ASSESSING THE INFLUENCE OF NEW URBANIZATION PILOT POLICIES ON GREEN LAND USE EFFICIENCY IN CITIES: EVIDENCE FROM THE YANGTZE RIVER DELTA, CHINA

JIANG, W.[1] – HU, X. L.[2,3*] – MA, X.[4*] – WEN, Z. Q.[5]

[1]*School of Business, Zhejiang Industry Polytechnic College, Shaoxing 312000, China*
(e-mail: jiangwei@zjipc.edu.cn)

[2]*School of Accounting, Guangzhou College of Commerce, Guangzhou 511363, China*
(e-mail: F23092100176@cityu.edu.mo)

[3]*Faculty of Finance, City University of Macau, Macao 999078, China*

[4]*School of Management, Guangdong University of Science and Technology, Dongguan 523083, China*
(e-mail: maxiang@pukyong.ac.kr)

[5]*Graduate School of Management of Technology, Pukyong National University, Busan 48548, Republic of Korea*
(e-mail: wenzhongqi@pukyong.ac.kr)

**Corresponding authors*
e-mail: F23092100176@cityu.edu.mo (Hu, X. L.); maxiang@pukyong.ac.kr (Ma, X.)

(Received 6th Sep 2025; accepted 3rd Dec 2025)

Abstract. Previous studies on new urbanization and green land use efficiency lack comprehensive frameworks to explain policy effects and to distinguish between traditional and new types of urbanization. Therefore, this study examines panel data from 27 cities in China's Yangtze River Delta (YRD) urban agglomeration (2012–2022) to empirically analyze the impact of new urbanization policies on urban green land use efficiency (UGLUE). We employed a super-efficiency slack-based measure (SBM) model to measure UGLUE and a difference-in-differences (DID) approach to evaluate policy impacts. Robustness was verified using instrumental variable (IV) and propensity score matching difference-in-differences (PSM-DID) methods. The results indicated a significant positive policy impact on UGLUE, mediated primarily through three channels: intensive land use, green technological innovation, and industrial structure upgrading. These effects were more pronounced in less developed regions, non-resource-based cities, and small-to-medium-sized cities. The findings provide a valuable framework for understanding the policy-efficiency nexus and offer critical insights for balancing urbanization with ecological sustainability in the YRD and similar regions in China.
Keywords: *difference-in-differences (DID), green technology innovation, industrial upgrading, land intensification, Yangtze River Delta (YRD)*

Introduction

Urbanization in the Yangtze River Delta (YRD) has been a significant driver of regional economic and social development, demonstrating an exemplary growth trajectory and high level of effectiveness over time. Since China's economic reforms, the region has undergone substantial urbanization, with the proportion of urban residents increasing by 53 percentage points (from 17% to 70%). While this growth has provided sustained economic momentum, it has also introduced challenges such as inefficient land use and ecological degradation. These issues underscore the urgent need to shift away

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

from traditional development models. New-type urbanization is a uniquely Chinese approach to urbanization that emphasizes people-centered development, a balanced integration of the “Four Modernizations” (industrialization, informatization, urbanization, and agricultural modernization), an optimized spatial layout, ecological civilization, and cultural preservation. It represents a fundamental shift from the traditional, expansion-driven model of urbanization toward a more sustainable, efficient, and inclusive development. In response to these challenges and the urgent need for sustainable urban development, the Chinese government introduced the New Urbanization Plan (2014–2020) to increase the urban green land use efficiency (UGLUE) from 0.622 in 2012 to over 0.800 by 2022, emphasizing smart, green, intensive, and low-carbon urban development. Evaluating the impact of these policies on UGLUE is crucial for refining urban development strategies, both theoretically and practically.

The current academic research on new urbanization and green land use efficiency primarily explores three dimensions: (1) the direct impact of urbanization policies on UGLUE, (2) the indirect mechanisms through which policies affect land use efficiency, and (3) the heterogeneity of policy effects across regions and city types. However, it has notable theoretical and methodological limitations. For instance, An et al. (2025) demonstrated that new urbanization has had a significant and positive impact on UGLUE. Similarly, Cheng et al. (2023) confirmed that new urbanization policies improved urban land use performance. However, Zhang et al. (2025) found that policy effects tend to exhibit a time lag of two to three years. Nevertheless, these studies lack a comprehensive theoretical framework to explain the intrinsic mechanisms behind policy effects and fail to distinguish effectively between traditional and new urbanization.

In examining indirect influence mechanisms, Chang et al. (2023) established that improvements in the industrial structure mediate the association between new urbanization and UGLUE. Wang et al. (2021) emphasized technological innovation as a crucial pathway, while Cheng et al. (2023) highlighted planning and ecological effects as dual mechanisms. However, one methodological constraint is that many of these studies use a comprehensive index of new urbanization as the explanatory variable, which limits the scientific rigor of causal inference, particularly regarding the quasi-natural experimental characteristics of national pilot policies.

Regarding the impact of heterogeneity, Tan et al. (2021) noted significant variations in UGLUE in the YRD, forming identifiable dominant, balanced, and weak zones. According to Cheng et al. (2023), policy effects are moderated by urbanization stage and city size. While regional differences have been acknowledged, a more thorough analysis of the root causes of this heterogeneity is needed, particularly regarding key moderating factors.

Existing research has yielded three key findings and exhibited three fundamental limitations. First, policy interventions have measurable effects with distinct temporal patterns. Second, multiple transmission channels exist. Third, significant spatial heterogeneity emerges. However, deficiencies in the literature hinder comprehensive policy evaluation: (1) theoretical fragmentation across analytical scales that fails to integrate micro-level institutional factors with macro-level environmental outcomes; (2) insufficient examinations of how different policy mechanisms interact synergistically; and (3) inadequate investigations of contextual moderators, particularly developmental stages and resource endowments. These gaps are especially problematic when assessing China’s new urbanization policies because they require a simultaneous consideration of economic, environmental, and spatial factors.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

To address these gaps, we use YRD city-level panel data from 2012 to 2022 to employ super-slack-based (SBM) measures for land efficiency and a differences-in-differences (DID) approach for policy evaluation. The study also examines underlying mechanisms and regional heterogeneities. Our contributions are threefold: (1) We construct a systematic "policy intervention–mechanism transmission–efficiency enhancement" framework that integrates transaction cost theory, the environmental Kuznets curve (EKC), and new economic geography; (2) we empirically validate three synergistic pathways through rigorous quasi-natural experiments; and (3) we reveal how policy effects vary across development stages, city types, and city sizes. These findings not only fill research gaps but also provide operational support for the implementation of new urbanization with Chinese characteristics.

The rest of the paper is structured as follows. Section 2 outlines the theoretical background. Section 3 details the research design. Section 4 reports the empirical analysis. Section 5 provides the discussion. Section 6 concludes the paper.

Theoretical analysis and research hypotheses

Theoretical analysis

Three theoretical approaches are employed regarding how new-type urbanization affects UGLUE.

First, according to Williamson's (1975) transaction cost theory, new urbanization can reduce information search and coordination costs by establishing smart city management systems and using digital technologies to manage land resources. In particular, big data analytics can precisely match land supply with demand, reducing idle land resources and inefficient development.

Second, the EKC hypothesis (Grossman and Krueger, 1995) provides a theoretical framework for understanding the dynamic interplay between urban development and land use. The EKC suggests that, as economic growth and urbanization advance, the industrial structure shifts toward high-value, low-pollution industries, such as the service and high-tech sectors. The widespread adoption of technologies, such as green buildings and ecological restoration, reduces the environmental pollution intensity of land use, eventually leading to environmental improvement.

Finally, Krugman's (1991) new economic geography theory suggests that the spatial concentration of population and economic activity enables more intensive use of land resources. This agglomeration effect is exemplified by development models such as mixed-use zoning and transit-oriented development (TOD), which improve land use efficiency through economies of scale.

