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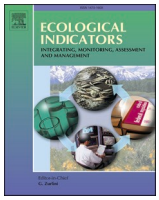



How does urban-rural integration shape land green use efficiency? Spatial and non-linear effects from Northeast China

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A R T I C L E I N F O

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A B S T R A C T

Urban-rural integration(URI) is a key pathway to promoting the equitable distribution of land resources and achieving sustainable land use in developing countries. However, how URI influences land green use efficiency (LGUE) remains insufficiently understood, especially in the context of regions characterized by pronounced urban-rural disparities. This study constructs a systematic analytical framework combining the Super-SBM model for LGUE measurement, a Spatial Durbin Model (SDM) to decompose the direct and spillover effects of URI on LGUE, and a TabPFN-SHAP pipeline capable of capturing nonlinear threshold effects to identify vital drivers across production, living, and ecological functions. The results reveal that: (1) URI and LGUE display divergent temporal patterns, with URI following an S-shaped trajectory(increased by 28.23%) and LGUE exhibiting a fluctuating upward trend (rose by 49.72%), accompanied by significant heterogeneity across city types; (2) URI significantly promotes the improvement of LGUE, with evident spillover effects on neighboring cities, showing marked regional heterogeneity;(3)SHAP decomposition reveals that labor mobility and asset allocation within production function, alongside ecological greening levels in ecological function, are the primary drivers of LGUE, all exhibiting significant nonlinear dose-response patterns. The findings provide empirical evidence and policy insights for developing countries undergoing industrial structural transitions on the potential role of URI in optimizing land green use transformation.

1. Introduction

Over the past five decades, accelerated urbanization has resulted in the chaotic expansion of cities into surrounding rural areas, posing a global challenge. From 1975 to 2020, the urbanized areas of large cities in developing countries expanded faster than those in high-income countries (Mudau et al., 2020). In the last 15 years, the average compound annual growth rate of built-up areas in sub-Saharan Africa outpaced the growth rate of urban populations (Forget et al., 2021). Between 1990 and 2020, megacities in East Asia like Beijing, Seoul, and Shanghai expanded their built-up areas by over 150%. This process inevitably led to the disorderly urban land use sprawl. Disorderly urban land use expansion intensifies land-use conflicts (Liao et al., 2023; Searchinger et al., 2018), primarily manifesting in persistent encroachment on agricultural and ecological spaces, unequal residential space distribution, and spatial cost transfer of green space renewal (Wu et al., 2025). Left unaddressed, these spatial contradictions may trigger systemic crises, including food insecurity, resource scarcity (Ma et al., 2024a), and biodiversity loss (World Cities Report, 2022). Such conflicts fundamentally stem from competing demands among social actors for limited land resources and their associated benefits. Therefore, identifying models that coordinate economic growth, efficient land use, and ecological preservation is critical to achieving the United Nations Sustainable Development Goal (SDG 11.3) of building inclusive, safe, resilient, and sustainable cities.

Rapid urbanization in developing nations has precipitated profound spatial restructuring, driving massive demographic shifts that manifest as concurrent urban sprawl and rural hollowing. For example, China's urbanization rate rose from 17.92% in 1978 to 64.72% in 2021(Liu et al., 2024a). This unprecedented transition has engendered severe structural distortions, notably the attrition of arable land, spatial congestion in urban cores, and the proliferation of idle suburban resources (Liu et al., 2012; Yang et al., 2020). This exacerbates functional imbalances across urban and rural systems. To mitigate these disparities, integrated urban-rural development has emerged as a pivotal spatial planning strategy. By systematically modulating the trajectory and velocity of labor, land, and capital flows, urban-rural integration (URI) seeks to optimize spatial allocation and ensure the long-term resilience

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of regional socioeconomic systems (Niu et al., 2023).

Currently, resource and environmental constraints are tightening, and the extensive land development model can no longer satisfy humanity's growing demand for enhanced living standards and ecological quality. Consequently, improving land use efficiency and fostering green transitions have become pivotal for reconciling intensified human-land contradictions (Sun et al., 2024). The LGUE serves as a comprehensive indicator for assessing the coordination of economic, social, and ecological benefits in land use processes, effectively mapping the efficiency and sustainability of various resource inputs throughout economic and social development (Tan et al., 2021). However, while various factors influence land efficiency, fragmented urban-rural structures often represent a notable institutional and spatial barrier that restricts optimal factor flows, thereby impeding the maximization of LGUE. Therefore, exploring how URI affects LGUE through a Production-Living-Ecological Space (PLES) lens is essential for optimizing national spatial configurations and achieving high-quality regional development.

