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Smart city development and urban sustainability: A study on green-land use efficiency in China's urban agglomerations

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Abstract

As smart cities continue to develop rapidly, improving the green efficiency of urban land use has become essential for fostering long-term urban sustainability. This study employs empirical analysis to explore the impact of smart city development on urban green land-use efficiency. It adopts a super-efficiency slack-based measure model to evaluate the green efficiency of urban land use and applies a difference-in-differences approach to assess the effects of smart city development. The analysis is based on data from 50 prefecture-level cities across three major urban regions in China, covering the period from 2009 to 2023. The results indicate that smart city advancements significantly increase urban green land-use efficiency. The findings also highlight heterogeneity in policy effects, with cities characterized by advanced infrastructure, higher human capital, and substantial capital investment showing more pronounced improvements. The study provides valuable insights into how smart city development influences land-use efficiency and offers empirical evidence to guide the design of more effective, context-specific strategies for optimizing resource management and fostering sustainable urban development.

Keywords: Smart cities; Urban green land-use efficiency; Super-efficiency slack-based measure model; Difference-in-differences model; Policy implementation

1. Introduction

As digital transformation accelerates globally, the development of smart cities has become a key strategy for governments to drive urban modernization. Following China's initiation of the smart city pilot program in 2012, smart city development has transitioned into a more structured and strategic phase, with increasing emphasis on integrating smart cities with sustainable development goals. A central objective of this development is to facilitate urban low-carbon transformation, with green land-use efficiency emerging as a critical indicator of urban sustainability (J. Guo *et al.* 2025). Consequently, under national frameworks such as the "dual carbon" goals and territorial spatial planning, exploring how smart cities can enhance urban green land-use efficiency (UGLUE) has become a pivotal issue in both policy-making and academic research.

Existing research on smart cities has largely focused on technological domains such as intelligent transportation and smart energy, revealing how digital technologies enhance efficiency in specific areas; however, systematic evaluation of comprehensive benefits for land use remains insufficient (Q. Guo *et al*., 2023; Jiang *et al*., 2021). While prior studies have often concentrated on the environmental impacts of individual sectors such as transportation, construction, or industry, they have overlooked the requirement that green land-use efficiency balance economic outcomes with social well-being (Wen & Li, 2024). Although some research suggests that smart cities may improve land-use efficiency through industrial upgrading, the mediating pathways through which this occurs still lack robust empirical support (L. Zhang *et al*., 2025). Urban system theory highlights the substantial role of innovation capability in optimizing spatial layouts, while the potential of green policies to strengthen environmental governance remains underexplored (Salih & Mohammed, 2024). Based on sustainable development theory, stringent green policies can induce technological innovation, and technological innovation (including green innovation) is itself a core mediating variable for enhancing production efficiency and sustainability. Together, these factors constitute a crucial transmission pathway through which environmental regulation or smart city policies may drive comprehensive development (G. Zhou *et al*., 2024). Particularly in a country characterized by significant regional disparities, such as China, existing studies have not systematically explained why the same smart city policies yield varied effects across cities with different developmental levels and resource endowments.

To address these gaps, this study constructs a "technology-enablement→governance-reinforcement" dual-path theoretical framework and systematically integrates the super-efficiency slack-based measure (SSBM) model with the difference-in-differences (DID) method in a long-term analysis. This approach addresses limitations in mechanism explanation and methodology, supporting causal inference (under standard DID assumptions) and heterogeneity analysis of the impact of smart city policies on UGLUE. By employing an integrated efficiency model to assess the overall benefits of land utilization and comparing policy effectiveness across different urban agglomerations, this research aims to provide more targeted theoretical insights and practical references for smart city development and sustainable land management.

2. Literature review

2.1. Smart cities

Smart cities have become a major focus in the evolution of urban development. They aim to improve urban governance, increase the efficiency of resource use, and promote sustainability through advanced technologies such as artificial intelligence, big data, the Internet of Things, and information technology (Batty, 2013). Smart city development spans multiple sectors, including infrastructure, transportation, energy management, governance, and community service. At its core, the concept revolves around the seamless integration of information technology with urban systems to optimize resource allocation and refine governance practices for more efficient and sustainable cities (J. Guo *et al*., 2025; Khan *et al*., 2020).

Urban system theory emphasizes the critical role of information flow in resource allocation. Through platforms such as the Internet of Things, smart city development enables real-time perception and systematic integration of land, energy, environmental, and other key elements. This integration can improve coordination between land use and ecological conservation, thereby enhancing system-level green efficiency (Salih & Mohammed, 2024). In addition, smart city development facilitates the use of spatial information systems and remote sensing technologies, offering detailed land-use data to support urban planning and optimize land layouts. While smart city construction may improve land-use efficiency through infrastructure upgrades, industrial upgrading, and environmental management, high capital requirements and complex governance demands may result in heterogeneous policy outcomes across regions (Wang, 2022). Therefore, rigorous measurement is needed to examine the effects of smart city development on land-use efficiency and to clarify the underlying mechanisms.

2.2. Urban green land-use efficiency

Urban green land-use efficiency represents a comprehensive approach to land resource utilization that aims to balance economic growth, social well-being, and ecological sustainability, thereby minimizing land degradation and environmental harm (G. Zhou *et al*., 2024). Early studies often equated land-use efficiency with economic output per unit area, whereas more recent research emphasizes its multidimensional nature by incorporating ecological and social dimensions (Huang & Yang, 2024). However, the operational definition of UGLUE remains contested, particularly regarding how to quantify and integrate non-economic indicators without compromising analytical rigor (H. Li *et al*., 2023).