Based on Alnafrah's (2025) systematic framework for assessing environmental efficiency, this study integrates transaction cost theory, new economic geography theory and the EKC. At the micro level, digital policy tools optimize the allocation of land resources by reducing transaction costs. At the meso level, spatial agglomeration effects enhance land use efficiency. At the macro level, environmental regulation policies promote the transformation of industrial structures. The "policy–mechanism–efficiency" transmission framework illustrates the influence of new urbanization policies on green land use.

Guided by these theoretical insights, we have derived the following testable hypothesis:

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

H1. *The emergence of novel forms of urbanization considerably enhances the ecological efficiency of urban land.*

Mechanisms through which new urbanization enhances UGLUE

In the course of urban development, new urbanization primarily improves UGLUE through three key pathways: land use intensification, green technological innovation, and industrial structure upgrading. Together, these pathways form a theoretical framework for understanding how new urbanization influences land use efficiency.

Land use intensification mechanism

Existing studies have found that new urbanization significantly improves UGLUE through the land use intensification pathway. For instance, Chen et al. (2016) showed that optimizing Nanjing's polycentric spatial structure increased land use efficiency by 28%. Using a global comparative analysis, Seto et al. (2012) confirmed that compact development models can reduce land consumption by 38–52% compared to traditional low-density patterns. Zheng et al. (2013) estimated that transit-oriented development associated with high-speed rail projects increased green land use efficiency by 26.5%. Furthermore, an Organisation for Economic Co-operation and Development (OECD, 2020) policy assessment found that pilot cities reduced the rate of ecological land encroachment by 23% through regulatory measures such as floor area ratio (FAR) controls. Altogether, these findings suggest that new-type urbanization improves UGLUE through strategies such as optimizing spatial structures, intensifying development, and implementing mixed-use planning.

Green technological innovation mechanism

A growing body of research shows that new-type urbanization significantly enhances UGLUE through green technological innovation. For example, Zhang et al. (2024) examined the integration of cities in the central region of the Yangtze River and confirmed that the coordination mechanism between urbanization and ecological well-being improved ecological efficiency via green technological innovation. A quantitative study conducted by Yuan et al. (2020) shows that an 8.7% increase in green patent authorization was caused by a 1-percentage-point increase in the urbanization rate. This reveals the direct positive effect of urbanization on green innovation. Using a DID model based on Chinese city data, Li et al. (2024) found that smart city pilot policies increased R&D investment and optimized innovation environments. The result was a 32% surge in the quantity of green technological innovations and a 45% increase in quality. Similarly, in a comparative study of 19 U.S. cities, Hoover et al. (2023) showed that cities adopting green infrastructure standards experienced significant ecological gains and social co-benefits, such as enhanced community resilience, through technology spillovers. Overall, these findings demonstrate that new-type urbanization improves UGLUE through innovation-oriented strategies such as enhanced R&D investment, improved innovation environments, and technology standard settings.

Industrial structure upgrading mechanism

A growing body of empirical research shows that new-type urbanization enhances UGLUE by promoting industrial restructuring. For example, Tang et al. (2020) found that upgrading the industrial structure improved land ecological use efficiency by 22–28%,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

primarily due to the substitution of traditional industries with high-value sectors. Using panel data from 115 Chinese cities, Chang et al. (2023) reported that industrial advancement and rationalization increased green land use efficiency by 18.6% and 21.3%, respectively. The scale effects in technology-intensive industries are particularly prominent. At the provincial level, Wang et al. (2023) demonstrated a nonlinear correlation between industrial upgrades and land use efficiency. When the urbanization rate was below 65%, the elasticity coefficient was 0.35. However, above this threshold, the marginal effect diminished. Ma and Shi (2023) used a multi-model simultaneous analysis and found that new-type urbanization contributed up to 42.3% of the high-quality urban–rural development driven by green industrial transformation. Environmental regulation and resource reallocation are core transmission channels. Together, these findings establish a comprehensive "industrial upgrading–resource allocation–environmental constraint" framework that provides systematic theoretical and empirical support for understanding how new-type urbanization enhances UGLUE.

Based on the above analysis, this study proposes the following core hypotheses:

H2a. *New urbanization enhances UGLUE by promoting land use intensification.*

H2b. *New urbanization enhances UGLUE by driving green technological innovation.*

H2c. *New urbanization enhances UGLUE by facilitating industrial structure upgrading.*

Figure 1 illustrates the theoretical model.

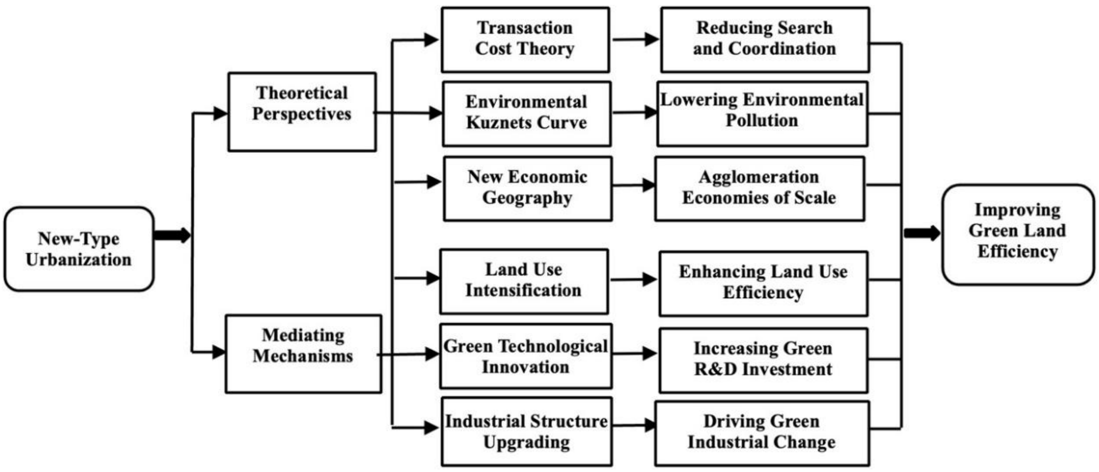

Figure 1. *Theoretical model*

Materials and methods

Empirical models

Baseline model

The formulation and promulgation of the National New Urbanization Plan (2014–2020) are of great significance in accelerating socialist modernization and promoting economic transformation and upgrading. China has designated Ningbo and 62 other cities as comprehensive national pilot areas for new urbanization. This provides a suitable quasi-natural experimental premise for testing new urbanization policies regarding industrial structure and land use efficiency. Given the exogenous nature of policy proposals, this study employs a DID method to assess the policy effects of new

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

urbanization. The pilot cities served as the experimental group for the quasi-natural experiment, whereas cities that were not included in the program served as the control group.

The study employs the DID for three reasons. First, most existing literature focuses on the correlation between urbanization levels and land use efficiency. This study uses a quasi-naturalistic experimental design to identify the net effect of the new urbanization policy. Second, the NDRC-designated pilot cities satisfy the DID model's core identification assumptions, and their selection process is independent of local characteristics. Third, the DID model more precisely captures the effects of policy shocks at the 2016 policy implementation node than do dynamic panel models while avoiding the sensitivity of dynamic models to lags and the loss of efficiency in non-parametric methods with small samples. Thus, this study constructed the DID benchmark model (*Eq.1*), drawing on Zhang et al.'s (2025) research method.

$$ULGUE_{it}=\alpha_0+\alpha_1 DID_{it}+\sum_{p=2}^{6} a_p X_{it}+\mu_j+\lambda_t+\varepsilon_{it} \quad \text{(Eq.1)}$$

where i and t denote city and year, respectively. $ULGUE$ is urban land green use efficiency. DID represents the new urbanization policy; X_{it} is a vector of controls, including economic development, industrial structure, openness, environmental regulation intensity, and transport infrastructure. μ_j and λ_t are province and year fixed effects. ε_{it} is the random error term. α_0 is the constant. a_p are the coefficients on the controls. We mainly focus on α_1, the estimated coefficient that captures the effect of the new urbanization policy on UGLUE in the YRD city.

