on the relationship between nfcc and USR (as well as its sub-dimensions, US and UR). Detailed Equations 4–15 specify the estimation strategy for assessing these indirect channels.

$$hc_{it} = \beta_0 + \beta_1 nfcc_{it} + \beta_2 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{4}$$

$$ai_{it} = \eta_0 + \eta_1 nfcc_{it} + \eta_2 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{5}$$

$$gs_{it} = \delta_0 + \delta_1 nfcc_{it} + \delta_2 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{6}$$

$$usr_{it} = \gamma_0 + \gamma_1 nfcc_{it} + \gamma_2 hc_{it} + \gamma_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{7}$$

$$usr_{it} = \lambda_0 + \lambda_1 nfcc_{it} + \lambda_2 ai_{it} + \lambda_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{8}$$

$$usr_{it} = \varepsilon_0 + \varepsilon_1 nfcc_{it} + \varepsilon_2 gs_{it} + \varepsilon_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{9}$$

$$us_{it} = \zeta_0 + \zeta_1 nfcc_{it} + \zeta_2 hc_{it} + \zeta_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{10}$$

$$us_{it} = \theta_0 + \theta_1 nfcc_{it} + \theta_2 ai_{it} + \theta_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{11}$$

$$us_{it} = \vartheta_0 + \vartheta_1 nfcc_{it} + \vartheta_2 gs_{it} + \vartheta_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{12}$$

$$ur_{it} = \kappa_0 + \kappa_1 nfcc_{it} + \kappa_2 hc_{it} + \kappa_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{13}$$

$$ur_{it} = \xi_0 + \xi_1 nfcc_{it} + \xi_2 ai_{it} + \xi_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{14}$$

$$ur_{it} = \sigma_0 + \sigma_1 nfcc_{it} + \sigma_2 gs_{it} + \sigma_3 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \tag{15}$$

Here, hc_{it} denotes the human capital in region i at time t, ai_{it} denotes the artificial intelligence in region i at time t, and gs_{it} denotes the government intervention in region i at time t.

4 Results and analysis

4.1 Descriptive statistics

First, descriptive statistical analyses were conducted for all variables to provide an intuitive understanding of the data's distribution and characteristics, as well as to assess its quality. The results are presented in Table 3. The findings indicate that no data set exhibits abnormally high or low values, the level of dispersion is moderate, and the overall distribution trends are favorable.

(1) Spatial Distribution Characteristics of NFCC Policy Implementation.

Since 2004, the implementation of NFCC policies across the nation has exhibited significant spatial heterogeneity (Figure 2). In the early stages (e.g., in 2008), policy implementation was mainly concentrated in regions with higher economic development and urbanization levels. Such areas, endowed with strong economic strength and high administrative efficiency, received policy support earlier. Over time (e.g., from 2016 to 2023), the policy gradually extended to central, western, and inland regions. Although the expansion rate was relatively slow, this trend reflects the government's strategic intent to narrow regional disparities and achieve balanced development. Further analysis reveals a clear scale effect. Large and medium-sized cities, with well-developed infrastructure and efficient resource allocation, often serve as key targets of NFCC, whereas smaller cities tend to lag behind. This spatial distribution pattern not only illustrates the constraining role of economic development and urban scale on policy implementation but also reflects the government's consideration of regional differentiation in promoting green urban transformation. In summary, the spatial distribution of NFCC policy implementation demonstrates a diffusion process from east to west and from large to small cities. This pattern is closely aligned with the geographic distribution of economic, social, and administrative resources in China, and it provides critical background information for further assessing the policy's effect on enhancing USR.

(2) Spatial Distribution Characteristics of USR.

Figure 3 illustrates the spatial distribution characteristics of USR in Chinese prefecture-level cities for 2008, 2016, and 2023. Cities along the eastern coastal regions exhibit higher USR indices, which is closely related to their developed economies, comprehensive infrastructure, and advanced environmental governance. Simultaneously, as NFCC policies and green transition measures continue to expand, several cities in central and western regions have shown notable improvements in USR, indicating both policy diffusion and enhanced local adaptability. Further analyses suggest that economic vitality, levels of social development, and improvements in the ecological environment are critical drivers of high-level USR. In addition, technological innovation and the development of green infrastructure play important roles in bolstering a city's capacity to counter natural disasters and

TABLE 3 Descriptive statistics of variables.

Variable	Obs	Mean	Std.Dev.	Min	Max
usr	7200	0.116	0.038	0.045	0.358
us	7200	0.092	0.044	0.019	0.369
ur	7200	0.131	0.041	0.046	0.406
nfcc	7200	0.205	0.404	0	1
pd	7200	416.461	329.802	5	3005
doow	7200	89.444	289.802	0	4773
nd	7200	78.673	137.023	0.001	5174
inf	7200	1.058	43.51	0.001	3019.248
hc	7200	0.102	2.306	0.012	129.43
ai	7200	3.88	2.268	0.693	11.539
gs	7200	0.201	0.275	0.027	4.831

economic fluctuations. Overall, this spatial pattern validates the fundamental tenets of SDT and RT, provides scientific evidence for region-specific green transition policies, and offers guidance for future urban planning and governance.

(3) Spatial Distribution Characteristics of US.

Figure 4 presents the spatial distribution of US among prefecture-level cities for 2008, 2016, and 2023. Overall, cities in the eastern coastal areas display generally higher levels of US. This pattern is largely attributed to mature economic systems, efficient resource allocation, and stringent environmental governance measures. According to SDT, US is not only about achieving economic growth but also about maintaining a balance with social and environmental progress; hence, cities in the east perform well across these dimensions. In contrast, although cities in some central and western areas show relatively lower US levels, many regions have witnessed significant improvements in recent years due to the deepening of green transition policies and the promotion of technological innovations. Specifically, these regions are gradually enhancing their ecological protection, resource utilization efficiency, and public service provision, which lays the foundation for future balanced, coordinated, fair, efficient, and multidimensional development. Overall, the spatial distribution of US is characterized by regional clusters, reflecting the combined influences of regional economic development, resource endowments, and policy execution intensity—factors that serve as important references for devising region-specific green development strategies.