Urban system theory enriches this discussion by highlighting spatial and structural determinants of land-use efficiency, such as urban location, infrastructure quality, and connectivity patterns (Batty, 2013). Nevertheless, critics argue that this theoretical perspective often underestimates the role of institutional and policy factors in shaping land-use outcomes, especially in contexts of rapid urbanization (Salih & Mohammed, 2024).

Therefore, compared with general land-use efficiency metrics that are primarily economic in focus, UGLUE represents a conceptual and methodological extension that explicitly incorporates environmental costs as undesirable outputs alongside economic and social benefits within a unified analytical framework, consistent with sustainable development principles.

Methodologically, traditional efficiency assessment tools such as data envelopment analysis (DEA), though widely applied, may not explicitly account for undesirable outputs such as pollution and carbon emissions in many conventional applications (Khezrimotlagh *et al*., 2019). In response, the SSBM model has gained attention for its ability to incorporate both desirable and undesirable outputs, enabling a more refined evaluation of land-use performance under sustainability constraints (Färe & Zelenyuk, 2020). Nevertheless, SSBM, such as other non-parametric methods, can be sensitive to indicator selection and data quality, underscoring the need for transparency in model specification and assumptions (J. Zhang & Sun, 2024).

In the context of smart city development, studies such as G. Zhou *et al*. (2024) suggest that digital technologies can enhance UGLUE by improving resource monitoring and allocation. Conversely, other studies emphasize that technological interventions alone may be insufficient without complementary governance reforms and equitable policy implementation (Wen & Li, 2024). Therefore, evaluating whether and how smart city policies influence UGLUE remains an important academic question for further exploration.

2.3. Smart cities and UGLUE

Smart city policies may influence UGLUE through multiple mechanisms. A study of 281 Chinese cities found that technology finance is associated with higher UGLUE productivity, with green utilization and urban digitization playing a particularly crucial role in driving the performance of green utilization in these regions (J. Zhang & Sun, 2024). Further investigations suggest that digitalization-driven smart city development can foster technological innovation and reduce resource misallocation, thereby promoting industrial agglomeration and reducing inefficiencies in land use and waste (C. Zhou & Li, 2025). Other studies highlight concerns that high-emission and high-consumption industries have shifted from coastal regions to inland areas, potentially disrupting ecological conditions and diminishing urban green space utilization in some cities (F. Li *et al*., 2019). Based on this literature, the following hypotheses are proposed:

- H_1: Smart city development has a positive impact on UGLUE
- H_2: Smart city development promotes UGLUE through technological innovation
- H_3: Smart city development enhances UGLUE through green policies.

2.4. Heterogeneity of smart cities and UGLUE

Smart city development is shaped by critical factors such as infrastructure quality, human capital, and financial investment. Previous research indicates that cities at different development stages, particularly in eastern and southern regions, experience significant improvements in UGLUE, with growth in online financial services identified as an important contributor (Xu *et al*., 2021). Non-resource cities may be better positioned to respond to financial incentives for efficient land use because they are less dependent on extractive resource endowments than resource-based cities. Furthermore, the impact of smart city initiatives may be more pronounced in cities with limited natural resources, lower economic growth pressures, stable developmental trajectories, and more balanced levels of digital infrastructure and human capital (W. Li *et al*., 2024). Cities with stronger human capital may also be more capable of adopting and applying emerging technologies, which can accelerate smart industry development and improve the effectiveness of smart city technologies in optimizing land-use efficiency. Building on these findings, the following hypotheses are proposed:

- H_4: Smart city development exerts a stronger influence on UGLUE in cities with well-developed infrastructure
- H_5: Smart city development has a stronger effect on UGLUE in cities with high levels of human capital
- H_6: Smart city development leads to a more pronounced improvement in UGLUE in cities with higher financial investment.

Based on the theoretical foundations of smart city policy implementation and urban green development, this study constructs a research framework (Figure 1). The framework centers on the relationship between smart city development and UGLUE. It systematically incorporates two mediating pathways—technological innovation and green policies—and considers three moderating conditions: infrastructure, human capital, and financial resources. Together, these components form a theoretical model encompassing policy treatment, mechanism transmission, and boundary conditions.

3. Research methodology

3.1. Data sources and sample selection

The data for this study were primarily sourced from publicly available statistical yearbooks. Urban-level socioeconomic data were mainly obtained from the