Mediation effect models

To probe how the new urbanization policy shapes land green use efficiency, we estimate mediation effect models based on *Eq.2* and *Eq.3*.

$$M_{it}=\beta_0+\beta_1 DID_{it}+\sum_{p=2}^{6}\beta_p X_{it}+\mu_j+\lambda_t+\varepsilon_{it} \quad \text{(Eq.2)}$$

$$ULGUE_{it}=\lambda_0+\lambda_1 DID_{it}+\sum_{p=2}^{6}\lambda_p X_{it}+\lambda_7 M_{it}+\mu_j+\lambda_t+\varepsilon_{it} \quad \text{(Eq.3)}$$

where M_{it}denotes the mediators: land use intensification, green technological innovation, and industrial upgrading. All other variables follow *Eq.1*. We focus on the economic meaning and policy implications of β_1, λ_1, and λ_7.

Variables measurement

Explained variable: UGLUE

UGLUE measures a city's performance in balancing economic output with ecological and environmental sustainability during land use. The core concept is to maximize socioeconomic benefits with the minimal use of land, capital, labor, and energy while minimizing negative environmental impacts under given technological conditions. This efficiency is characterized by intensive, environmentally friendly land use.

This study builds a system to measure UGLUE including inputs, outputs, and unexpected outputs. It uses the SBM model for unexpected output super-efficiency, proposed by Tone (2001). This method has two advantages over traditional models: It

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

directly addresses issues of excessive inputs and insufficient outputs, and it allows efficiency values of decision units to exceed 1.

UGLUE is a dimensionless relative efficiency value. A higher value indicates a city's stronger green conversion capabilities for its land resources under equivalent resource and environmental constraints. Assuming n decision-making units (DMUs) with m inputs $x \epsilon R_{+}^{m}$ to produce s_1 desirable outputs $y^{g} \epsilon R_{+}^{s1}$ and s_2 undesired outputs $y^{b} \epsilon R_{+}^{s2}$, the super-efficiency SBM model for the k_{th} DMU is defined by *Eq.4*:

$$\rho_k^* = \frac{\min\left(1 + \left(\frac{1}{m}\right)\Sigma\left(\frac{s_i^-}{x_{ik}}\right)\right)}{1 - \left(\frac{1}{s_1 + s_2}\right)\left(\Sigma\left(\frac{s_r^g}{y_{rk}^g}\right) + \Sigma\left(\frac{s_t^b}{y_{tk}^b}\right)\right)} \quad \begin{aligned} s.t. \sum_{j=1, j\neq k}^{n} \lambda_j x_{ij} &\leq x_{ik} - s_i^- \ (i = 1, \dots, m) \\ \sum_{j=1, j\neq k}^{n} \lambda_j y_{rj}^g &\geq y_{rk}^g + s_r^g \ (r = 1, \dots, s_1) \\ \sum_{j=1, j\neq k}^{n} \lambda_j y_{tj}^b &= y_{tk}^b - s_t^b \ (t = 1, \dots, s_2) \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^g &\geq 0\ s_t^b \geq 0 \end{aligned} \tag{Eq.4}$$

where ρ_k^* denotes the UGLUE value for city k, s_i^-, s_r^g, and s_t^b represent the slack variables for excess input, shortfall in expected output, and excess non-expected output, respectively. The study used STATA 17.0 software to implement the model's calculation (*Eq. 4*) and to derive UGLUE values for each city.

This study draws upon the methodologies of Tan et al. (2021), Cai et al. (2025), Liu et al. (2024), and Bixia et al. (2018) in constructing the indicator system. The study measures UGLUE using the following indicators, which are organized into three categories: inputs, expected outputs, and unintended outputs.

(1) Input indicators: Four factors are covered: land, capital, labor, and energy. Specifically, built-up area represents land input; fixed asset stock, capital input; number of employees, labor input; and total energy consumption, energy input.

(2) Expected output indicators: The sum of secondary and tertiary industry value added reflects direct economic output from urban land use.

(3) Non-desired output indicators: A composite environmental pollution index measures these indicators. The entropy method is used to weight and synthesize this index. Industrial wastewater discharge, industrial sulfur dioxide emissions, and industrial particulate matter emissions are foundational indicators. *Table 1* provides specific definitions, measurement methods, and units for each indicator.

***Table 1.** Evaluation index system of ULGUE*

Indicator Type	Factor Category	Indicator Measurement Method	Unit
Input indicators	Land factor	Urban built-up area	km^2
	Capital factor	Fixed capital stock (perpetual inventory method)	10^4 RMB
	Labor factor	Total number of employees at the end of the year	10^4 persons
	Energy factor	Energy consumption (measured in standard coal equivalent, based on natural gas, liquefied petroleum gas, and electricity usage)	10^4 tons of standard coal
Expected outputs	Economic benefits	The sum of the secondary and tertiary sectors' value-added	10^4 RMB
Undesirable outputs	Environmental pressure	The Environmental Pollution Intensity Index is a weighted composite of industrial wastewater, SO2, and particulate matter emissions using the entropy weighting method.	dimensionless

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

The built-up area ratio in YRD cities increased from 2012 to 2022, highlighting the region's rapid urban expansion. The ratio increased from 10.74% in 2012 to 11.88% in 2022, an increase of 1.14 percentage points. This expansion exhibited distinct phases: steady growth from 2012 to 2014, a plateau or slight decline from 2015 to 2016, and stronger growth after 2017. This aligns with the New-Type Urbanization pilot policy. The expansion of built-up areas provides context for interpreting UGLUE changes. The rise in both built-up area ratios and UGLUE following policy implementation indicates that the new urbanization model has steered urban expansion toward a more intensive and greener path.

Figure 2 shows the spatiotemporal evolution of UGLUE in the Yangtze River Delta urban agglomeration from 2012 to 2022. The results show that the average annual UGLUE value for the YRD urban agglomeration was 0.622 during the study period, indicating an overall upward trend from 0.514 in 2012 to 0.795 in 2022. This evolution primarily stems from the region's continuous optimization of industrial structures and enhancement of environmental regulatory systems, which are driven by regional coordinated development strategies.

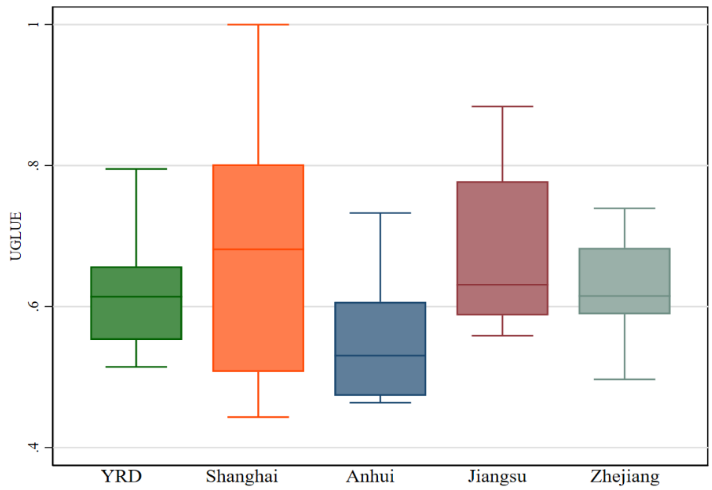

Figure 2. *Spatial and temporal trends of UGLUE in the YRD urban agglomeration*

At the provincial level, UGLUE exhibits distinct spatial gradients. Specifically, Shanghai recorded the highest annual average UGLUE value (0.677), followed by Jiangsu (0.666) and Zhejiang (0.627); meanwhile, Anhui registered a relatively lower value (0.558). These spatial differences reflect the provinces' varying stages of economic development, industrial upgrading processes, and environmental governance intensity.

Explanatory variable: New urbanization policy (DID)

We use $DID_{it} = Treat_i \times Post_t$ to measure new urbanization policy. Where Treat is the treatment group dummy variable, the value is 1 if the city is selected as a pilot city for "new urbanization" and 0 otherwise. Post is a time dummy variable. Cities were assigned a value of 1 for pilot designation and 0 for pre-treatment.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

Mediating variables

Land-intensive utilization (lnLiu): The economic output per unit of construction land area is used to measure land-intensive utilization efficiency.