(4) Spatial Distribution Characteristics of UR.

Figure 5 displays the spatial distribution of UR among Chinese prefecture-level cities for 2008, 2016, and 2023. In general, cities in the eastern coastal region exhibit higher UR levels. This is primarily due to stronger investments in risk management, infrastructure development, and intelligent emergency systems in those areas. According to RT, UR depends not only on robust physical infrastructure but also on effective risk-warning and emergency response mechanisms. Eastern cities can rapidly respond to and adjust their strategies when faced with natural disasters, economic fluctuations, or social emergencies, thereby demonstrating strong adaptability and recovery capabilities. Meanwhile, although cities in some central and western regions may have relatively weaker infrastructure and economic strength, many have shown gradual improvements in UR in recent years as a result of ongoing green transition policies and the enhancement of green infrastructure. This improvement reflects both local governments' efforts in risk prevention and intelligent governance, and the gradual coordination effects among regions. The internal gradient distribution of UR indicates that regions with more developed economies and stronger policy implementation generally have higher UR. In summary, the spatial distribution of UR follows a trend of gradual decrease from east to west, with noticeable clustering within regions. This pattern not only reflects the comprehensive differences in regional economic development, public service quality, and intelligent governance but also provides important insights for the formulation of region-specific risk prevention and urban recovery strategies.

4.2 Benchmark regression analysis

We adopt a multi-period Difference-in-Differences (DID) model using the NFCC policy as a quasi-natural experiment to

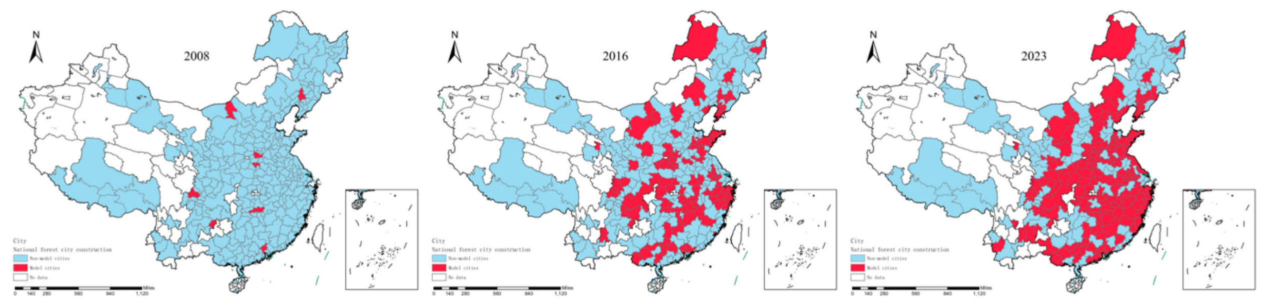

FIGURE 2
Spatial distribution map of NFCC policy implementation in 2008, 2016, and 2023. Note: Data from the National Forestry and Grassland Administration. The map was produced using ArcGIS based on the standard map provided by the Ministry of Natural Resources (GS [2024] 0650), with unmodified base boundaries.

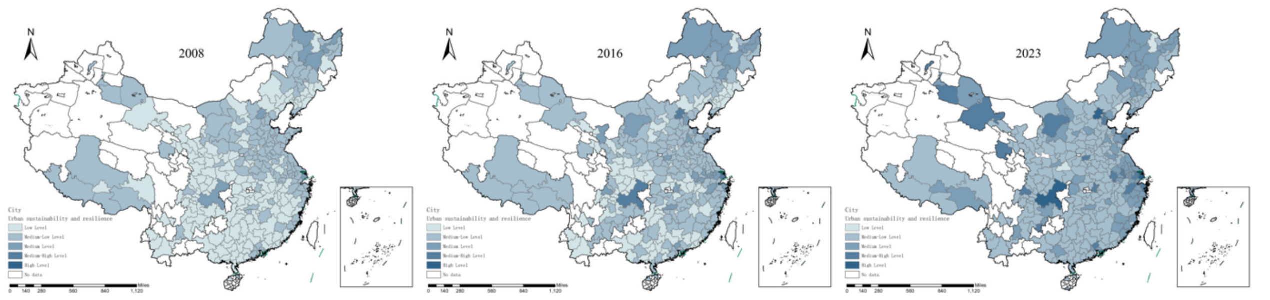

FIGURE 3
Spatial distribution map of USR in 2008, 2016, and 2023. Note: Data derived from the entropy-weighted TOPSIS method. The map was created using ArcGIS based on the standard map from the Ministry of Natural Resources (GS [2024] 0650), with unaltered base boundaries.

evaluate its impact on USR, US, and UR. In the preliminary regression results (see Table 4), models without control variables show that the coefficient for NFCC is 0.007 ($p< 0.01$) on the overall USR index, supporting H1; the coefficient is 0.011 ($p< 0.01$) on US, supporting H2; and the coefficient is 0.05 ($p< 0.01$) on UR, supporting H3. These findings indicate that even without controlling for other factors, the NFCC policy significantly improves overall urban development quality and risk management capabilities. After including control variables (pd, doow, nd, and inf), the regression coefficients remain robust. The model's R^2 values reach 0.852, 0.862, and 0.776 for USR, US, and UR, respectively, demonstrating that control variables greatly enhance the model's explanatory power while the nfcc coefficient remains positive and highly significant. Overall, the baseline regression results—both with and without control variables—consistently show a positive relationship, confirming the robust positive effect of the NFCC policy on USR. This result aligns with the coordinated economic, social, and environmental development emphasized by SDT and with RT's requirement for rapid adaptation and recovery amid external shocks, thereby providing a solid empirical foundation for subsequent mechanism analyses. Studies by Dang et al. (2025), Zheng et al. (2025), and Li and Zhao (2023). further support the conclusions of this paper. They respectively validated that national forest city initiatives exert significant positive impacts on local employment, urban environmental quality and welfare, and air pollution levels, thereby further substantiating the reliability of this paper's findings.