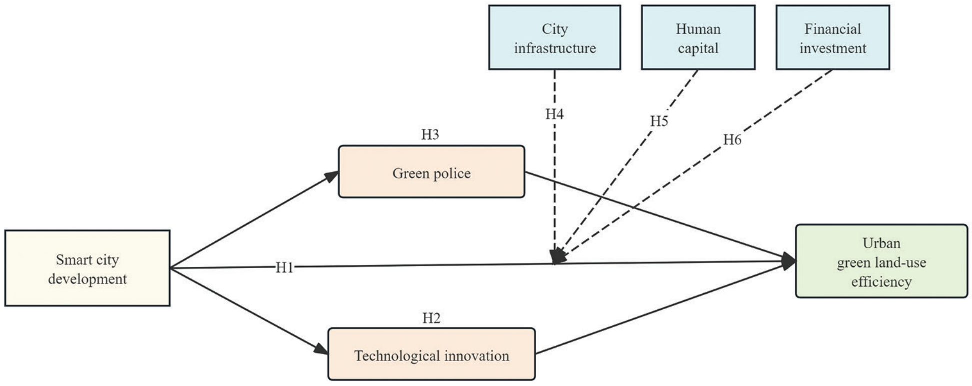

Figure 1. Theoretical Framework Diagram
Source: Diagram by the author

China City Statistical Yearbook (National Bureau of Statistics of China, 2023), which provides most of the core variables required for this study, including built-up area, fixed asset investment, value added and employment in the secondary and tertiary industries, GDP per capita, industrial structure, urban permanent population, and fiscal expenditure. Data on undesirable outputs, such as industrial wastewater discharge and industrial sulfur dioxide emissions, were obtained from the *China Environmental Statistical Yearbook* (Ministry of Ecology and Environment of China, 2023) and the environmental sections of the *China City Statistical Yearbook*. Data on the green coverage rate of built-up areas were extracted from the *China City Statistical Yearbook*.

The study period was defined as 2009 to the end of 2023. Although some 2024 data were available in monthly reports and statistical bulletins, these data were incomplete and, in some cases, were not fully comparable due to differences in coverage and calculation methods. Therefore, 2024 was excluded to ensure consistency and accuracy.

Considering the extensive coverage of smart city pilot policies and regional variation in economic development, the empirical analysis used a panel dataset covering prefecture-level cities within three major urban agglomerations in China: the Beijing–Tianjin–Hebei region, the Yangtze River Delta, and the Pearl River Delta. These regions were selected due to their leading roles in China's economic development and smart city pilot programs. Focusing on these agglomerations allows for a focused examination of the relationship between advanced urban policy (smart city development) and land-use efficiency in high-density, economically critical areas.

After excluding cities with significant data gaps or substantial inconsistencies in the timing of policy implementation, a total of 50 prefecture-level cities with complete data were selected as the analysis sample. The study emphasizes comparisons in UGLUE between smart city pilot and non-pilot cities to mitigate potential estimation biases and improve the reliability of the findings.

3.2. Variable definition and indicator system

3.2.1. Definitions and descriptions of variables

This study developed a comprehensive framework for evaluating UGLUE, drawing on the measurement methodologies proposed by L. Zhang *et al.* (2024) and W. Li *et al.* (2024). To reflect the environmental costs of land use, industrial wastewater discharge, and industrial sulfur dioxide emissions were selected as the core indicators for undesirable outputs. These indicators were comprehensively reported in the *China City Statistical Yearbook* and were widely used to assess industrial pollution and urban environmental pressure.

This study treated the smart city pilot policy as a quasi-natural experiment. The pilot policy was not implemented simultaneously across cities but was approved by the central government in multiple batches (e.g., 2012, 2013, and 2014). Accordingly, the timing of cities entering the "treatment group" (i.e., the policy shock timing) varied, constituting a staggered DID design. Within this framework, the core explanatory variable, SCD × Post, was a time-varying treatment indicator. For a city approved as a pilot in year t_0, this variable equaled 1 for year t_0 and all subsequent years, and 0 otherwise. This specification controlled for time-invariant city characteristics and common time trends, thereby helping to identify the net effect of the policy shock. Robustness analyses, such as the parallel trend test, were conducted based on this model specification. Utilizing an input–output approach, the study specified the indicators for assessing UGLUE and defined the variables used in the regression model examining the impact of smart city development on UGLUE (Tables 1 and 2).

Table 1. Definitions and descriptions of variables

Variable category	Symbol	Variable name
Input	x_1	Built-up Area
	x_2	Fixed Asset Investment
	x_3	Secondary and Tertiary Industry Employment
Desirable output	y_1^+	Economic Output of the Secondary and Tertiary Sectors
	y_2^+	Average wage of employed workers
	y_3^+	Green coverage rate of built-up areas
Undesirable output	y_1^-	Industrial wastewater discharge
	y_2^-	Emissions of sulfur dioxide in industrial sectors
Explained variable	UGLUE	Urban green land-use efficiency
Explanatory variables	SCD	Smart city pilot
	Post	Policy time
	SCD×Post	Interaction term
Control variables	z_{1t}	GDP
	z_{2t}	Industrial structure
	z_{3t}	City size
	z_{4t}	Fixed asset investment
	z_{5t}	Fiscal expenditure

Abbreviation: UGLUE: Urban green land-use efficiency.