As a traditional industrial base and a key grain-producing region, Northeast China faces multiple challenges, including persistent population outflows, slowing economic growth, and industrial structural imbalances. Over the past two decades, most cities in this region have experienced persistent shrinkage or stagnation, characterized by the concurrent phenomena of rural farmland abandonment and inefficient urban construction land utilization, underpinned by a deficiency in endogenous momentum for economic growth (Li et al., 2025a). Driven by the imperatives of a low-carbon transition, advancing URI is essential for Northeast China to recalibrate land allocation and elevate LGUE. As a quintessential case of industrial decline, this region offers critical land-use transition pathways and empirical lessons for other resource-dependent areas facing the decline of traditional industries.

2. Literature review and theoretical framework

2.1. Research on urban–rural integration and land green use efficiency

LGUE refers to the capacity to maximize socioeconomic benefits through efficient allocation of inputs such as land, capital, and labor while minimizing ecological and environmental losses. Early studies focused on the ratio of land input to economic output, aiming to maximize the economic value per unit of land (Zitti et al., 2015). This unidimensional economic perspective overlooks the intrinsic ecological value inherent in land use. Consequently, prevailing scholarship increasingly examines land utilization by reconciling economic productivity with environmental sustainability (Zhang et al., 2024a). Methodologies have evolved from single ratio-based approaches toward Data Envelopment Analysis (DEA), capable of accommodating multi-input and multi-output systems. Notably, the Super-efficiency Slacks-Based Measure (Super-SBM) model effectively remedies the limitations of radial DEA measures by rigorously incorporating slack variables and undesirable outputs (Du et al., 2010). Current research on LGUE focuses on characterizing spatiotemporal evolution patterns (Li et al., 2023; Li et al., 2024a), identifying key determinants (Zhu et al., 2025), and elucidating underlying driving mechanisms (Li et al., 2023; Xie et al., 2018). Existing literature predominantly explores LGUE's spatiotemporal evolution and its underlying determinants. Scholars have established a systematic “efficiency measurement–spatiotemporal effects–mediating mechanism” paradigm, revealing that LGUE is profoundly shaped by institutional innovations, such as digital governance (Feng et al., 2023; Xu et al., 2025) and low-carbon pilot policies (Jiang et al., 2023). Furthermore, transparent and secure land tenure arrangements support the optimal allocation of land resources by stabilizing investment expectations and incentivizing long-term stewardship (Koroso and Zevenbergen, 2024; Ma et al., 2024b). At the spatial and structural levels, factors such as the economic development model (Bian, 2024), regional integration model (Zhang et al., 2025), urban scale and expansion patterns (Guastella et al., 2017;He et al., 2020) exert complex influences on reshaping LGUE.

The urban-rural relationship of China has evolved from fragmentation to integration. The urban-biased policies before 1978, which segregated rural and urban areas for industrial accumulation, were gradually dismantled by market-oriented reforms and the rise of rural industries in the late 20th century. Since 2002, the state has prioritized synergistic urban-rural development, enacting a series of policies to foster equitable relations. Key initiatives, such as the historic abolition of agricultural taxes and the institutionalization of a unified pension insurance system, have been instrumental in bridging the urban-rural divide (Guan et al., 2025). The launch of the ‘Rural Revitalization Strategy’ in 2017 heralded a pivotal shift, indicating China's formal entry into integrated urban-rural development.

As urban-rural relations undergo restructuring, URI is essentially a coupling process involving bidirectional flows among multiple agents and factors. This research aims to facilitate urban-rural equivalence by fostering greater coordination across production-living-ecological (PLE) functions through factor mobility and institutional synergy (Zhan et al., 2023). URI has transitioned from static indicators of urban-rural societies through economic, demographic, social, and environmental dimensions (Jain et al., 2021;Liu et al., 2023) to dynamic evaluative frameworks grounded in factor mobility (Yang et al., 2021). In terms of impact mechanisms, scholarship has extensively explored the bifurcated effects of land system reforms (Guan et al., 2025; Chen and Long, 2019) and tourism development (Tan and Wang, 2025) on urban-rural relations, as well as the restructuring processes of urban and rural areas driven by infrastructure systems (Gutierrez-Velez et al., 2022) and neoliberal reforms (Jain et al., 2021).

Existing literature on the relationship between URI and land use primarily explores three themes. First, from a spatial restructuring perspective, studies emphasize how land market reforms and spatial planning reconfigure urban-rural land functions (Chen et al., 2020; Chen and Long, 2019). Second, research investigates how URI affects the transition of agricultural land and its associated efficiency. Existing studies confirm that URI underpins the optimization of agricultural industrial structures through the bidirectional flow of production factors. This process drives the implicit transition of cultivated land use while reshaping the multifunctional morphology of urban agricultural areas (Pan et al., 2024; Zhang and Li, 2024). Thirdly, a carbon emission perspective facilitates the evaluation of macro-level spatial effects of URI on both low-carbon land-use efficiency and carbon-emission intensity (Li et al., 2025b; Liu et al., 2024b). These studies suggest that URI shapes land use efficiency through two overarching pathways: institutional restructuring, which dismantles barriers between urban and rural land markets to enable functional reconfiguration, and factor reallocation, which redirects labor, capital, and technology across the urban-rural boundary to drive transitions in land use intensity and structure.