4.3 Parallel trend test

A key assumption of the multi-period DID model is that the treatment and control groups share a similar trend before policy implementation—that is, the parallel trend assumption holds. Since the timing of NFCC policy shocks varies across cities, relative time dummies are assigned to each city based on the NFCC implementation timeline. The parallel trend test equations are constructed as follows:

$$\begin{aligned} usr_{it} = {} & \rho_0 + \rho_1 \mathrm{Dpre\_j}_{it} + \rho_2 \mathrm{Dcurrent}_{it} + \rho_3 \mathrm{Dpost\_k}_{it} \\ & + \rho_4 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \end{aligned} \tag{16}$$

$$\begin{aligned} us_{it} = {} & \varrho_0 + \varrho_1 \mathrm{Dpre\_j}_{it} + \varrho_2 \mathrm{Dcurrent}_{it} + \varrho_3 \mathrm{Dpost\_k}_{it} \\ & + \varrho_4 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \end{aligned} \tag{17}$$

$$\begin{aligned} ur_{it} = {} & \omega_0 + \omega_1 \mathrm{Dpre\_j}_{it} + \omega_2 \mathrm{Dcurrent}_{it} + \omega_3 \mathrm{Dpost\_k}_{it} \\ & + \omega_4 Control_{it} + \mu_i + \varphi_t + \varepsilon_{it} \end{aligned} \tag{18}$$

Where the time dummies represent the observations for each city in the 10 years prior to, the year of, and the 15 years after NFCC

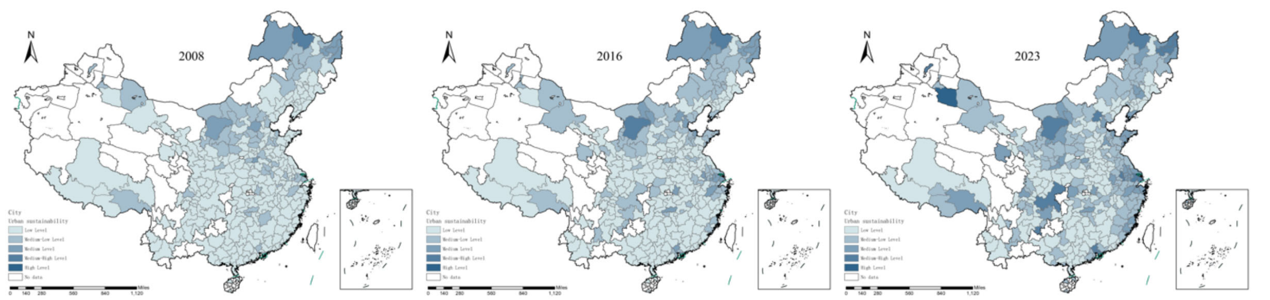

FIGURE 4
Spatial distribution map of US in 2008, 2016, and 2023. Note: Data obtained via the entropy-weighted TOPSIS method. The map was produced using ArcGIS based on the standard map from the Ministry of Natural Resources (GS [2024] 0650), with unmodified base boundaries.

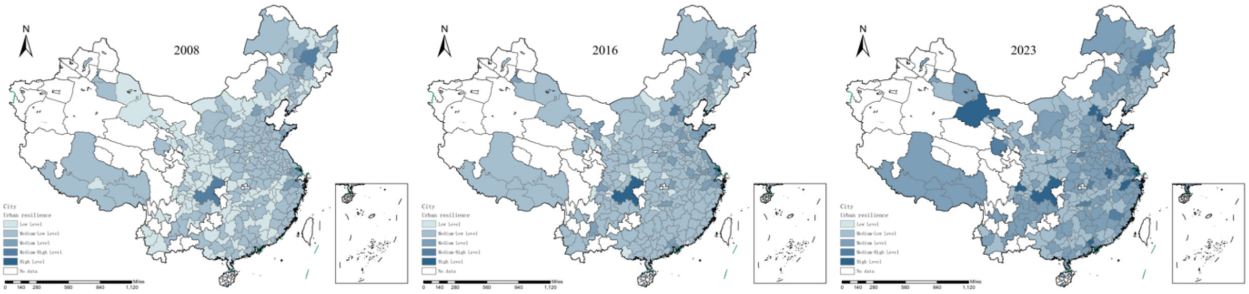

FIGURE 5
Spatial distribution map of UR in 2008, 2016, and 2023. Note: Data obtained via the entropy-weighted TOPSIS method. The map was created using ArcGIS based on the standard map from the Ministry of Natural Resources (GS [2024] 0650), with unmodified base boundaries.

recognition, while non-treated cities have a value of 0 (Equations 16–18).

Figures 6, 7, and 8 display the dynamic changes in overall USR, US, and UR, respectively, across these relative periods. The results show that before policy implementation, the regression coefficients for both the treatment and control groups are insignificant and close to zero, indicating no systematic trend differences pre-intervention. In contrast, after policy implementation, all indices exhibit significantly positive changes, with the differences growing over time. These dynamics confirm that the NFCC policy's effects are genuine and help rule out potential confounding time trends. The parallel trend test thus strongly supports our DID model's assumptions, enhancing the credibility of our subsequent empirical results.