Table 2. Super-efficiency slack-based measure model symbols and meanings

Model symbol	Meaning	Corresponding variables
ρ	Efficiency score	UGLUE value
m	Number of input variables	Built-up area (x_1), fixed asset investment (x_2), and secondary/tertiary employment (x_3).
q_1	Number of desirable outputs	Economic output of secondary/tertiary sectors (y_1^+), average wage (y_2^+), and urban green coverage (y_3^+).
q_2	The number of undesired outputs	Industrial wastewater discharge (y_1^-) and industrial sulfur dioxide emissions (y_2^-).
s_i^-	Slack (excess) of the i-th input	Corresponding to the input redundancy of x_1, x_2, x_3.
s_r^+	Shortfall of the r-th desirable output	Corresponding to the output shortfall of y_1^+, y_2^+, y_3^+ .
s_t^-	The excess in the t-th undesirable output	Corresponding to the undesirable output excess of y_1^-, y_2^- .
x_{i0}	Observed value of the i-th input for the evaluated DMU	Observed values of a specific city for x_1, x_2, x_3.
y_{t0}^-	Observed value of the r-th desirable output for the evaluated DMU	Observed values of a specific city for y_1^+, y_2^+, y_3^+ .
y_{r0}^+	Observed value of the t-th undesirable output for the evaluated DMU	Observed values of a specific city for y_1^-, y_2^- .
DMU	Decision-making unit	Individual city sample

Abbreviation: UGLUE: Urban green land-use efficiency.

3.3. Methods

3.3.1. Measurement method of UGLUE

The SSBM model was employed to measure UGLUE. Compared with conventional DEA models, SSBM can incorporate slack variables and undesirable outputs (e.g., resource inefficiency and environmental pollution), thereby enabling a more comprehensive efficiency assessment. The efficiency scores derived from this model were used as the dependent variable in the subsequent empirical analysis examining the impact of smart city development on UGLUE.

3.3.2. Empirical analysis method

To comprehensively examine the impact of smart city development on UGLUE, this study utilized the DID method for causal inference and conducted robustness checks using the propensity score matching (PSM). Furthermore, a three-stage validation procedure was employed to assess heterogeneity and mediation effects, with a focus on technological innovation and green policies.

3.3.3. Construction of the research model

To evaluate the impact of smart city pilot policies on UGLUE, this study constructed an empirical framework integrating the SSBM efficiency measurement model (Model 1) and the DID evaluation model (Model 2) (explanations of the model symbols are provided in Table 2). This framework first measured efficiency using a non-radial directional distance function and then conducted causal identification within a quasi-experimental design. The models were specified as follows:

$$\min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{r0}^+} + \sum_{t=l}^{q_2}\frac{s_t^-}{y_{t0}^-}\right)} \tag{1}$$

$$\begin{aligned} \text{UGLUE}_{it} &= \alpha + \beta_1\left(SCD_{it} \times Post_t\right) + \beta_2 SCD_i \\ &+ \beta_3 Post_t + z_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{2}$$

In this context, μ_i represents the city fixed effects, controlling for unobservable heterogeneity at the city level; λ_t represents the time-fixed effects, controlling for the impact of macroeconomic and policy changes; and ε_{it} represents the random error term.

4. Results

4.1. Urban green land-use efficiency values of cities

This study employed the SSBM model and Max-DEA Basic 6.3 (Worcester Polytechnic Institute, United States) to assess UGLUE across 50 prefecture-level cities within three major urban agglomerations from 2009 to 2023 (Table 3).

As shown in Figure 2, the three major urban agglomerations exhibited a pattern of rapid improvement, followed by adjustment and recovery. The Yangtze River Delta generally maintained relatively high UGLUE, increasing from 0.685 in 2009 to 0.716 in 2023. This pattern may be associated with the region's strengths in regional coordination and its low-carbon industrial foundation. The Beijing–Tianjin–Hebei region showed a pronounced increase from 0.589 in 2009 to 0.721 in 2023, peaking at 0.783 in 2014. This improvement may reflect the region's low-carbon energy transition goals and stringent controls on coal and coal-fired power, suggesting policy-driven characteristics. The Pearl River Delta increased from 0.559 in 2009 to 0.674 in 2023, with higher values observed in some years (e.g., 2014 and 2022), which may be related to its relatively advanced low-carbon energy and industrial development and progress in regional new power system construction.

Table 3. Average urban green land-use efficiency (UGLUE) in three major urban agglomerations (selected years, 2009–2023)

Area	Indicator	Year					
		2009	2012	2013	2014	2022	2023
Urban cluster 1 (BTH)	Average UGLUE	0.589	0.620	0.678	0.783	0.595	0.721
Urban cluster 2 (YRD)	Average UGLUE	0.685	0.724	0.802	0.708	0.624	0.716
Urban cluster 3 (PRD)	Average UGLUE	0.559	0.608	0.792	0.761	0.737	0.674

Abbreviations: BTH: Beijing–Tianjing–Hebei; PRD: Pearl River Delta; YRD: Yangtze River Delta.

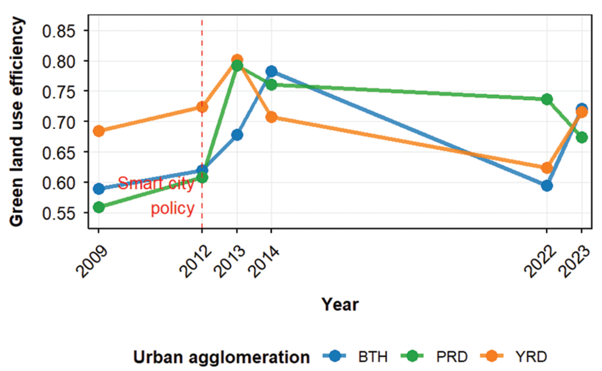

Figure 2. Average urban green land-use efficiency trends of three major urban agglomerations (selected years, 2009–2023). The red dashed line represents the starting year of the smart city policy implementation
Source: Graph by the author
Abbreviations: BTH: Beijing–Tianjing–Hebei; PRD: Pearl River Delta; YRD: Yangtze River Delta

4.2. Impact of smart city pilot implementation on UGLUE

4.2.1. Sample classification

Based on the implementation of the smart city pilot policy, the 50 cities were classified into two groups (Table 4). The treatment group included 29 cities designated as smart city pilots, while the control group included 21 cities that were not selected. Notably, to improve the robustness of the DID estimates, Zhanjiang was included in the control group. Although Zhanjiang is not part of the core Pearl River Delta region, it is a comparable non-pilot city within Guangdong province and thus serves as a useful comparator for evaluating the policy effect.