Despite abundant research findings, three critical gaps persist in current literature. First, the measurement scope of LGUE remains confined to specific categories of land. Scholars often evaluate land utilization efficiency for urban and rural sectors in isolation, lacking an objective assessment of actual land use levels across the entire urban-rural area. This perspective bias is reflected in the construction of the indicator system: selecting the built-up area of cities as the land factor input while neglecting core productive elements in rural areas (Xu et al., 2025; Zhang et al., 2024b). Second, there is a lack of a decomposition process to analyze how the intensity of spatial effects evolves across different stages of URI development. Third, prior studies concentrate on the effects of a single policy or factor on the efficiency of green land utilization, lacking a theoretical framework of the influence of the urban-rural comprehensive integration process on LGUE from production, living, and ecological functions.

2.2. Theoretical framework

URI is a process that uses land as the spatial carrier to ameliorate contradictions between humans and land within urban-rural regional systems through the flow of people, information, and capital. This indirectly alters the thresholds and rates of material cycling and energy transfer within land use systems (Liu et al., 2024c). Because its impact on land green use efficiency encompasses highly complex socioeconomic and spatial interactions, this study anchors its theoretical foundation in factor market dynamics and spatial reproduction theories. Consequently, a comprehensive analytical framework from a production, living, and ecological perspective is constructed to systematically untangle the interactive mechanisms driving this relationship (Fig.1).

In the production dimension, URI entails the optimal restructuring of production factors across urban-rural physical spaces. Factor market theory highlights the crucial regulatory roles of factor markets, input scale, and pricing mechanisms in producers' resource allocation processes (Lin and Chen, 2018). Dismantling urban-rural barriers facilitates the diffusion of capital, advanced technologies, and labor into rural hinterlands, thereby correcting historical resource misallocations(Zhan