Green technological innovation (lnGti): Based on Du et al. (2019), replacing the output of green technological innovation with the "logarithm of green patent authorization."

Industrial structure upgrading (Isa): Chang et al. (2023) used the industrial structure hierarchy coefficient as a proxy variable. The calculation formula is: ISA = 1 × primary + 2 × secondary + 3 × tertiary (primary, secondary, and tertiary refer to the proportion of output from the primary, secondary, and tertiary industries, respectively).

Control variables

Consistent with the literature on the determinants of urban land efficiency, we operationalized the control variables using theoretically grounded metrics. These metrics include: (i) Economic development is measured by the logarithm of real GDP per capita, (ii) industrial structure is measured by the ratio of tertiary to secondary industry output, (iii) openness is measured by the ratio of foreign direct investment to GDP, (iv) environmental regulation is measured by a textual analysis of government reports following Wang et al., 2024, and (v) transportation infrastructure is measured by the logarithm of total freight volume.

Table 2 provides a concise overview of all variable definitions.

Table 2. *Variable definitions*

Variables	Measurement	Symbol	Definitions
Explained variable	Urban green land use efficiency	UGLUE	Efficiency values based on non-expected output super-efficiency SBM model measurements
Explanatory variable	New urbanization policy	DID	Double differentials for "new urbanization" pilot cities
Mediating variables	Land-intensive utilization	lnLiu	Logarithm of economic output per unit of land area
	Green technological innovation	lnGti	Log of green technology patent grants
	Industrial structure upgrading	Isa	1 × primary + 2 × secondary + 3 × tertiary
Control variables	Economic development	Lned	Logarithm of real GDP per capita
	Industrial structure	Ind	Share of tertiary sector output/secondary sector output
	Openness	Open	Ratio of foreign direct investment (FDI) that is actually utilized to the total GDP
	Environmental rules	ER	Number of words in the sentence in which the environmental word frequency is located/total number of words in the government work report
	Transportation infrastructure	Lngt	Logarithm of total volume of goods transported

Sample selection and processing

In this study, 27 cities in the YRD urban agglomeration from 2012 to 2022 were selected as research subjects, and a panel dataset containing 297 city-year observations was constructed. *Table 3* provides the complete list of these 27 sample cities along with

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

their classifications as pilot or non-pilot cities for the new urbanization policy and their categorization by size.

Table 3. *Classification of sample cities*

City Name	Province	Pilot City	City Size	City Name	Province	Pilot City	City Size
Shanghai	Shanghai	YES	Large	Huzhou	Zhejiang	YES	Small
Nanjing	Jiangsu	YES	Large	Shaoxing	Zhejiang	NO	Medium
Wuxi	Jiangsu	YES	Medium	Jinhua	Zhejiang	YES	Medium
Changzhou	Jiangsu	YES	Medium	Zhoushan	Zhejiang	NO	Small
Suzhou	Jiangsu	YES	Large	Taizhou	Zhejiang	YES	Medium
Nantong	Jiangsu	YES	Medium	Hefei	Anhui	YES	Large
Yancheng	Jiangsu	YES	Medium	Wuhu	Anhui	YES	Small
Yangzhou	Jiangsu	YES	Medium	Maanshan	Anhui	YES	Small
Zhenjiang	Jiangsu	YES	Small	Tongling	Anhui	YES	Small
Taizhou	Jiangsu	YES	Small	Anqing	Anhui	YES	Small
Hangzhou	Zhejiang	NO	Large	Chuzhou	Anhui	YES	Small
Ningbo	Zhejiang	YES	Medium	Chizhou	Anhui	YES	Small
Wenzhou	Zhejiang	NO	Medium	Xuancheng	Anhui	YES	Small
Jiaxing	Zhejiang	YES	Small				

Note: City size classification (Large: >5 million; Medium: 3-5 million; Small: <3 million) is based on the average year-end population, following the criteria of Xu et al. (2019)

The raw data for the UGLUE evaluation system in *Table 1* came from the China City Statistical Yearbook (http://www.stats.gov.cn/sj/) and the EPS Statistical Data Retrieval and Forecasting Platform (https://www.epsnet.com.cn/). The UGLUE values in *Table 2* were calculated using the super-efficiency SBM model based on these data. Data on green technological innovation (lnGti) came from the patent database of the China National Intellectual Property Administration (https://www.cnipa.gov.cn), which is open to the public. Data on environmental regulation intensity (ER) were retrieved through a textual analysis of municipal government work reports accessed via official government portals (e.g., Shanghai Municipal People's Government Portal http://www.shanghai.gov.cn, Nanjing Municipal People's Government Portal http://www.nanjing.gov.cn). Additional variables, including socioeconomic and infrastructure indicators, were collected from provincial and municipal statistical yearbooks and bulletins (2013–2023) covering the YRD region. All the data sources are publicly accessible. To address missing values, we employed linear interpolation for intermittent year gaps. To control for potential distortions caused by outliers, we applied 1% bilateral winsorization to all continuous covariates.

Descriptive statistics

Table 4 presents descriptive statistics of the key variables. The balanced panel dataset included city-year observations from the YRD region from 2012 to 2022. Descriptive statistics revealed an average UGLUE score of 0.622 (SD = 0.178), aligning with established literature benchmarks (Liu et al., 2020). All measured variables exhibited acceptable dispersion, as evidenced by the standard deviations not exceeding 1.8, suggesting stable cross-sectional variation.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

***Table 4.** Descriptive statistics*

Variables	Obs	Means	SD	Min	Max
UGLUE	297	0.622	0.178	0.328	1
DID	297	0.609	0.489	0	1
lnLiu	297	3.204	0.449	2.16	5.043
Isa	297	2.417	0.113	2.111	2.729
lnGti	297	6.564	1.307	3.526	9.381
lned	297	2.146	0.413	1.138	2.923
ind	297	1.052	0.4	0.379	2.751
fdi	297	2.701	1.807	0.153	9.234
ER	297	0.955	0.236	0.5	1.798
lngt	297	9.945	0.577	8.709	11.844

Note: See Table 2 for variable definitions. SD = Standard Deviation; Obs = Number of observations

Results and analysis

Baseline results

Table 5 provides robust empirical evidence that the new urbanization policies significantly improved UGLUE, as estimated by the baseline model (*Eq.1*). The DID estimator yields consistently positive coefficients across all specifications. The initial results in column 1 demonstrate a statistically significant policy effect ($p < 0.01$) in the simple regression framework. This positive association persists in column 2 without fixed effects, suggesting preliminary policy effectiveness. The subsequent analyses in columns 3–6 reveal that the DID estimates remain statistically significant ($p < 0.01$) after the introduction of the regional and temporal fixed effects and comprehensive control variables. The coefficient stabilizes at 0.109 under the full fixed effects specification. These robust results demonstrate both economic and statistical significance at the 1% level. They provide compelling evidence that the new urbanization initiative effectively promotes sustainable land use practices in the YRD regions (Cheng et al., 2023). Thus, the results from *Eq.1* validate H1.

Drawing on the empirical results of the analysis and discussion methods of Alnafrah et al. (2025), the policy effect identified in this study—a 10.9% increase in UGLUE—is consistent with previous research findings. However, it also reveals some subtle differences. For instance, Zhang et al. (2025) discovered an almost identical effect size (11.2 percentage points) in their investigation into the impact of urbanization on UGLUE in eastern China, which further validates the reliability of our findings. Meanwhile, Wang et al. (2021) reported that smart city pilot policies in 152 Chinese cities yielded a greater policy effect (an increase in UGLUE of 15%). This suggests that the extent of policy impacts may vary depending on the specific type of urbanization initiative and regional context. These findings further support the results of this study. These mutually corroborating results suggest that different types of new urbanization policies have comparable effects in enhancing land green utilization efficiency.