4.4 Robustness checks

4.4.1 Placebo test

To further ascertain that our results are not driven by unobserved factors, we conduct a placebo test. Given the lagged policy impacts in the multi-period DID framework, pseudo treatment dummies and pseudo policy shock variables are generated. Specifically, from the 300 cities, 100 are randomly selected as NFCC cities (treatment group) while the remaining 200 serve as controls; this procedure is repeated 500 times, with 500 baseline regressions estimated. As shown in Figure 9, the coefficients for the interaction terms generated in the placebo tests are mostly concentrated around zero, and the p-values are generally above 0.1. This outcome supports the robustness of the baseline regression results.

4.4.2 Changing dependent variables

To further validate the robustness of our findings, we conduct a robustness check by substituting the main dependent variables (Table 5). In this test, alternative measures of USR—such as total retail sales of consumer goods and the ratio of local fiscal revenue to expenditure—are used as proxies. After re-estimating the model with these alternative indicators, the coefficient on nfcc remains significantly positive with effect sizes similar to those in the original model. This demonstrates that regardless of the measurement approach, the NFCC policy reliably enhances USR.

4.5 Heterogeneity analysis

4.5.1 Regional heterogeneity

To explore potential differences in the policy effect of NFCC across regions, the sample is divided into three geographic areas: eastern, central, and western regions. Separate multi-period DID models are then estimated for each region. As shown in Table 6, the policy effect is most pronounced in the eastern region, where nfcc has a coefficient of 0.007 ($p< 0.01$). This indicates that eastern regions—characterized by high economic development, robust infrastructure, and efficient administrative capacities—provide favorable conditions for policy implementation. In the central region, nfcc's coefficient is 0.005 ($p< 0.01$), slightly lower than in the east, potentially due to differences in economic development levels and resource allocation, while also reflecting the gradual acceleration of the green transition in the central region. In the western region, the effect is still positive but with a lower coefficient of 0.003 ($p< 0.01$), possibly owing to lagging infrastructure, limited technology adoption, and less vigorous policy enforcement. These regional heterogeneity findings suggest that NFCC policy effects are moderated by differences in regional economic bases, resource endowments, and administrative efficiency.

4.5.2 Heterogeneity by city size

To examine the impact of NFCC across different city sizes, we classify cities into three categories—small/medium, large, and extra-large/ultra-large—according to the 2014 State Council notice on urban scale standards. The regression results indicate that while nfcc yields a positive effect for all categories, the intensity and significance vary considerably. In small and medium cities, the nfcc coefficient is 0.005 ($p< 0.01$), indicating a higher sensitivity to the

TABLE 4 Baseline regression results.

Variable	*Usr*		*Us*		*Ur*	
	(1)	(2)	(3)	(4)	(5)	(6)
nfcc	0.007***	0.005***	0.011***	0.009***	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pd		0.001***		0.001***		0.001***
		(7.93)		(7.45)		(8.86)
doow		-2.05		-0.001**		3.81
		(3.99)		(5.14)		(3.65)
nd		0.001**		0.001**		0.001**
		(0.001)		(0.001)		(0.001)
inf		-0.001***		-7.87***		-0.001***
		(3.37)		(1.37)		(4.69)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	7200	7200	7200	7200	7200	7200
R^2	0.852	0.862	0.776	0.786	0.873	0.883

** and *** indicate significance at the levels of 5 and 1%, respectively. Standard errors are reported in parentheses.

policy, likely because these cities have relatively weaker infrastructure and resource allocation, making the benefits of green transition more pronounced. In large cities, nfcc's coefficient is 0.003 ($p< 0.01$), suggesting that, despite the positive impact, the marginal effect is diminished in cities with more substantial resources and technological advantages. In extra-large/ultra-large cities, the nfcc coefficient is 0.004 ($p< 0.1$); although the effect remains positive, the lower statistical significance reflects that in these complex and massive urban centers, management complexities and scale effects lead to diminishing marginal

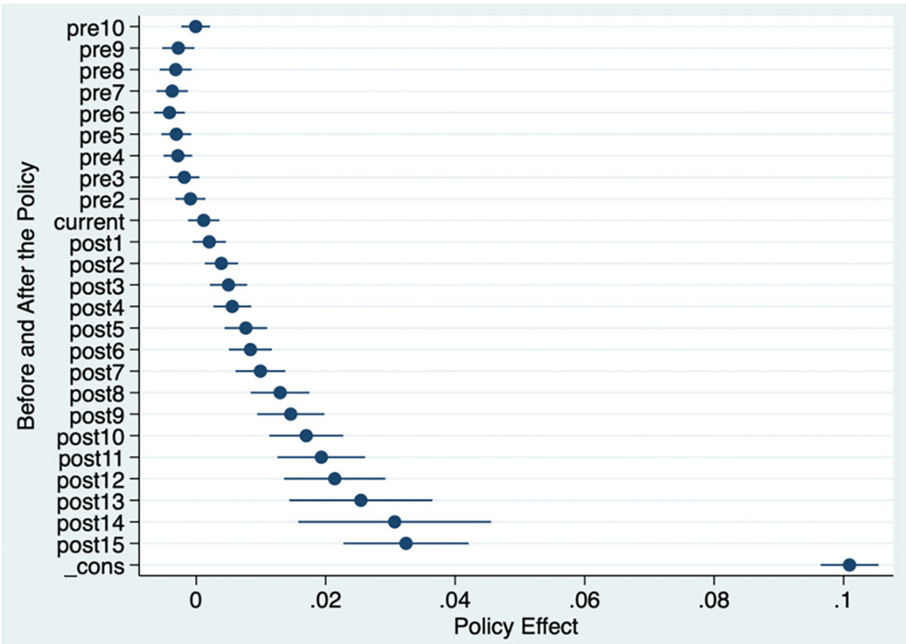

FIGURE 6
Parallel trend test for USR.