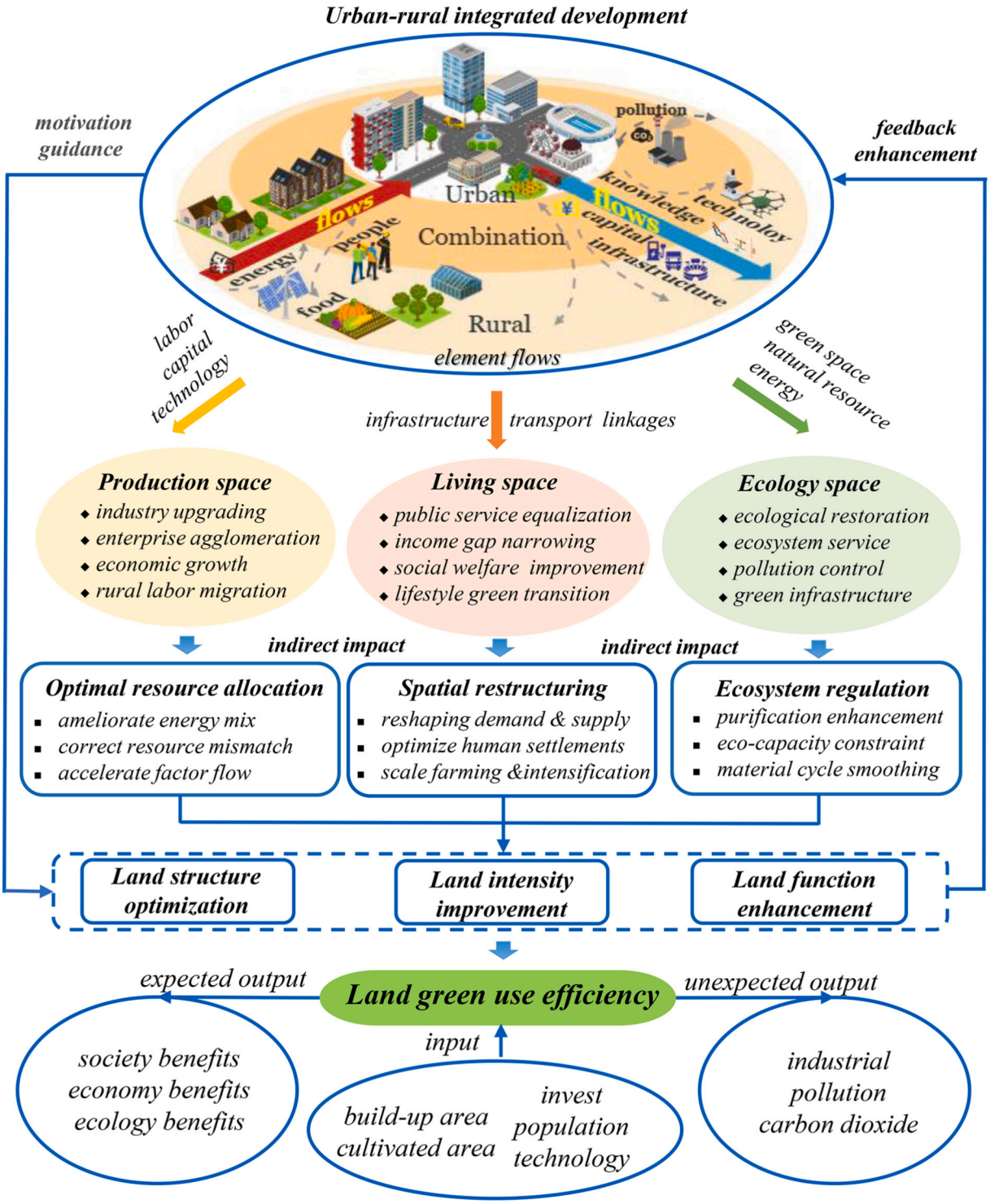

Fig. 1. Theoretical framework.

et al., 2023; Zhang et al., 2020). Technological spillovers from urban centers drive rural industrial agglomeration, effectively curbing scattered pollution and minimizing energy consumption per unit of output to enhance land use intensity. Concurrently, the labor factor initially migrates from rural to urban and subsequently flows back to the countryside, accelerating the development and utilization of construction land. This process transforms rural land from fragmented operations to scaled and intensive management, achieving complementarity of production factors between urban and rural areas.

In the living function, URI indirectly alleviates land carrying capacity pressures by dismantling the rigid functional patterns in the urban-rural dual structure, progressively reconstructing the spatial order and social relationships of urban and rural living environments (Ma et al., 2020). Space is not merely a site of production, but also a product of social relations (van Lanen and Meij, 2026). This process reconstructs the spatial order of human settlements. By advancing rural infrastructure and ensuring the equitable provision of public services, URI eliminates invisible barriers to resource allocation and promotes spatial justice (Zhao, 2025). The restructuring of spatial order has facilitated a rational distribution of population, enhanced the resilience in residential and consumption spaces, and alleviated inefficient land use caused by "urban ills" and "rural hollowing-out" (Fan et al., 2023). This process improves quality of life for urban and rural residents and narrows income disparities, shifting societal demands from basic material security to aspirations for a better living environment. This shift catalyzes the transformation toward sustainable lifestyles, reducing pressure on land systems and carbon emission intensity at the source.

In the ecology integration, URI reshapes the interaction model between people and land. It transforms the previous imbalance where cities generated pollution and rural areas absorbed it, shifting ecosystems from passive constraints to core assets that drive regional sustainable development. The establishment of urban-rural ecological corridors and environmental zoning dismantles fragmented landscape patterns, fostering a functionally integrated ecological community that directly amplifies the ecosystem service capabilities of land resources (Li et al., 2024b). Additionally, this process has fostered a positive feedback mechanism, facilitating the transformation of energy-intensive industries and reducing carbon emissions. The land's inherent capacity for water retention, purification, and carbon sequestration has been restored, effectively enhancing the ecological benefits of land use (Miroshnyk et al., 2022; Woodruff et al., 2021). By internalizing ecological conservation as a voluntary practice rather than an external mandate, integration provides a sustainable, endogenous impetus for continuous LGUE enhancement.