4.2.2. Parallel trend test

A fundamental assumption of DID is that, before the policy implementation, the treatment and control groups follow parallel trends in the outcome variable. If this assumption holds, post-policy differences in UGLUE can be more plausibly attributed to the smart city policy rather than pre-existing divergent trends. Therefore, this study included a set of pre-policy dummy variables (pre_terms) to test whether coefficients in the years before policy implementation differed significantly from zero.

The results are shown in Figure 3 and Table 5. The estimated coefficients for the key explanatory variables pre_4 to pre_1 were close to zero and not statistically significant (p>0.1), indicating no evidence of differential pre-trends between the treatment and control groups. After policy implementation, the coefficients (current, post_1, post_2, post_3) were positive and statistically significant, demonstrating a post-policy increase in UGLUE in pilot cities relative to non-pilot cities. For example, the post_3 coefficient (0.057) indicates that, by the third year after implementation, pilot cities exhibited an additional increase of approximately 0.057 units in UGLUE relative to non-pilot cities, consistent with a dynamic policy effect.

4.2.3. Impact of smart city development on UGLUE

The regression results presented in Table 6 support the study's core finding that smart city development

Table 4. Sample cities in the treatment and control groups for the difference-in-differences model

Major urban agglomeration	Treatment group	Control group
BTH	5 groups: Beijing, Tianjin, Shijiazhuang, Qinhuangdao, Langfang	5 groups: Tangshan, Baoding, Zhangjiakou, Chengde, Cangzhou
YRD	17 groups: Shanghai, Nanjing, Hangzhou, Suzhou, Wuxi, Bengbu, Jinhua, Wenzhou, Ningbo, Taizhou, Changzhou, Yancheng, Zhenjiang, Xuzhou, Huai'an, Nantong, Wuhu	13 groups: Hefei, Lianyungang, Yangzhou, Jiaxing, Huzhou, Shaoxing, Quzhou, Zhoushan, Taizhou, Lishui, Ma'anshan, Anqing, Chuzhou
PRD	7 groups: Guangzhou, Shenzhen, Zhuhai, Foshan, Dongguan, Zhongshan, Zhaoqing	3 groups: Huizhou, Zhanjiang, Jiangmen

Abbreviations: BTH: Beijing–Tianjin–Hebei; PRD: Pearl River Delta; YRD: Yangtze River Delta.

is associated with higher UGLUE. In both models, the coefficient for the interaction term SCD × Post is positive and statistically significant ($p<0.001$), with estimated coefficients of 0.039 and 0.044, respectively. This indicates that, relative to non-pilot cities, pilot cities experienced an average increase of approximately 3.9–4.4 units in UGLUE after policy implementation, supporting H_1.

This suggests that pilot cities achieved greater post-policy improvements in UGLUE than the control group. Among the control variables, GDP and city size show significant positive effects, supporting the role of economic development level and urban scale in enhancing UGLUE. Other control variables are not statistically significant. Overall, the results support the conclusion that the smart city policy is associated with improved UGLUE, consistent with H_1.

4.2.4. Robustness check

4.2.4.1. PSM–DID

To verify the robustness of the DID model, this section employed PSM as an additional testing approach. PSM was used to reduce selection bias caused by non-random assignment and to improve comparability between the treatment and control groups before policy implementation. The robustness analysis consisted of two stages. First, nearest-neighbor matching was applied to assess whether covariates were balanced across the two groups. Second, the DID model was re-estimated using the matched sample to examine whether the smart city policy remained statistically significantly associated with UGLUE.

The effectiveness of the matching procedure was supported by balance diagnostics. After matching, the absolute standardized bias for all covariates was reduced to below 10%, with most below 5%, indicating improved covariate balance between the treatment and control groups. This was also reflected in the kernel density plot (Figure 4): before matching, the propensity score distributions of the treatment and control groups differed significantly, whereas after matching, the distributions became more closely aligned, demonstrating a successful matching process that mitigates selection bias and addresses endogenous differences arising from pre-existing group characteristics. The DID estimation on the

Table 5. Regression results of the parallel trends test

Variable	Estimated coefficient	*t*-value	*p*-value
pre_4	0.012	0.95	0.342
pre_3	−0.008	−0.62	0.535
pre_2	0.005	0.4	0.689
pre_1	−0.015	−1.21	0.227
current	0.032	2.55	0.011
post_1	0.041	3.28	0.001
post_2	0.05	4.01	0.000
post_3	0.057	4.59	0.000
Constant	0.17	15.1	0.000
R2		0.081	

Table 6. Regression results

Variables	(1)	(2)
SCD	0.015* (1.35)	0.013* (1.14)
Post	0.012** (2.86)	0.010** (2.65)
SCD×Post	0.039*** (6.12)	0.044*** (6.58)
GDP	–	0.042* (2.78)
Industry structure	–	0.093 (0.02)
City size	–	0.024* (2.01)
Fixed asset investment	–	-0.041 (0.46)
Fiscal expenditure	–	0.012 (0.89)
Constant	0.518*** (10.76)	0.385*** (5.16)
R^2	0.182	0.225
Number of groups	50	50
μ	Yes	Yes
λ	Yes	Yes

Notes: *$p<0.05$; **$p<0.01$; ***$p<0.001$.