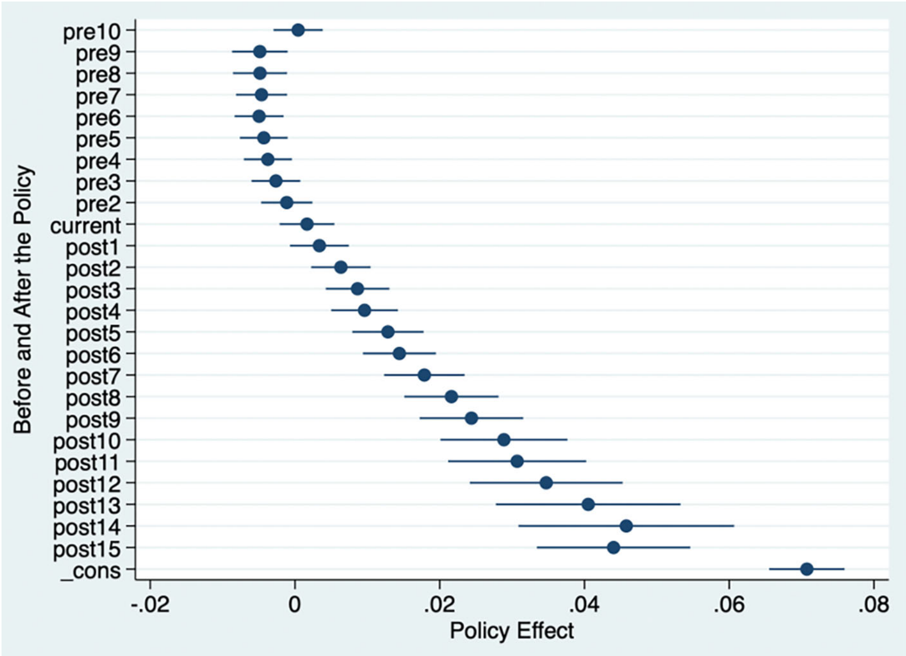

FIGURE 7
Parallel trend test for US.

benefits. These heterogeneity results are consistent with SDT and RT, underscoring that infrastructural, resource, and management differences across regions and city sizes yield varied policy effectiveness, thereby providing empirical guidance for region-specific and size-sensitive green transition strategies.

4.6 Mechanism verification

To further explore how the NFCC policy influences various dimensions of urban development through internal transmission mechanisms, we conduct detailed analyses based on the results in

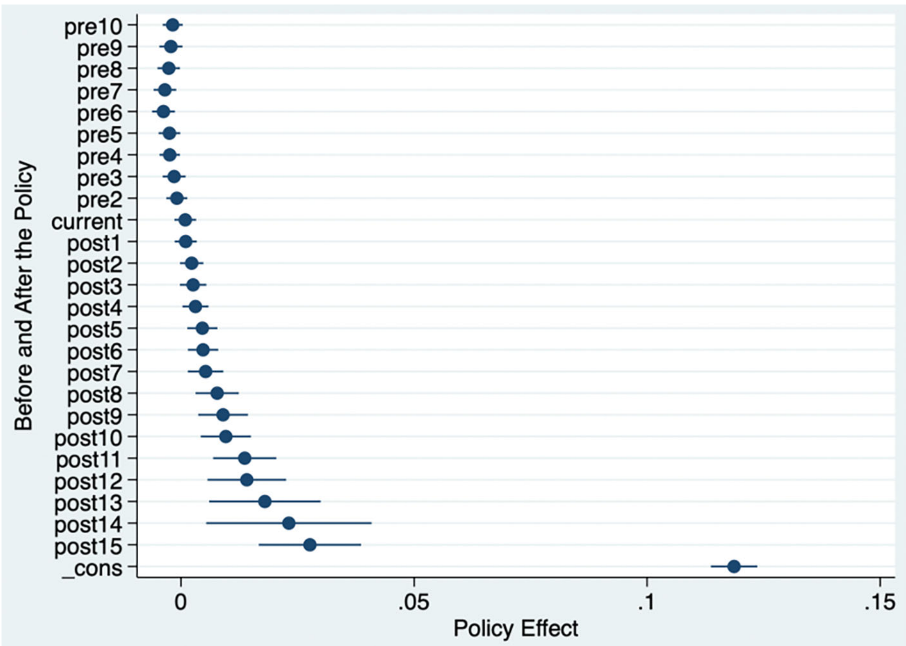

FIGURE 8
Parallel trend test for UR.

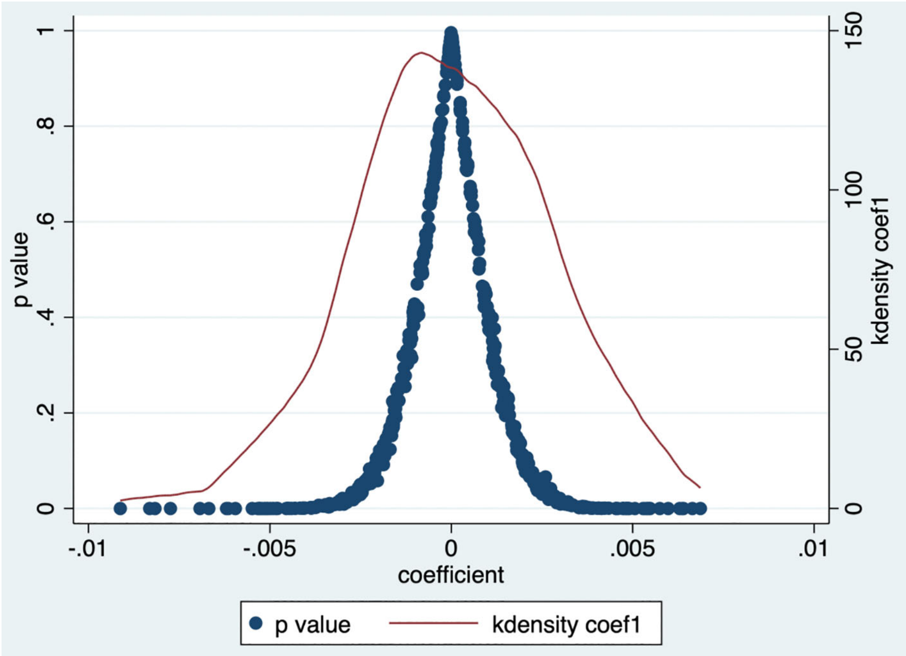

FIGURE 9
Placebo test results.