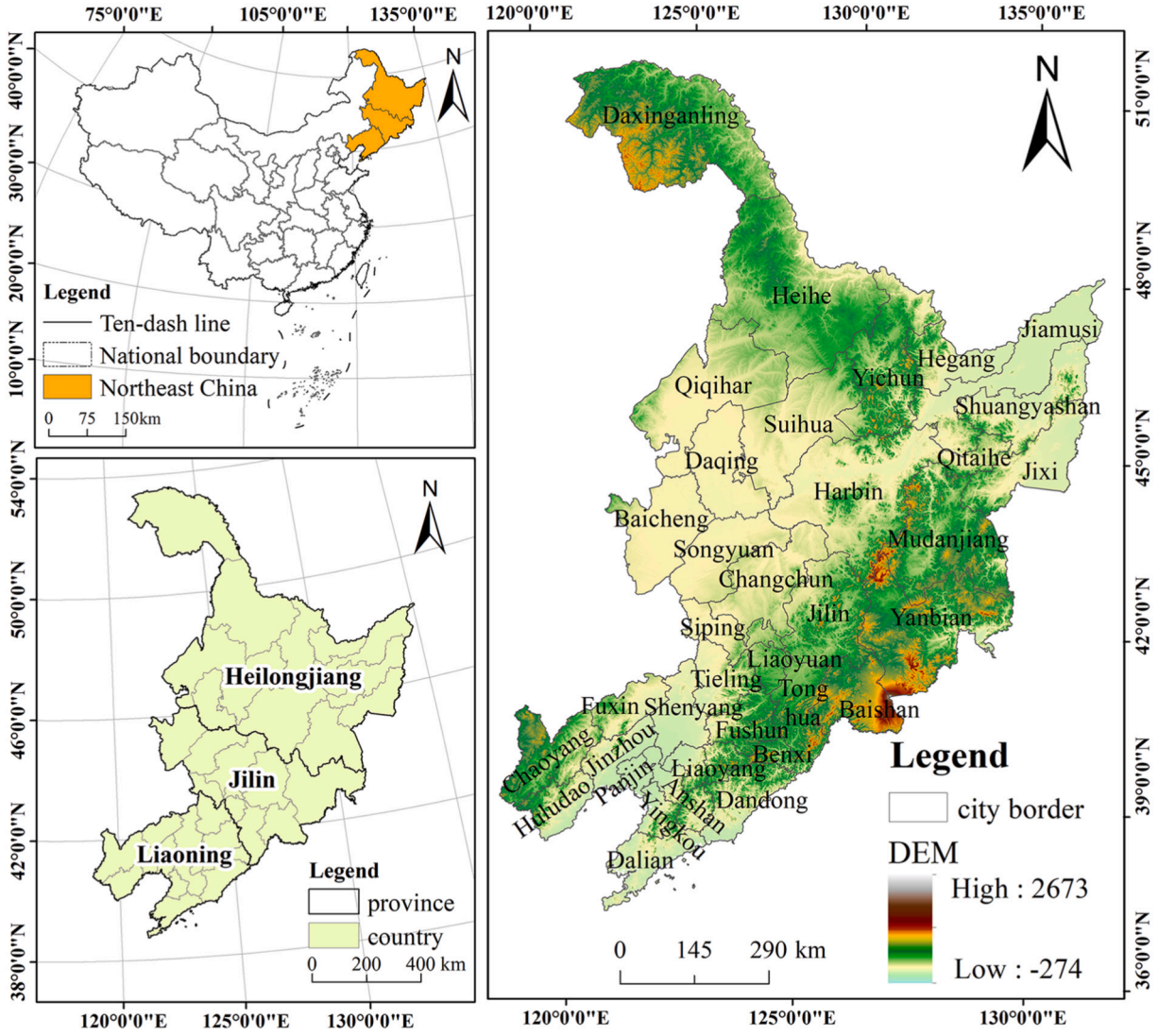

Fig. 2. Study area.

3. Study area and data resource

3.1. Study area

Northeast China, encompassing Jilin, Heilongjiang, and Liaoning provinces, represents the country's archetypal resource-based industrial base. Since 1949, the region has transitioned from rapid urbanization and industrial prosperity to gradual decline. Following the 1978 reform and opening up, the area faced multiple challenges, including resource depletion, population outflow, and land idleness, primarily due to the dominance of heavy industry and lagging tertiary development. In 2023, the region's urbanization rate reached 68.43%, surpassing most provinces nationally; yet total regional GDP remains among the lowest in the country, with an urban shrinkage rate as high as 44.12% (Yu et al., 2019). This mismatch between a high urbanization rate and low economic output perpetuates inefficient land use and widens the urban-rural income gap, hindering comprehensive revitalization of the old industrial base. Thus, the three northeastern provinces constitute a typologically representative study area (Fig.2).

This study uses 36 cities as the basic research unit. According to the National Sustainable Development Plan for Resource-Based Cities (2013−2020), 21 cities in the region are designated as resource-based, while the remaining 15 are classified as non-resource-based. Resource-based cities are further subdivided by natural endowment into comprehensive, coal-based, petroleum-based, mineral-based, and forest-based types (Table 1).

3.2. Data source

Socioeconomic data were drawn from official statistical yearbooks covering 2000–2023, including China Urban Statistical Yearbook, China Energy Statistical Yearbook, and China Rural Statistical Yearbook, and others supplemented by city-level statistical yearbooks and national economic and social development bulletins. Spatial and environmental data were sourced from multiple channels: cultivated land area and construction land area were extracted from the CLCD dataset (Yang and Huang, 2026); PM2.5 data were obtained from China's air quality monitoring stations (https://www.cnemc.cn/); forest area was derived from the CATCD (https://code.earthengine.google.com/a28dcf064bba1975f5a6c28400c41edb) dataset, patent authorization data was provided by the China National Intellectual Property Administration (https://www.cnipa.gov.cn/col/col61/index.html), energy consumption was estimated following the calculation method proposed by Wang and Zhang (2024) , carbon emissions data was sourced from the National Climate Data Center (https://www.ncdc.noaa.gov/cdo-web/datasets). The remaining missing values were imputed using multiple linear interpolation, moving averages, and trend extrapolation to ensure the continuity and scientific validity of the indicator system.