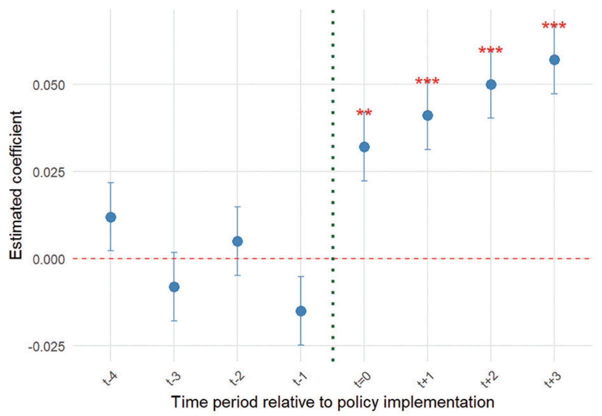

Figure 3. Parallel trends test plot
Note: The vertical dotted line indicates the time of policy implementation (t = 0). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively
Source: Graph by the author

Figure 4. Matched kernel density comparison plot
Source: Plot by the author

matched sample further indicates that the positive and significant association between the smart city pilot policy and UGLUE remained robust.

4.2.4.2. Regression results after matching

After performing PSM and excluding observations outside the common support (and those with matching weights equal to zero), 267 observations remained. Running the DID regression model on the matched sample showed that the interaction term SCD × Post remained statistically significant, with coefficients of 0.048 and 0.050 (p<0.05). These results indicate that, after addressing observable selection differences, the smart city pilot policy remained associated with improved UGLUE.

The statistically significant interaction term suggests that the smart city policy exerts a substantial influence on UGLUE, with a marked contrast between the treatment and control groups. The R^2 value increased from 0.189 to

Table 7. Regression results after matching

Variables	(3)	(4)
SCD	0.044** (5.63)	0.052** (6.14)
Post	0.014** (5.86)	0.016** (4.32)
SCD×Post	0.048*** (8.73)	0.050*** (8.17)
GDP	–	0.061* (3.22)
Industry structure	–	0.125 (0.04)
City size	–	0.046 (0.05)
Fixed asset investment	–	−0.063 (0.64)
Fiscal expenditure	–	0.018 (0.93)
Constant	0.654*** (11.42)	0.591 (0.09)
R^2	0.189	0.208
Observations	267	267
Number of groups	50	50

Notes: *p<0.05; **p<0.01; ***p<0.001.

0.208, indicating an enhancement in the model's goodness of fit following the matching process. This improvement underscores that the matching procedure has strengthened the explanatory power of the model (Table 7).

4.3. Mediation effect analysis

To further investigate the influence of smart city policies on UGLUE, this study conducted a mediation effect analysis to examine whether innovation capability and green policies mediate the link between smart city policies and UGLUE. A three-step regression approach was applied utilizing Models 3, 4, and 5. Innovation capability was measured using a composite index constructed with the entropy weight method. This index integrated three city-level dimensions: R&D investment intensity (R&D expenditure as a percentage of GDP), innovation output density (number of invention patents granted per 10,000 people), and market transformation vitality (value of technology contract transactions as a percentage of GDP). Data for these indicators were sourced from the *China City Statistical Yearbook*. Green policy was quantified through textual analysis. Specifically, Python was used to segment and process annual government work reports of prefecture-level cities. The frequency of keywords related to themes such as "energy conservation and emission reduction" and "ecological protection" was calculated as a proportion of the total word count in each report. This ratio was used as a proxy for local government policy attention to environmental issues. The original texts of these reports were obtained from the official websites of the respective municipal governments.

$$M_{it} = \alpha + \delta SCD_{it} + z_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

$$\mathrm{UGLUE}_{it} = \alpha + \beta SCD_{it} + z_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

$$UGLUE_{it} = \alpha + \beta^{'} SCD_{it} + \theta M_{it} + z_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

As shown in Table 8, the association between smart city development and innovation capability is statistically significant (β = 0.152, p<0.01). The association between smart city development and UGLUE is also statistically significant (β = 0.085, p<0.01). When innovation capability is included in the regression, its effect remains significant (β = 0.291, p<0.01), and the coefficient for smart city development decreases from 0.085 to 0.041. This pattern is consistent with innovation capability partially mediating the relationship between smart city development and UGLUE, supporting H_2.

Table 9 shows that smart city development is significantly associated with green policy attention (β = 0.123, p<0.01), and it is also significantly associated with UGLUE (β = 0.083, p<0.01). When green policy attention is included in the regression, its coefficient remains statistically significant (β = 0.267, p<0.01), and the coefficient for smart city development decreases from 0.083 to 0.048. This pattern is consistent with green policy attention partially mediating the relationship between smart city development and UGLUE, supporting H_3.