Table 7. We examine three key dependent variables—overall USR, US, and UR—and test the roles of HC, AI, and GS, interpreting the findings in light of SDT and RT.

4.6.1 Analysis of USR

For the overall USR indicator, when mechanism variables are incorporated, the results reveal multiple transmission channels. First, in the HC pathway, NFCC exerts a direct effect on HC of –0.074 ($p< 0.1$). This negative effect suggests that, in the early phase, resource reallocation or structural adjustment may temporarily reduce the accumulation of high-quality talent, possibly due to the reallocation of administrative resources and funding affecting college enrollment and training efforts. Subsequently, however, the mediating role of HC becomes positive: NFCC has a coefficient of 0.005 ($p< 0.01$) in its positive transmission to USR, while HC itself shows a coefficient of 0.001 ($p< 0.01$). This indicates that as high-quality talent gradually accumulates, its positive effect eventually compensates for and surpasses the initial negative impact, thereby promoting coordinated urban development. This phenomenon supports H5 and is consistent with SDT's emphasis on long-term endogenous drivers.

Regarding the AI pathway, NFCC demonstrates a significantly positive effect on AI (coefficient = 0.064, $p< 0.01$), confirming that the policy effectively promotes the diffusion of intelligent technology. The adoption of AI, by improving resource scheduling efficiency and enhancing risk alert capabilities, contributes positively to overall urban development, supporting H8. However, the mediating effect of AI in the transmission from NFCC to USR is statistically insignificant (coefficient= -0.001, $p > 0.1$), leading to the rejection of H9. This result implies that although

TABLE 5 Robustness check: alternative measures of the dependent variable.

Variable	Dependent variable	
	Total retail sales of consumer goods	Ratio of local fiscal revenue to expenditure
nfcc	256.411***	0.009***
	(66.578)	(0.003)
Control Variables	Yes	Yes
City Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
N	7200	7200
R^2	0.803	0. 893

*** indicates significance at the level of 1%. Standard errors are reported in parentheses.

TABLE 6 Heterogeneity analysis by region and city size.

Variable	(1) Regional differences			(2) Differences in city size		
	(1) Eastern	(2) Central	(3) Western	(4) Small/medium cities	(5) Large cities	(6) Extra-large/ultra-large cities
nfcc	0.007***	0.005***	0.003***	0.005***	0.003***	0.004*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2472	2424	2304	1320	4968	912
R^2	0.896	0.89	0.857	0.854	0.845	0.873

* and *** indicate significance at the levels of 10 and 1%, respectively. Standard errors are reported in parentheses.

the policy advances digital transformation, the progress in AI does not manifest a statistically significant transmission effect on overall USR.

In the GS pathway, NFCC positively influences GS (coefficient = 0.019, p< 0.01), which supports H12. Further government support has a significant negative mechanism effect on USR. Consequently, H13 is rejected. Overall, despite an initial negative adjustment in the HC channel, high levels of HC eventually produce a significant positive impact on overall USR.

4.6.2 Analysis of US

For the US indicator, upon incorporating mechanism variables, the regression results reveal the presence of multiple transmission channels with notable differences in their effects. In the HC channel, the mediating regression indicates that HC (coefficient = 0.001, p< 0.01) significantly transmits the positive effect of NFCC (coefficient = 0.009, p< 0.01) on US, supporting H6. This finding suggests that as high-quality talent accumulates over time, its long-term positive effect compensates for any initial negative adjustment, thereby promoting balanced economic, social, and environmental development in line with SDT's perspective on endogenous drivers.

In contrast, in the AI channel, although AI does mediate the impact of NFCC on US (with NFCC showing a coefficient of 0.009, p< 0.01), the transmitted effect of AI is negative (coefficient = –0.004, p< 0.01), resulting in the rejection of H10. This negative effect may indicate that in the early stages of policy implementation or transition, the promotion of AI might be associated with issues such as high energy consumption, frequent equipment updates, and the costs of technology substitution (Chen et al., 2023; Fu et al., 2025), all of which may have short-term adverse impacts on urban environmental quality and resource utilization efficiency (Yigitcanlar et al., 2021; Stecuła et al., 2023). Additionally, potential information asymmetries and uneven resource allocation during digital transformation may inhibit AI's effectiveness in promoting balanced US in the initial phase.

Furthermore, GS exhibits a significant negative mediating effect in the NFCC–US channel (GS coefficient = –0.013, p< 0.01; NFCC coefficient = 0.009, p< 0.01), leading to the rejection of H14. This result suggests that at the current stage, elevated GS may reflect inefficient resource allocation or overreliance on administrative intervention, thereby negatively affecting balanced economic, social, and environmental development in the short term.

4.6.3 Analysis of UR

For the UR indicator, the inclusion of mechanism variables also reveals distinct transmission channels, with differing directions and significance levels. In the HC pathway, regression results show that HC (coefficient = 0.001, p< 0.01) significantly transmits the positive effect of NFCC (coefficient = 0.003, p< 0.01) on UR, supporting H7. This implies that the gradual accumulation of high-quality talent enhances a city's capability in risk management, emergency response, and rapid recovery, thereby strengthening UR—a result that aligns with RT's emphasis on long-term endogenous drivers improving system adaptability and recovery capacity.

In the AI pathway, AI exhibits a significant positive mediating effect on UR (coefficient = 0.002, p< 0.01; with NFCC at 0.003, p< 0.01),

TABLE 7 Mechanism test results.