Table 1
The types of city functions in northeast China.

City types	City name
Non-resource-based cities	Dandong, Jiamusi, Harbin, Siping, Dalian, Chaoyang, Shenyang, Baicheng, Suihua, Yingkou, Liaoyang, Tieling, Jinzhou, Changchun, Qiqihar
Comprehensive cities	Huludao, Jilin, Tonghua, Baishan, Songyuan Mudanjiang, Heihe, Yanbian
Coal-based cities	Fushun, Fuxin, Liaoyuan, Jixi, Hegang, Shuangyashan, Qitaihe
Oil-based cities	Panjin, Daqing
Forestry-based cities	Yichun, Daxing'anling
Mining-based cities	Anshan, Benxi

4. Method and data processing

4.1. Indicator design

4.1.1. Indicator and calculation of URI

URI fundamentally reflects the degree of connectivity by which urban and rural areas form a shared developmental destiny, achieved through the reciprocal flows of physical factors (labor, land, capital) and intangible factors (institutions, planning, development paradigms). However, existing research predominantly characterizes the mobility and dynamic interaction of physical elements across demographic, social, environmental, economic, and spatial dimensions (Chen and Long, 2019). Drawing on Production-Living-Ecology (PLE) space theory and production factor theory, this study categorizes urban-rural system functions into three domains: production, living, and ecology, where the production function forms the material foundation for urban-rural development, the living function captures residents' well-being, and the ecological function serves as a vital safeguard for maintaining the system's resilience (Qin et al., 2024; Zhou et al., 2017). Therefore, a dynamic analytical framework for URI encompassing production, living, and ecological integration was constructed. Specifically, the framework comprises three dimensions: production integration (5 secondary indicators and 10 measurement factors), living integration (3 secondary indicators and 9 measurement factors), and ecological integration (4 secondary indicators and 10 measurement factors), with the detailed indicator system presented in Appendix Table S1.

4.1.2. The construction of LGUE

LGUE quantifies land value per unit area by balancing economic output and ecological benefits. Unlike previous studies that treat urban and rural land systems separately (He et al., 2020; Yan et al., 2025), this study integrates both into a unified analytical framework to construct an indicator system for assessing the overall LGUE of the urban-rural land system. The input indicators include both construction and arable land factors. For expected outputs, GDP value-added is used to reflect the comprehensive economic benefits of the entire region. Unexpected outputs include carbon emissions and a composite pollutant index calculated via the CRITIC method. All economic indicators undergo price inflation adjustments using 2000 as the base year to ensure data consistency and comparability (Table 2).

4.2. Method

4.2.1. Super-SBM model

DEA is an efficiency evaluation method based on linear programming. Building on this, Tone proposed the Super-SBM model, incorporating non-desirable outputs (Tone, 2001), and adopted a fractional

Table 2
LGUE index system.

Variable Types	Indicators	Index interpretation
Input	Land area	Urban built-up area (square kilometers) Cultivated land area (square kilometers)
	Invest factor	Total fixed asset investment (10^4 yuan)
	Labor population	Number of employed persons (10,000 people)
	Technology	Total agricultural machinery power (10,000 kW)
Expected Output	Economic benefits	Value added of GDP (hundred million yuan)
	Social benefits	Total retail sales of consumer goods (10,000 yuan)
	Ecological benefits	Green area of built-up areas (square kilometers)
Unexpected Output	Industrial pollution	Composite pollutant index
	Greenhouse gases	Carbon emissions (Million tons)

objective function for optimization. Compared with traditional CCR and BCC models, this approach directly handles slack variables and facilitates differentiation among efficient decision-making units (DMUs) with efficiency scores of 1, improving analytical precision. This study applies the variable returns-to-scale (VRS) Super-SBM model to measure LGUE across 36 northeastern cities from 2000 to 2023. The formula is as follows:

$$\min\theta = \frac{1}{n}\sum_{i=1}^{n}\frac{\overline{X_i}}{X_{ik}} \Big/ \frac{1}{t+s}\left(\sum_{r=1}^{t}\frac{\overline{Y_r}}{Y_{rk}} + \sum_{l=1}^{s}\frac{\overline{Z_l}}{Z_{lk}}\right) \tag{4.1}$$