Endogeneity tests

Instrumental variable method

To address potential endogeneity concerns, we employ one-period lagged policy variable (DID) as an instrumental variable (IV). As shown in *Table 5*, the empirical results are as follows. The first-stage regression in column (1) demonstrates a statistically significant positive relationship (1% level) between L.DID and the current-period policy variable, satisfying the relevance condition for instrumental validity, and the second-stage results in column (2) reveal that the IV-adjusted DID coefficient (0.131) maintains both its positive sign and statistical significance (p <0.01). These findings confirm that our baseline conclusion that new urbanization policies significantly enhance ULGUE, as estimated by *Eq.1*, even when accounting for endogeneity through appropriate instrumentation.

Table 5. *Baseline regression results*

Variables	UGLUE					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
DID	0.056*** (0.021)	0.035* (0.021)	0.067*** (0.022)	0.041* (0.024)	0.070** (0.034)	0.109*** (0.035)
lned		0.089*** (0.029)		0.034 (0.039)		-0.031 (0.047)
ind		0.026 (0.033)		0.071* (0.040)		0.128*** (0.041)
ER		-0.098** (0.042)		-0.105** (0.042)		-0.103** (0.040)
fdi		-0.020*** (0.006)		-0.015** (0.007)		-0.008 (0.006)
lngt		0.032 (0.022)		0.056** (0.024)		0.046** (0.023)
_cons	0.587*** (0.016)	0.213 (0.205)	0.581*** (0.016)	0.038 (0.218)	0.579*** (0.023)	0.149 (0.204)
Province FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	Yes	Yes
N	297	297	297	297	297	297
R^2	0.024	0.162	0.092	0.181	0.268	0.338

Notes: Standard errors are indicated in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. FE represents fixed effects. The same applies to the other tables

Parallel trend test

Figure 3 presents the temporal evolution of UGLUE metrics for YRD cities from 2012 to 2022. The blue line represents the treatment group (pilot cities), and the red line represents the control group (non-pilot cities). Both pilot and non-pilot cities exhibit the evolutionary characteristics of “stable growth, followed by a brief retraction, and then accelerated improvement.” A stable increase was observed between 2012 and 2016, while a significant decrease was observed between 2016 and 2017. After 2017, the rapid growth phase began. Before the policy was implemented, the development trajectories of the two groups of cities converged. After the policy was implemented, the pilot cities showed a sustained and rapid upward trend, whereas the non-pilot cities showed fluctuating growth. A comparative analysis shows that, except for individual years such as 2018 and 2020, pilot cities consistently outperform non-pilot cities in terms of efficiency levels. Specifically, when the policy was launched in 2016, the UGLUE values of the pilot and non-pilot cities were 0.65 and 0.57, respectively, with a gap of 0.08. By 2022, the efficiency of the two types of cities had increased to 0.82 and 0.70, respectively, and the gap had widened to 0.12. These results strongly confirm that the “new urbanization”

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

policy has significantly increased the efficiency of pilot cities. They also confirm that the "new urbanization" pilot policy has improved the UGLUE and continues to widen the gap between pilot and non-pilot cities.

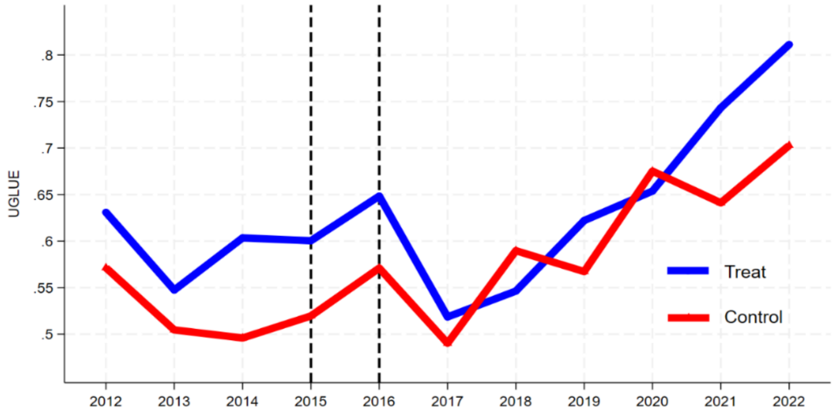

Figure 3. *Urban green Land use efficiency trend in the YRD (2012–2022). Note: The blue line represents the treatment group (pilot cities). The red line represents the control group (non-pilot cities). The vertical line indicates the policy implementation year (2015-2016)*

PSM-DID test

To strengthen the robustness of our analysis, we employ a propensity score matching difference-in-differences (PSM-DID) approach to address potential selection bias. The implementation process comprises three key steps. First, we estimate propensity scores through a logit regression incorporating city-level characteristics, drawing on Huang et al.'s (2024) methodology. Second, we categorize the cities into treatment and control groups based on their participation in the new urbanization pilot program. Third, we perform matching using three complementary methods: 0.1 caliper matching, one-to-one nearest-neighbor matching, and kernel matching. Matching is conducted in the pre-policy period (t - 1). The matching diagnostics confirmed a satisfactory balance between the treatment and control groups across observable characteristics, including digital innovation indicators. This matching procedure helps approximate the quasi-experimental conditions. As shown in *Table 6* (columns (3) and (4)), the PSM-DID estimates indicate statistically significant treatment effects of 0.099 (caliper matching) and 0.104 (kernel matching), supporting our conclusion that the urbanization pilot program effectively enhanced green land use efficiency.

Robustness tests

To verify the robustness of the research findings, we present a test based on three dimensions.

Lagged effect test

To account for potential delays in policy impacts, we use a one-period lagged policy variable in our analysis. The results in *Table 7* (column (1)) show two key findings: The lagged treatment effect is still statistically significant at the 1% level, and the effect size is similar to our baseline estimates. This matches the dynamic effect patterns documented in Chen et al.'s (2021) study on similar urban development policies.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

Table 6. *Endogeneity tests*

Variables	Instrumental variable test		PSM-DID test	
	DID	**UGLUE**	**Cal**	**Kernel**
	(1)	**(2)**	**(3)**	**(4)**
L.DID	0.804*** (0.0621)			
DID		0.131*** (0.045)	0.099* (0.040)	0.104* (0.033)
First-stage F statistic	167.490***			
Cragg-Donald Wald F statistic		382.876		
Kleibergen-Paak rk LM statistic		47.238***		
Control variables	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	270	270	134	286
R^2	0.882	0.138	0.280	0.315

Note: L.DID is the one-period lagged DID variable. PSM-DID = Propensity Score Matching Difference-in-Differences; Cal = Caliper matching. Kernel = kernel matching

Table 7. *Robustness tests*

Variables	Lagged effect	Sample exclusion	Policy controls	
	One-period lagged policy	**Municipalities excluded**	**LCCP**	**SCC**
	(1)	**(2)**	**(3)**	**(4)**
L.DID	0.105*** (0.035)			
DID		0.101*** (0.036)	0.102*** (0.035)	0.107*** (0.035)
LCCP			0.031 (0.021)	
SCC				0.030 (0.023)
Control variables	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	270	286	297	297
R^2	0.372	0.323	0.343	0.342

Note: LCCP = Low Carbon City Pilot policy dummy; SCC = Smart City Construction policy dummy

Special sample handling

To address the potential estimation bias from outlier values, we conducted additional analyses by removing municipal-level observations. As shown in column (2) of *Table 7*, the DID estimates maintain their statistical significance while demonstrating notable consistency with our baseline results. This robustness check aligns with the methodological approach outlined by Ferrara et al. (2012) and ensures that our key findings are largely unaffected by the inclusion of specific administrative samples.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

Competitive policy control

Research has shown that both the Low Carbon City Pilot (LCCP) and Smart City Construction (SCC) initiatives affect UGLUE (Wang et al., 2021; Liu et al., 2022). In accordance with Athey and Imbens' (2022) methodological approach, we incorporate policy dummy variables for these programs in our baseline specification to account for potential confounding effects. As shown in columns (3) and (4) of *Table 7*, the key explanatory variables continue to show positive significance, with effect sizes similar to our initial estimates. This multiple validation process aligns with the robust analysis framework proposed by Roth et al. (2023), further confirming the reliability of the findings.