Variable	Mechanism variable			Transmission mechanism								
	(1) hc	(2) ai	(3) gs	(4) usr	(5) usr	(6) usr	(7) us	(8) us	(9) us	(10) ur	(11) ur	(12) ur
nfcc	-0.074*	0.064***	0.019***	0.005***	0.005***	0.005***	0.009***	0.009***	0.009***	0.003***	0.003***	0.003***
	(0.042)	(0.014)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
hc				0.001***			0.001***			0.001***		
				(0.001)			(0.001)			(0.001)		
ai					-0.001			-0.004***			0.002***	
					(0.001)			(0.001)			(0.001)	
gs						-0.012***			-0.013***			-0.008***
						(0.002)			(0.003)			(0.002)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7200	7200	7200	7200	7200	7200	7200	7200	7200	7200	7200	7200
R2	0.618	0.98	0.771	0.862	0.862	0.864	0.786	0.786	0.787	0.883	0.884	0.884

* and *** indicate significance at the levels of 10 and 1%, respectively. Standard errors are reported in parentheses.

supporting H11. This positive effect indicates that the promotion of intelligent technology increases resource scheduling efficiency, reinforces risk monitoring, and improves emergency response capabilities, all of which contribute substantially to enhancing UR. This finding is in line with RT, which underscores the role of AI in bolstering urban emergency management capabilities.

Finally, in the GS pathway, further mechanism analysis shows that GS has a significantly negative transmission effect on UR (GS coefficient = –0.008, $p < 0.01$; NFCC coefficient = 0.003, $p < 0.01$), leading to the rejection of H15. This negative effect may imply that at the current stage, high GS levels might signal inefficient resource allocation or an excessive reliance on administrative intervention, which in the short term dampens the city's risk management and emergency response capabilities. This finding indicates that during the green transition process, it is critical for GS to focus on improving investment efficiency and optimizing resource allocation to ensure a positive contribution to UR.

5 Conclusions and policy recommendations

5.1 Research conclusions

Based on panel data from 300 Chinese prefecture-level cities spanning 2000–2023, this study employs a multi-period Difference-in-Differences (DID) model as a quasi-natural experiment to systematically examine the impact of the NFCC policy on USR, US, and UR. The findings indicate that, overall, the policy exerts a significantly positive effect on urban development. Specific conclusions are as follows:

(1) Significant Direct Effects.

The baseline regression analysis shows that, regardless of the inclusion of control variables, NFCC significantly enhances overall USR, as well as US and UR. This finding confirms that, as an important green transformation initiative, the policy plays a positive role in improving the urban ecological environment, optimizing resource allocation, and enhancing public service levels.

(2) Multiple Transmission Mechanisms.

HC Channel: Although NFCC initially exerts a significantly negative impact on HC—possibly reflecting short-term resource reallocation or structural adjustment—the positive transmission effect through HC becomes significant as high-quality talent gradually accumulates. This underscores the essential role of HC accumulation in enhancing long-term coordinated development and risk management capacity.

AI Channel: NFCC notably promotes AI development. However, its mediating effect on US is negative, while AI contributes positively to UR. This suggests that intelligent technology has a clear advantage in improving risk-warning and emergency response capabilities, even though its benefits on US may be less immediate.

GS Channel: NFCC substantially increases governmental support in terms of fiscal investment and environmental governance; however, the transmission effects via GS on both US and UR are negative. This result implies that at the current stage, GS may suffer from inefficient resource allocation or excessive administrative intervention, thus falling short of the expected positive effects in the short term.

(3) Regional and City Size Heterogeneity.

Heterogeneity analyses further reveal that policy effects vary significantly across eastern, central, and western regions, as well as among different city sizes. The policy exhibits the most pronounced effects in the eastern region and in large to medium-sized cities, reflecting the moderating impacts of regional economic bases, infrastructure, and administrative efficiency on green transformation policies. Overall, this study demonstrates that the NFCC policy directly enhances urban green transformation and operates through multiple endogenous mechanisms. Although some channels display short-term negative effects, the policy ultimately improves USR through HC accumulation and AI implementation. In contrast, the negative transmission via GS highlights the need to optimize resource allocation and administrative efficiency. These findings provide robust empirical evidence and theoretical support for advancing green urban governance, refining region-specific green transition policies, and improving urban risk management and emergency response capabilities.

5.2 Policy recommendations

Based on our empirical analysis, we propose the following policy recommendations to further strengthen the role of the NFCC policy in promoting USR, while addressing variations across transmission channels, regions, and city sizes:

(1) Deepen the Green Transformation Strategy.

The evidence shows that the NFCC policy directly improves urban ecological environments, resource allocation, and public service levels, thereby laying the foundation for coordinated economic, social, and environmental development. However, the policy process exhibits short-term adjustment effects, such as an initial decline in HC. To mitigate these shocks, government agencies should establish buffering mechanisms and gradually enhance supporting measures. This approach will ensure that talent cultivation and the recruitment of high-quality personnel proceed in tandem with the green transition, thus unlocking long-term positive endogenous drivers.

(2) Promote Intelligent Technology Integration.

Although NFCC significantly accelerates AI development, its negative transmission effect on US may be related to factors such as high energy consumption, frequent equipment updates, and technology substitution costs. Therefore, relevant authorities should not only increase investment in intelligent technologies but also emphasize technology integration and cost–benefit analyses. By exploring green, low-carbon AI application models and optimizing digital resource allocation, the adjustment period can be shortened so that AI truly transforms into a force for improving urban resource utilization efficiency and environmental governance.

(3) Optimize Governmental Support.

The negative mediating effect observed via the GS channel suggests that current government support may be hampered by inefficient resource allocation or an overreliance on administrative intervention. To address this, policymakers should continue increasing investments in green infrastructure and environmental governance while simultaneously strengthening performance evaluations and enhancing resource utilization efficiency. Optimizing fiscal expenditure structures can help prevent short-term inhibitory effects on coordinated development. Moreover, encouraging market and private capital participation through diversified financing and cooperative models can further boost overall investment efficiency.