$$s.t.\overline{X_i} \geq \sum_{j=1,j\neq k}^{m} x_{ij}\lambda_j, i = 1,2,\ldots,n$$
$$\overline{Y_r} \leq \sum_{j=1,j\neq k}^{m} y_{rj}\lambda_j, i = 1,2,\ldots,t$$
$$\overline{Z_l} \leq \sum_{j=1,j\neq k}^{m} z_{lj}\lambda_j, i = 1,2,\ldots,s$$
$$\lambda_j \geq 0, \mathrm{j} = 1,2,\ldots,\mathrm{m}, \mathrm{j} \neq \mathrm{k}$$
$$\overline{X_i} \geq X_{ik}, i = 1,2,\ldots,n$$
$$\overline{Y_r} \geq 0, \overline{Y_r} \leq Y_{rk}, r = 1,2,\ldots,t$$
$$\overline{Z_l} \geq 0, \overline{Z_l} \leq Z_{lk}, l = 1,2,\ldots,s$$

where min θ represents LGUE; n, t, and s denote the number of input, desired output, and undesired output variables, respectively;$\overline{X_i}$、$\overline{Y_i}$、$\overline{Z_i}$ are the corresponding slack vectors; λ_j is the weight value for each DMU on a specific indicator.

4.2.2. Spatial durbin model

Spatial econometric models are widely applied to quantify the spatial correlation among observed values within a specific region, primarily involving spatial error models (SEM), spatial lag models (SLM), and spatial durbin models (SDM). The SDM subsumes both the SEM and SLM as special cases, offering greater generality by incorporating spatial lag terms for both dependent and independent variables. Therefore, the SDM model is adopted to quantify the spatial effects of URI on LGUE. The model is as follows:

$$GLUE = \rho\sum_{i=1}^{n} W \times GLUE + \beta_1 URB + \beta_3 TR + \beta_4 PD + \beta_5 TEC +$$
$$\beta_6 OPEN + \beta_7 GOV + \theta_1\sum_{i=1}^{n} W \times URB + \theta_2\sum_{i=1}^{n} W \times TR + \theta_3\sum_{i=1}^{n} W \times PD$$
$$+\theta_4\sum_{i=1}^{n} W \times TEC + \theta_5\sum_{i=1}^{n} W \times OPEN + \theta_6\sum_{i=1}^{n} W \times GOV + \mu_i + \lambda_t + \delta_{it} \tag{4.2}$$

where ρ is the spatial autoregressive coefficient of the dependent variable, β_1-β_7 are direct effect coefficients; $\theta_j WX_j$ captures spatial lag terms reflecting spillover effects, θ reflects the degree of spatial spillover effects; λ_t, μ_i, and δ_{it} denote time effects, individual fixed effects, and the error term, respectively.

(1) Construction of spatial weight matrix

Three spatial weight matrices are constructed: W1 is based on economic distance. W2 is a geo-economic weight matrix that effectively balances geographic proximity and economic similarity. Following the research of Janatabadi and Ermagun (2024), a symmetric gravity matrix W3 is constructed to comprehensively capture complex economic-spatial interactions. The specific formulation is as follows.

$$W1_{ij} = \begin{cases} 1/|perGDP_i - perGDP_j| & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \tag{4.3}$$

$$W2_{ij} = \begin{cases} 1\Big/d_{ij}^{geo} \times \left(d_{ij}^{econ} + 1\right) & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \tag{4.4}$$

$$W3_{ij} = \begin{cases} perGDP \times perGDP_j \Big/ \left(d_{ij}^{econ}\right)^2 & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \tag{4.5}$$

where $perGDP_i$ is the average per capita GDP from 2000 to 2023 of city i;d_{ij}^{geo} is the actual geographic distance (km) between cities i and j, reflecting geographic accessibility; d_{ij}^{econ} denotes the absolute difference in average GDP between cities i and j, reflecting the economic distance gap.

(2) Variables

LGUE serves as the dependent variable, and URI as the core independent variable. Based on existing relevant literature and comprehensive consideration of factors such as economic development and ecological environment changes, five control variables are incorporated: population density (PD), openness to the outside world (OPEN), technological investment (TEC), government support intensity (GOV), and transportation infrastructure level (TR). The specific interpretation is available in Appendix S3.