Table 8. Regression results with innovation capability (IC) as a mediating variable

Variable	(1)	(2)	(3)
SCD	0.152*** (4.892)	0.085*** (5.430)	0.041** (2.521)
IC	-	-	0.291*** (6.732)
GDP	0.107** (3.211)	0.072** (2.865)	0.063**(2.432)
Industrial Structure	0.089** (2.905)	0.041* (2.118)	0.028* (1.905)
City Size	0.042** (2.510)	0.025* (1.976)	0.017* (1.683)
R-square	0.233	0.257	0.279
μ	Yes	Yes	Yes
λ	Yes	Yes	Yes

Notes: *p<0.05; **p<0.01; ***p<0.00.

Table 9. Regression results with green policy (GP) as a mediating variable

Variable	(1)	(2)	(3)
SCD	0.123*** (4.215)	0.083*** (5.670)	0.048** (2.752)
GP	–	–	0.267*** (6.134)
GDP	0.092** (2.982)	0.067** (2.901)	0.065** (2.723)
Industrial structure	0.072** (2.710)	0.045* (2.220)	0.029* (1.982)
City size	0.037* (2.115)	0.028* (1.982)	0.020* (1.809)
μ	Yes	Yes	Yes
λ	Yes	Yes	Yes

Notes: *p<0.05; **p<0.01; ***p<0.001.

4.4. Urban heterogeneity analysis

To deepen the understanding of how smart city policies influence UGLUE across cities with different characteristics, this study conducted heterogeneity analysis to examine whether infrastructure development (INF), human capital (HC), and financial investment (FI) moderate the policy effects.

As shown in Table 10, the coefficient for SCD × Post × INF is 0.021 (p<0.05), indicating a stronger association between smart city policies and UGLUE in cities with better-developed infrastructure. Improvements in roads, communications, energy, and other infrastructure provide crucial support for the deployment of smart city technologies, thereby enhancing land-use efficiency more effectively. The coefficient for the interaction term SCD × Post × HC is 0.032 (p<0.05), suggesting that the policy impact is more pronounced in cities with higher levels of human capital. A more educated workforce is better equipped to absorb and apply smart city technologies, which in turn enhances land-use efficiency through intelligent management. The coefficient for the interaction term SCD × Post × FI is 0.026 (p<0.05). This result indicates that the policy effect is stronger in cities with higher levels of financial investment. Sufficient funding and social capital are essential for building smart city infrastructure and promoting intelligent management systems, contributing to improved UGLUE. Overall, these results support H_4–H_6.

Table 10. Regression results of urban heterogeneity analysis

Variable	(1)	(2)	(3)
SCD×Post	0.074*** (3.872)	0.065*** (3.412)	0.082*** (4.005)
SCD×Post×INF	0.021** (2.517)	–	–
SCD×Post×HC	–	0.032** (2.801)	–
SCD×Post×FI	–	–	0.026** (3.009)
GDP	0.015** (2.758)	0.013** (2.531)	0.018** (2.832)
Industrial structure	0.027** (2.982)	0.019*(2.412)	0.024** (2.682)
City size	0.009* (2.212)	0.012** (2.632)	0.011** (2.540)
R^2	0.320	0.325	0.298
μ	Yes	Yes	Yes
λ	Yes	Yes	Yes

Notes: *p<0.05; **p<0.01; ***p<0.001.
Abbreviations: FI: Financial investment; HC: Human capital; INF: Infrastructure development.

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5. Discussion

This study uses data from 50 cities in China to examine the association between smart city development and urban UGLUE. The results indicate that smart city development is significantly associated with higher UGLUE in pilot cities, consistent with relevant theoretical perspectives. These findings suggest that smart city policies may contribute not only to short-term improvements but also to longer-term adjustments in land-use efficiency.

5.1. Smart city development significantly enhances UGLUE

This study finds that smart city policies are associated with higher UGLUE in pilot cities, aligning with existing research suggesting that smart technologies can improve land-use efficiency by optimizing resource allocation (J. Zhang & Sun, 2024). From the perspective of urban system theory and its emphasis on co-evolution, smart cities should not be viewed merely as a collection of technological tools but as a form of systemic intervention that can restructure urban systems through digitalization (Batty, 2013). The results suggest that smart city development may promote more efficient coupling of land, energy, and ecological elements by increasing information transparency and improving decision-making responsiveness, thereby extending beyond the linear logic of traditional input–output optimization.

From the perspective of sustainability transition theory, these results indicate that smart city policies may help weaken path dependency in urban land development and support greener development trajectories (Grin *et al.*, 2010). While existing literature has predominantly focused on the environmental effects of smart cities in specific sectors such as transportation or energy, evidence regarding land use has been relatively insufficient (F. Li *et al.*, 2019). The results further suggest that smart city development may contribute to improved environmental governance in industrial transfer-receiving regions through comprehensive monitoring and intelligent management, potentially mitigating tensions between traditional industrialization and land ecological degradation. This provides additional empirical insight into how digital technologies may influence spatial development patterns.