Mechanism tests

In line with the theoretical framework presented in Section 2, the following mediation analyses provide empirical validation of the three hypothesized pathways: land use intensification, green technological innovation, and industrial structure upgrading. This study used the mediating model specified in *Eq.2* and *Eq.3* to systematically examine the impact of new urbanization policies on green land use efficiency. The main findings are as follows.

Land use intensification

The test of the mediating effect of intensive land use (columns (1) and (2) of *Table 8*) shows that the new urbanization policy indirectly promotes green land use efficiency by enhancing intensive land use levels. Specifically, implementing the policy significantly increased the average GDP of construction land (lnLiu) by 0.233 units ($p < 0.01$). This led to an increase in the green land utilization efficiency of 0.136 units ($p < 0.01$). These results support the research hypothesis of H2a and validate the policy's role in enhancing comprehensive land use efficiency by optimizing land resource allocation, including promoting compact city development and mixed land use planning.

Table 8. *Mechanism tests*

Variable	Land use intensification		Green technological innovation		Industrial structure upgrading	
	lnLiu	**UGLUE**	**lnGti**	**UGLUE**	**Isa**	**UGLUE**
	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.233*** (0.079)	0.078** (0.033)	0.479*** (0.149)	0.079** (0.034)	0.038*** (0.009)	0.094*** (0.036)
lnLiu		0.136*** (0.025)				
lnGti				0.064*** (0.013)		
Isa						0.417* (0.233)
_cons	3.718*** (0.468)	-0.357* (0.215)	-1.425 (0.875)	0.240 (0.197)	2.214*** (0.052)	-0.775 (0.555)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	297	297	297	297	297	297
R^2	0.451	0.402	0.773	0.388	0.891	0.345

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

Green technological innovation

Green technological innovation is a significant channel through which the new urbanization policy enhances UGLUE, as shown in columns (3) and (4) of *Table 8*. This is confirmed by the statistically significant coefficients, which show that policy-induced technological advancements contribute to sustainable land use. The empirical results indicate that implementing the policy increases the number of green patents granted (lnGti) by 0.479 units ($p < 0.01$) and consequently increases green land use efficiency by 0.064 units ($p < 0.01$). These results validate research hypothesis H2b, confirming that policy incentives such as R&D subsidies and tax breaks effectively encourage enterprises to innovate environmentally friendly technologies, thereby reducing the carbon emission intensity of land use.

Industrial structure upgrading

As shown in columns (5) and (6) of *Table 8*, the mediation analysis indicates that upgrading the industrial structure is an effective channel through which the new urbanization policy enhances land use efficiency. Policy implementation was found to increase the industrial structure hierarchy coefficient (Isa) by 0.038 units ($p < 0.01$), thereby increasing land green utilization efficiency by 0.417 units ($p < 0.1$). These findings support the policy's role in optimizing land use efficiency by promoting the transformation of industries into green, high-end sectors through strict industrial access standards and environmental regulatory systems. Thus, the reasonableness of research hypothesis H2c is illustrated.

Heterogeneity analysis

Spatial heterogeneity

Regional economic disparities play a critical role in shaping green urban development. Given the substantial variations across regions in economic development, ecological conditions, and land use patterns, the impacts of the new urbanization pilot policy likely exhibit pronounced spatial heterogeneity. To examine these differential effects, we conducted separate empirical analyses for the Anhui, Jiangsu, and Zhejiang provinces within the YRD region using the specification shown in *Eq.1*. The sub-regional regression results (*Table 9*) reveal distinct policy effects: Anhui Province demonstrates the strongest response, with a coefficient of 0.353, substantially exceeding the YRD average (0.109); Zhejiang Province shows an effect (0.133) comparable to the regional mean, maintaining statistical significance; and Jiangsu Province's estimated coefficient remains statistically insignificant. This regional difference is mainly due to the differences in the development stages and industrial structures of the three provinces. Anhui, as a late-developing region, has a more significant policy dividend release; Jiangsu has a higher level of urbanization, so the marginal effect of the policy is relatively limited; and in Zhejiang, owing to its balanced urban–rural development model, the effect of the policy is synchronized with that of the region as a whole.

Economic development level

This study uses Rodrik et al.'s (2004) analytical framework to examine regional heterogeneity in policy effects. The GDP per capita is a key indicator of the level of economic development. Cities were classified into high- and low-development groups

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

based on the median sample values for subgroup analysis. Applying *Eq.1* to these subgroups, the regression results in *Table 10* columns (1) and (2) demonstrate pronounced regional disparities. Highly developed cities exhibited a strong policy effect (coefficient = 0.137, p <0.01), whereas less-developed cities showed a weaker, statistically insignificant impact (coefficient = 0.087). These results underscore the importance of urban economic development as a moderating factor in the effectiveness of new urbanization policies in promoting land greening. This observed variation arises primarily from the superior capabilities of developed regions in green technology adoption and environmental governance. This enables more efficient translation of policy inputs into tangible efficiency gains. Conversely, less-developed areas encounter implementation barriers owing to resource and technological limitations that constrain policy effectiveness.

Table 9. *Spatial heterogeneity*

Variables	UGLUE			
	YRD	**Anhui**	**Jiangsu**	**Zhejiang**
	(1)	**(2)**	**(3)**	**(4)**
DID	0.109*** (0.035)	0.353*** (0.110)	-0.040 (0.096)	0.133*** (0.045)
Control variables	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	297	88	99	99
R^2	0.338	0.538	0.500	0.382

Table 10. *Internal conditions heterogeneity analysis*

Variables	UGLUE						
	High economic development level	**Low economic development level**	**Resource-based cities**	**Nonresource -based cities**	**Large cities**	**Medium cities**	**Small cities**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
DID	0.137*** (0.041)	0.087 (0.061)	-0.078 (0.169)	0.133*** (0.034)	-0.022 (0.074)	0.114** (0.044)	0.098** (0.022)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	143	154	66	231	55	110	132
R^2	0.560	0.389	0.622	0.320	0.837	0.398	0.410

Resource endowment

In this study, the sample cities were categorized as either resource or non-resource types according to the State Council's classification criteria for the National Sustainable Development Plan for Resource-Based Cities (2013–2020). As *Table 10* (columns (3) and (4)) shows, the estimation results based on *Eq.1* demonstrate significant heterogeneity in policy effectiveness across city types. In non-resource-based cities, the new urbanization policy has a positive, statistically significant effect on green land use

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

efficiency ($\beta = 0.133$, $p < 0.01$), confirming its effectiveness in promoting sustainable land management. By contrast, the estimated coefficient in resource-dependent cities is negative and statistically insignificant ($\beta = -0.078$), suggesting limited policy impact. These results imply that a policy's effectiveness depends on the urban economic structure. Non-resource cities benefit substantially from greater adaptability and diversified industrial bases. This difference stems from the different developmental characteristics of the two types of cities, which are limited by the locking effect of resource-dependent industries and face greater barriers to transformation. Compared with cities that depend on natural resources, non-resource cities have a competitive advantage in terms of industrial diversification. This strengthens their ability to adapt to policy changes and undertake structural transformation. These results highlight the important moderating role of a city's industrial base characteristics on the effectiveness of policy implementation.

City size

This study used the city size division criteria adopted by Xu et al. (2019), which classify cities based on their average year-end population size. According to population size, the sample cities were divided into three categories: small (< 3 million), medium (3–5 million), and large (> 5 million) cities. According to the regression results from *Eq.1*, as shown in *Table 10* in columns (5)–(7), the urbanization initiative has had a significant impact on UGLUE in small and medium-sized cities ($p < 0.05$), while its effect on large cities remains statistically insignificant. This heterogeneous feature may stem from three factors. First, small- and medium-sized cities are in an accelerated period of urbanization, so the marginal effects of policy interventions are more pronounced. Second, large cities have already established a relatively mature development model, so there is limited space for institutional innovation. Third, small- and medium-sized cities demonstrate stronger resilience in implementing policies regarding land intensification and environmental governance, whereas large cities face more complex systemic transformation constraints. These findings provide an important basis for formulating differentiated urbanization policies.