(4) Tailor Strategies by Region and City Size.

Given that our analysis indicates significant heterogeneity across regions and among cities of different sizes, differentiated green transition strategies should be developed. In the developed eastern region, efforts should focus on further integrating intelligent governance with high-end talent cultivation. In contrast, central and western regions and small to medium-sized cities should prioritize improving infrastructure and administrative efficiency. Targeted policy support in these areas can gradually narrow regional development gaps and achieve common, coordinated, equitable, and efficient growth.

5.3 Limitations and future directions

Our work makes several contributions: it is the first to jointly evaluate the impacts of NFCC on urban sustainability and resilience using a multi–period DID design; it constructs an entropy–weighted TOPSIS framework and identifies three endogenous transmission channels—HC, AI and GS—thus enriching the theoretical integration of sustainability and resilience. We also explore regional and city–size heterogeneity, providing targeted policy insights. Nevertheless, the study has limitations. First, the macro–level panel data cannot capture household–level or firm–level behaviors; second, although multiple controls are included, unobserved factors may still bias the estimates; third, the selection of indicators for USR and mechanism variables inevitably involves subjective judgment. Future research could incorporate micro–data and alternative sustainability–metrics to validate and extend our conclusions.

Data availability statement

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

Author contributions

SJ: Writing – original draft, Funding acquisition, Software, Formal analysis, Conceptualization, Validation, Methodology, Supervision, Investigation. JY: Data curation, Conceptualization, Project administration, Methodology, Resources, Software, Writing – review & editing, Writing – original draft, Visualization. YJ: Conceptualization, Resources, Funding acquisition, Validation, Formal analysis, Methodology, Writing – original draft, Data curation, Writing – review & editing, Software.

Funding

The author(s) declare financial support was received for the research and/or publication of this article. This work was supported in part by the general project of the National Social Science Fund of China, “Function Mechanism and Effect Analysis of the Coupling Development between Forestry Factor Endowment and Technological Progress Bias on Industrial Structure Upgrading in China”, grant number 20BJY077; in part by the China Business Statistics Society Planning Project titled, “Research on the Implicit

Collaborative Innovation Mechanism and Coupling Effects of Scientific Research Project Teams from the Perspective of Intellectual Property Protection", grant number 2024STY134.

Conflict of interest

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Appendix A

This study employs the entropy-weighted TOPSIS comprehensive evaluation method to measure and assess urban sustainability and resilience. The core idea is to use the entropy weighting method to assign weights to each indicator based on their standardized values, and then to apply the TOPSIS method to quantitatively rank the levels of urban sustainability and resilience. The entropy weighting method relies on the amount of information reflected by the variation in each index, thereby reducing the influence of subjectivity in weight allocation. The TOPSIS method uses the cosine approach to determine the best and worst alternatives by calculating the relative distances between each evaluation object and the ideal and nadir solutions. Owing to its simplicity and the logical results produced, the entropy-weighted TOPSIS method combines the advantages of both methods and renders the measurement outcomes of urban sustainability and resilience more objective and reasonable. The specific implementation steps are as follows:

Step 1: Data Normalization and Standardization

If inverse indicators exist in the data, they must be converted into positive indicators. In this study, all 22 level-3 evaluation indicators in the urban sustainability and resilience indicator system are positive; therefore, no conversion is needed. To eliminate scale differences, each measurement indicator, X_{ij}, in the urban sustainability and resilience indicator system is first standardized.

$$x_{ij}^{'} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{19}$$

$$x_{ij}^{'} = \frac{\max(x_{ij})}{mac(x_j) - \min(x_j)} \tag{20}$$

where x_{ij} denotes the value of the j_{th} evaluation indicator for the i_{th} city, and the expressions in (19) and (20) represent the standardized (Equations 19, 20) values of the urban sustainability and resilience measurement indicators.

Step 2: Calculation of Information Entropy E_j

For each measurement indicator in the urban sustainability and resilience indicator system, calculate its information entropy E_j (Equation 21):

$$E_j = -k\sum_{i=1}^{n} R_{ij}\ln(R_{ij})\ ,\ k = \frac{1}{\ln n}\ ,\ R_{ij} = \frac{x_{ij}}{\sum_{i=1}^{n} x_{ij}^{'}} \tag{21}$$

Step 3: Calculation of Weights W_j

Compute the weight W_j for each measurement indicator within the system (Equation 22):

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{m}(1 - E_j)}\ ,\ \sum_{j=1}^{n} w_j = 1 \tag{22}$$

Step 4: Construction of the Weighted Matrix Z

Construct the weighted decision matrix Z by multiplying the standardized matrix by the weights for each indicator (Equation 23):

$$Z = (x_{ij}^{'} \times W_j)_{m\times n} \tag{23}$$

Step 5: Determination of the Ideal and Nadir Solutions

Determine the best alternative Z_j^+ and the worst alternative Z_j^- for the indicator system. Calculate the distances Z_j^+ and Z_j^- between each evaluation object and the ideal and nadir alternatives, respectively (Equations 24, 25):

$$D_j^+ = \sqrt{\sum_{j=1}^{m}(Z_{ij} - Z_j^+)^2} \tag{24}$$

$$D_j^- = \sqrt{\sum_{j=1}^{m}(Z_{ij} - Z_j^-)^2} \tag{25}$$

Step 6: Calculation of the Relative Closeness C_i

Calculate the relative closeness C_i of each evaluation object to the ideal solution (Equation 26):

$$C_i = \frac{D_i^-}{D_i^+ - D_i^-} \tag{26}$$

A larger value of C_i indicates a better level of urban sustainability and resilience for the i_{th} city; conversely, a lower C_i implies poorer performance.