5.2. Smart cities optimize land use through mediating mechanisms

The mediating analysis suggests that innovation capability and green policy attention play mediating roles in the relationship between smart city policies and UGLUE. This is consistent with the pathway through which smart cities may enhance land-use efficiency by promoting technological innovation (C. Zhou & Li, 2025). In addition, the results suggest that green policies constitute another parallel mediating mechanism. This indicates that the association between smart city development and UGLUE is not solely technology-driven, but may reflect both "technology empowerment" and "institutional reinforcement." In some cases, smart monitoring data may be incorporated into environmental performance assessments, reflecting how digital governance can strengthen policy implementation. This interpretation aligns with transition studies suggesting that niche innovations need to interact with institutional change to support systemic transformation (Geels, 2011), and it provides a more comprehensive mechanistic explanation for technology-driven environmental governance in China.

5.3. Urban heterogeneity moderates the effectiveness of smart city policies

This study identifies the moderating effects of infrastructure, human capital, and financial resources on policy outcomes, which extends the understanding of heterogeneity in smart city effects. On the one hand, these findings echo regional disparities noted by Xu *et al.* (2021); on the other hand, they shift attention from macro-level locational factors to cities' internal capacity attributes. The findings reveal that cities with better-developed infrastructure, stronger human capital, and greater financial resources exhibit stronger policy responsiveness. This corroborates the importance of "initial conditions" in technology absorption and institutional adaptation emphasized in urban system theory. The effects are also more pronounced in non-resource cities, aligning with the observations of W. Li *et al.* (2024). One possible explanation is that such cities face fewer constraints from traditional development pathways and may have greater institutional flexibility, enabling them to translate smart city investments into improved environmental governance outcomes.

Overall, these heterogeneous results indicate that the green effects of smart city policies are not uniform and may depend on local systemic attributes and transformational preparedness. This perspective shifts the explanatory framework for policy heterogeneity from traditional location determinism or resource endowment theory toward a systematic analysis based on a city's internal absorptive capacity and institutional flexibility. This perspective applies and extends innovation systems theory and institutional change theory in urban studies, suggesting that the translation of smart technology into green outcomes critically depends on a city's comprehensive transformational foundation, comprising its infrastructure, human capital, and fiscal resources.

6. Conclusion

This study provides empirical evidence that smart city development is associated with higher UGLUE. Based on the baseline regression coefficients, smart city pilot implementation is associated with an average increase in UGLUE of approximately 0.039–0.044 units in pilot cities relative to non-pilot cities. The results further suggest that this association is not solely technology-driven. Instead, smart city development may promote innovation capability and strengthen green policy attention through digitalization. The study also identifies heterogeneity in policy effectiveness: the association between smart city policies and UGLUE is more pronounced in cities with better-developed infrastructure, higher human capital, and greater financial investment. This indicates that the effectiveness of smart city-enabled green transformation may depend on local preparedness for transition and resource-mobilization capacity.

The core contribution of this study lies in integrating methodology, mechanism analysis, and a long observation period. Using a long-term framework (2009–2023), the research systematically combines SSBM efficiency measurement, a multi-period DID design, and PSM-based robustness testing to estimate the association between smart city pilot policies and UGLUE. Furthermore, the mediation analysis suggests two parallel pathways—technological innovation and green policy attention—thereby extending beyond a purely technology-centered perspective and providing an empirical foundation for understanding how smart city policies may influence sustainable land use outcomes.

These insights carry important implications beyond China. For many developing and emerging economies undergoing rapid urbanization alongside digitalization, this study offers a critical caution: the green dividends of smart city investments are not automatic. The validated dual-pathway mechanism and the emphasis on foundational capacities provide a valuable framework to avoid costly, context-blind technological replication. Specifically, the research highlights a strategic sequence: prioritizing modular digital infrastructure, cultivating relevant human capital, and ensuring coordinated financial support. This approach can guide cities toward a more incremental and adaptive smart transformation pathway that aligns with local realities.

Furthermore, this study directly contributes to the global sustainable development agenda. By demonstrating how smart cities can systematically enhance land use sustainability, it positions integrated urban digitalization as a practical lever for advancing urban low-carbon transitions and achieving related Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). The proven model of coupling technological innovation with policy reinforcement offers a replicable blueprint for cities worldwide to translate climate ambitions into concrete, efficiency-driven outcomes at the urban level.

Based on the empirical findings, this study proposes three targeted policy recommendations: (i) move beyond a "one-size-fits-all" model by tailoring strategies to city-specific capacities. Less-resourced cities should prioritize deploying modular, cost-effective digital solutions (e.g., Internet of Things sensor networks) and leverage regional cooperation platforms for knowledge and technology transfer; (ii) develop a dynamic UGLUE monitoring and evaluation platform. Pilot cities should integrate real-time data on key metrics into environmental performance assessments, enabling evidence-based and agile policy adjustment; (iii) create substantive incentives, such as preferential land or tax policies, for enterprises that adopt smart technologies for intensive land use and ecological restoration, fostering a market-policy synergy for sustainable development.

This study has certain limitations. The sample primarily focuses on major urban agglomerations in China, and the generalizability of the conclusions to medium-sized and small cities or different institutional contexts requires further validation. The data mainly rely on macro-level statistical sources, and as smart cities encompass multidimensional subsystems, the synergistic mechanisms among them necessitate more detailed cross-departmental analysis. Future research will pursue multiple methodological advancements. These include employing a dynamic DID approach to more precisely capture the evolving trajectory of policy effects and striving to identify more effective instrumental variables or utilize natural experiments to further mitigate potential endogeneity concerns, thereby strengthening causal inference within a more rigorous identification framework.

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