Discussion

The findings of this study align with and expand upon existing literature on urbanization and sustainable land use. Here, we compare our results with the theoretical expectations and prior findings reviewed in section 2 to offer new insights into the mechanisms and contextual factors that shape policy effectiveness.

Our baseline result confirms that new urbanization policies significantly improve UGLUE, supporting An et al. (2025) and Cheng et al. (2023). Our results corroborate Williamson's (1975) transaction cost theory by showing that new urbanization policies reduce inefficiencies through land use intensification (H2a). This finding aligns with the results of Chen et al. (2016) and Seto et al. (2012). Our results provide robust empirical support for their proposed compact development models. As discussed by Li et al. (2024) and Yuan et al. (2020), the positive impact of green technological innovation (H2b) lends support to the EKC hypothesis. The significant effect identified here provides causal evidence for the positive correlation observed by prior researchers. Meanwhile, industrial upgrading (H2c) validates agglomeration economies in new economic geography, as described by Krugman (1991) and observed by Tang et al. (2020). Our mediation analysis

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

quantitatively confirms the importance of this pathway, which was central to their theoretical framework.

However, our study diverges from Cheng et al. (2023) by revealing limited policy effects in resource-dependent cities and highlighting the path dependence in these contexts. Our findings on spatial heterogeneity, which show stronger effects in late-developing regions and smaller cities, complement Tan et al.'s (2021), but provide more detailed evidence of the economic and structural drivers of this heterogeneity. Methodologically, our quasi-natural experiment design addresses the endogeneity concerns raised in previous studies (Zhang et al., 2025), and our integrated "policy–mechanism–efficiency" framework bridges the fragmentation of theory in the literature. Together, these contributions advance our understanding of how institutional innovations can reconcile urbanization with ecological sustainability and offer a replicable model for similar regions around the world.

Theoretical contributions

This study achieved three significant theoretical breakthroughs, offering fresh insights and approaches for related fields of research.

First, it confirmed the significant role of new urbanization policies in enhancing the efficiency of green land use through a rigorous empirical analysis. This finding combines urban development and green transformation innovatively and constructs a three-dimensional theoretical framework of "policy intervention, mechanism transmission, and efficiency enhancement." This framework expands the research dimension of traditional urbanization theory and reveals the key role of institutional innovation in solving land resource constraints. This also opens a new path for the interdisciplinary study of development and environmental economics.

Second, in terms of research methodology, this study employed a quasi-natural experimental design and established a mediation effect analysis model that incorporated multiple tests. This significantly improved the scientific rigor and reliability of the policy assessment. The three core mechanisms identified in the study—intensive land use, green technology innovation, and industrial structure upgrading—not only validate the policy transmission path but also provide a replicable methodological paradigm for similar studies.

Finally, in terms of regional cognition, this study revealed that the effects of new urbanization policies exhibit significant spatial heterogeneity, particularly in regions with slower economic development, non-resource cities, and small-to medium-sized cities, which demonstrate stronger policy responses. This finding deepens the theoretical understanding of differences in regional development and provides an important basis for formulating differentiated policies that are valuable for improving the theory of coordinated regional development.

Policy implications

Based on the findings, the YRD city cluster should adopt the following differentiated policy recommendations.

First, it should implement a regional development strategy with categorized guidelines. Late-developing regions (e.g., some cities in Anhui Province) should receive increased policy support, a special green transformation fund should be established, priority should be given to the eco-infrastructure project layout, and a cross-regional eco-compensation mechanism should be created. The focus of core cities (e.g., Shanghai,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

Suzhou, Hangzhou, and Nanjing) should shift to improving the quality and efficiency of land usage, establishing a full life-cycle management system for industrial land, and strengthening energy consumption per unit of GDP indicators. Simultaneously, regional synergistic development must be promoted, cross-provincial and municipal land indicator trading platforms must be established, and industrial gradient transfer and free flow of factors must be promoted.

Second, policy support for these three core mechanisms should be strengthened. Regarding intensive land use, the "MU for Heroes" evaluation system has been improved, and the evaluation results are directly linked to land use indicators and financial subsidies. Regarding green technological innovation, special funds need to support the research, development, and application of green technologies, and a regional green technology trading market should be established. To upgrade the industrial structure, a differentiated negative list for industrial access should be formulated, and stricter spatial controls should be imposed on energy-consuming industries.

Third, the institutional environment for policy implementation should be optimized. A coordinating mechanism for urban development should be established at the provincial level, and standards and assessment systems for environmentally friendly land use should be formulated uniformly. At the same time, the policy implementation, monitoring, and evaluation systems should be improved. The effects of policies should be evaluated regularly, and a dynamic adjustment mechanism should be established. Additionally, grassroots innovation should be encouraged, and conditional cities and municipalities should be supported in implementing policy pilots. Successful experiences should be summarized and promoted in a timely manner.

Policymakers should prioritize upgrading the industrial structure in late-developing regions (e.g., Anhui), promoting green technological innovation in high-growth cities (e.g., Shanghai), and intensifying land use in small-to-medium-sized cities, where policy elasticity is the greatest.

Limitations and future research

This study has several limitations. First, as the sample data were primarily from prefecture-level cities, there was no in-depth examination of the differences between districts and counties. Second, the analysis of the mechanism of action was based mainly on macro-level data and has not been validated at the micro-enterprise level. Third, the impact of external shocks such as climate change has not been sufficiently considered. Future studies could expand upon this study by analyzing data with greater granularity, examining micro-transmission mechanisms through enterprise-level research, and incorporating new dimensions such as climate resilience. This will improve the theoretical framework for new urbanization and green land use.

Conclusions

This study utilizes panel data (2012–2022) from the Yangtze River Delta urban agglomeration and a DID approach to evaluate the causal effects of New Urbanization policies on UGLUE. The key findings are as follows:

(1) The new urbanization pilot policies have a significant positive effect on UGLUE, and this effect remains robust after stability tests and endogeneity treatments.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

(2) Mechanism analysis indicates that policies enhance UGLUE through three pathways: promoting intensive land use, stimulating green technological innovation, and facilitating industrial restructuring.

(3) Policy effects display notable heterogeneity, with more substantial impacts observed in less-developed regions, non-resource-based cities, and small-to-medium-sized cities. Conversely, the effects are relatively limited in economically developed regions, resource-dependent cities, and large cities.

These findings suggest that policymakers should abandon a uniform approach in favor of region-specific strategies. Less-developed regions should prioritize green industrial transformation and infrastructure investment, while resource-based and large cities should focus on improving existing land use efficiency and institutional innovation. Reinforcing the synergistic mechanism of "land intensification–green technology–industrial upgrading" is essential to continuously improving UGLUE.

Acknowledgements. This research was supported by the Commerce Statistical Society of China. (Grant number: 2024STZD04) and the Guangdong Planning Office of Philosophy and Social Science Foundation (Grant number: GD24XYJ32).

REFERENCES

[1] Alnafrah, I. (2025): Evaluating efficiency of green innovations and renewables for sustainability goals. – Renewable and Sustainable Energy Reviews 209: 115137. https://doi.org/10.1016/j.rser.2024.115137.

[2] Alnafrah, I., Alqararah, K., AlJaradin, M. (2025): From linear to circular: Evaluating the effects of circular economy on sustainable development progress in the EU economies. – Journal of Environmental Management 382: 125383. https://doi.org/10.1016/j.jenvman.2025.125383.

[3] An, J., Su, Q., Yuan, X. (2025): The Impact of New Urbanization on Urban Land Green Use Efficiency in the Middle and Lower Yellow River, China: An Analysis Based on Spatial Correlation Networks. – Land 14(3): 625. https://doi.org/10.3390/land14030625.

[4] Athey, S., Imbens, G. W. (2022): Design-based analysis in difference-in-differences settings with staggered adoption. – Journal of Econometrics 226(1): 62-79. https://doi.org/10.1016/j.jeconom.2021.03h.014.

[5] Bixia, H., Jing, L., Bing, K. (2018): Evolution characteristics and influencing factors of urban land use efficiency difference under the concept of green development. – Economic geography 38(12): 183-189. https://doi.org/10.15957/j.cnki.jjdl.2018.12.023.

[6] Cai, Z., Song, G., Li, W. (2025): Does digital economy promote urban land green use efficiency? – Environment, Development and Sustainability 27(3): 8043-8064. https://doi.org/10.1007/s10668-024-04474-5.

[7] Chang, J., Wang, W., Liu, J. (2023): Industrial upgrading and its influence on green land use efficiency. – Scientific Reports 13(1): 2813. https://doi.org/10.1038/s41598-023-29996-w.

[8] Chen, J., Gao, J., Chen, W. (2016): Urban land expansion and the transitional mechanisms in Nanjing, China. – Habitat International 53: 274-283. https://doi.org/10.1016/j.habitatint.2015.11.029.

[9] Cheng, Z., Li, X., Zhang, Q. (2023): Can new-type urbanization promote the green intensive use of land? – Journal of Environmental Management 342: 118150. https://doi.org/10.1016/j.jenvman.2023.118150.

[10] Du, K., Li, P., Yan, Z. (2019): Do green technology innovations contribute to carbon dioxide emission reduction? Empirical evidence from patent data. – Technological Forecasting and Social Change 146: 297-303. https://doi.org/10.1016/j.techfore.2019.06.010.

[11] Ferrara, E. L., Chong, A., Duryea, S. (2012): Soap operas and fertility: Evidence from Brazil. – American Economic Journal: Applied Economics 4(4): 1-31. https://doi.org/10.1257/app.4.4.1.

[12] Grossman, G. M., Krueger, A. B. (1995): Economic growth and the environment. – Quarterly Journal of Economics 110(2): 353-377. https://doi.org/10.2307/2118443.

[13] Hoover, F. A., Meerow, S., Coleman, E., Grabowski, Z., McPhearson, T. (2023): Why go green? Comparing rationales and planning criteria for green infrastructure in US city plans. – Landscape and Urban Planning 237: 104781. https://doi.org/10.1016/j.landurbplan.2023.104781.

[14] Huang, J., Zhang, J. (2024): Digital economy development and enterprise investment–a quasi-natural experiment from the pilot strategy of "broadband China". – Journal of the Asia Pacific Economy 30(4): 1388-1415. https://doi.org/10.1080/13547860.2024.2369384.

[15] Krugman, P. (1991): Increasing returns and economic geography. – Journal of Political Economy 99(3): 483-499. https://doi.org/10.1086/261763.

[16] Li, G., Wang, C. (2024): Can smart cities promote Green technology innovation? Evidence from Chinese cities. – Clean Technologies and Environmental Policy 27: 3879-3895. https://doi.org/10.1007/s10098-024-02795-1.

[17] Liu, S., Xiao, W., Li, L., Ye, Y., Song, X. (2020): Urban land use efficiency and improvement potential in China: A stochastic frontier analysis. – Land Use Policy 99: 105046. https://doi.org/10.1016/j.landusepol.2020.105046.

[18] Liu, J., Feng, H., Wang, K. (2022): The low-carbon city pilot policy and urban land use efficiency: A policy assessment from China. – Land 11(5): 604. https://doi.org/10.3390/land11050604.

[19] Liu, Y., Alnafrah, I., Zhou, Y. (2024): A systemic efficiency measurement of resource management and sustainable practices: A network bias-corrected DEA assessment of OECD countries. – Resources Policy 90: 104771. https://doi.org/10.1016/j.resourpol.2024.104771.

[20] Ma, Q., Shi, F. (2023): New urbanization and high-quality urban and rural development: Based on the interactive coupling analysis of industrial green transformation. – Ecological Indicators 156: 111044. https://doi.org/10.1016/j.ecolind.2023.111044.

[21] OECD| European Commission. (2020): A new perspective on urbanisation. – https://doi.org/10.1787/d0efcbda-en.

[22] Rodrik, D., Subramanian, A., Trebbi, F. (2004): Institutions rule: the primacy of institutions over geography and integration in economic development. – Journal of Economic Growth 9: 131-165. https://doi.org/10.3386/w9305.

[23] Roth, J., Sant'Anna, P. H., Bilinski, A., Poe, J. (2023): What's trending in difference-in-differences? A synthesis of the recent econometrics literature. – Journal of Econometrics 235(2): 2218-2244. https://doi.org/10.1016/j.jeconom.2023.03.008.

[24] Seto, K. C., Güneralp, B., Hutyra, L. R. (2012): Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. – Proceedings of the National Academy of Sciences 109(40): 16083-16088. https://doi.org/10.1073/pnas.1211658109.

[25] Tan, S., Hu, B., Kuang, B., Zhou, M. (2021): Regional differences and dynamic evolution of urban land green use efficiency within the Yangtze River Delta, China. – Land Use Policy 106: 105449. https://doi.org/10.1016/j.landusepol.2021.105449.

[26] Tang, M., Li, Z., Hu, F., Wu, B. (2020): How does land urbanization promote urban eco-efficiency? The mediating effect of industrial structure advancement. – Journal of Cleaner Production 272: 122798. https://doi.org/10.1016/j.jclepro.2020.122798.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883

[27] Tone, K. (2001): A slacks-based measure of efficiency in data envelopment analysis. – European Journal of Operational Research 130(3): 498-509. https://doi.org/10.1016/S0377-2217(99)00407-5.
[28] Wang, A., Lin, W., Liu, B., Wang, H., Xu, H. (2021): Does smart city construction improve the green utilization efficiency of urban land? – Land 10(6): 657. https://doi.org/10.3390/land10060657.
[29] Wang, Z., Fu, H., Liu, H., Liao, C. (2023): Urban development sustainability, industrial structure adjustment, and land use efficiency in China. – Sustainable Cities and Society 89: 104338. https://doi.org/10.1016/j.scs.2022.104338.
[30] Wang, W., Xiao, D., Wang, J., Wu, H. (2024): The cost of pollution in the digital era: Impediments of air pollution on enterprise digital transformation. – Energy Economics 134: 107575. https://doi.org/10.1016/j.eneco.2024.107575.
[31] Williamson, O. E. (1975): Markets and hierarchies: analysis and antitrust implications: a study in the economics of internal organization. – University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship. https://doi.org/10.2307/2392191.
[32] Xu, G., Jiao, L., Yuan, M., Dong, T., Zhang, B., Du, C. (2019): How does urban population density decline over time? An exponential model for Chinese cities with international comparisons. – Landscape and Urban Planning 183: 59-67. https://doi.org/10.1016/j.landurbplan.2018.11.005.
[33] Yuan, B., Zhang, Y. (2020): Flexible environmental policy, technological innovation and sustainable development of China's industry: The moderating effect of environment regulatory enforcement. – Journal of Cleaner Production 243: 118543. https://doi.org/10.1016/j.jclepro.2019.118543.
[34] Zhang, Q., Kong, Q., Zhang, M., Huang, H. (2024): New-type urbanization and ecological well-being performance: A coupling coordination analysis in the middle reaches of the Yangtze River urban agglomerations, China. – Ecological Indicators 159: 111678. https://doi.org/10.1016/j.ecolind.2024.111678.
[35] Zhang, T., Tan, Y., Robinson, G. M., Bai, W. (2025): China's New-Style Urbanization and Its Impact on the Green Efficiency of Urban Land Use. – Sustainability 17(5): 2299. https://doi.org/10.3390/su17052299.
[36] Zheng, S., Kahn, M. E. (2013): China's bullet trains facilitate market integration and mitigate the cost of megacity growth. – Proceedings of the National Academy of Sciences 110(14): E1248-E1253. https://doi.org/10.1073/pnas.1309245110.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_861883