4.2.3. Ensemble machine learning model selection

Conventional parametric models often fail to capture the complex nonlinear interactions and threshold dynamics inherent in multidimensional spatial data. To overcome these limitations, we employ ensemble machine learning models to decode the nonlinear effects of internal factors within urban-rural production, living, and ecological subsystems on LGUE. Six models are evaluated: linear regression (LR), random forest (RF), TabPFN, and three gradient-based ensemble algorithms. LightGBM integrates gradient-based one-sided sampling and exclusive feature bundling to accelerate training and reduce memory overhead, though it remains susceptible to overfitting on small samples. XGBoost incorporates regularization terms and second-order Taylor expansion to enhance generalization (Bentéjac et al., 2021), while CatBoost employs symmetric tree structures and Ordered Boosting to mitigate gradient bias and overfitting (Ding et al., 2021). Tabular Prior-data Fitted Network (TabPFN) is a transformer-based foundation model that uses structural causal models to pre-train on millions of synthetic datasets and to perform Bayesian predictions through in-context learning. Compared to traditional machine learning models, TabPFN exhibits the following optimizations for regression and classification of small sample data (≤10,000 samples): (1)inference speedups by separating the training and test samples; (2) By employing a two-way attention mechanism that focuses separately on rows (features) and columns (samples), the complexity of feature interactions is limited, reducing the risk of overfitting (Hollmann et al., 2025). While this model has already achieved cutting-edge advancements in fields such as cancer research, organic chemistry, and groundwater science, it still holds immense untapped potential in the realm of environmental sustainability (Granitto et al., 2025; Li et al., 2025c; Sun et al., 2026).

Although tree-based ensemble methods demonstrate competitive performance on tabular data at moderate-to-large scales (Shwartz-Ziv and Armon, 2022), their relative advantage deteriorates markedly as dataset size decreases, with TabPFN achieving superior generalization within precisely the small-sample regime (McElfresh et al., 2023). Compounding this scale-dependence, tree-based methods face heightened overfitting risk when available observations are insufficient to stabilize recursive feature partitioning that hyperparameter regularization cannot fully offset (Cawley and Talbot, 2010). The prior-data fitted architecture of the TabPFN model mitigates the risk of overfitting on

small-to-medium datasets (≤10,000 samples).

Model inputs comprise 12 secondary features across production, living, and ecological subsystems. The dataset is partitioned into 80% training and 20% test sets. Hyperparameters for ensemble models are optimized via Bayesian optimization using the Optuna framework (Xie et al., 2025), while TabPFN retains its default configuration. Ultimately, the optimal model is selected based on the comprehensive performance of R^2, root mean square error (RMSE), and mean absolute error (MAE).

4.2.4. Interpretable machine learning

To address the limited interpretability of ensemble models in capturing the correlation between input features and predicted values, the SHAP algorithm is applied to untangle the specific directional contributions of each input feature. Grounded in cooperative game theory, this algorithm calculates the marginal contribution of each variable to the final prediction, ensuring a uniquely fair allocation of feature importance without sacrificing local interpretability (Lundberg and Lee, 2017). The Shapley value for feature i is computed as:

$$SHAP_i = \sum_{S \subseteq Q \setminus \{i\}} \frac{|S|!(|Q| - |S| - 1)!}{|Q|!} [f_x(S \cup \{i\}) - f_x(S)] \quad (4.6)$$

where Q denotes the full feature set, S is an arbitrary subset excluding feature I, $|S|$ is the number of input features in subset S, $f_x(S \cup \{i\})$ denotes the model output value for feature subset $S \cup \{i\}$ when the model includes the feature i, $f_x(S)$ and the model output value for feature subset S when the model excludes the feature i. $[f_x(S \cup \{i\}) - f_x(S)]$ represents the pure marginal contribution of feature i when introduced into subset S.

To further delineate the nonlinear thresholds and optimal intervals through which individual features influence LGUE, a Generalized Additive Model (GAM) is applied to fit the SHAP value distributions. We performed GAM fitting with the raw values of each metric as independent variables and their corresponding SHAP values as dependent variables, obtaining smooth response curves. By analyzing the changes in the first derivative of the fitted curves, we could precisely identify the threshold where a feature's positive effect transitions to a negative one. This step transforms qualitative graphical observations into quantitative threshold measurements, enabling a more accurate assessment of each feature's influence trend (Zhu et al., 2025).

5. Analysis results

5.1. Dynamic evolution of the level of URI

The overall URI in Northeast China rose from 0.209 in 2000 to 0.268 in 2023. Provincial-level increases stood at 16.59%, 28.38%, and 36.90% for Jilin, Liaoning, and Heilongjiang, respectively (Fig.3). Temporally, URI evolves through three distinct stages: a latent period of low-level stability (2000–2005), a take-off phase of rapid acceleration (2006–2014), and an S-shaped adjustment phase characterized by volatility (2015–2023) (Fig.4). This trajectory underscores the complexity of the URI process, shaped by the interplay of economic transformation and population mobility, reflecting the complexity and uncertainty in the internal dynamics of urban-rural systems (Zhao et al., 2023a).

At the city level, heterogeneity is pronounced (Fig.5). Core metropolises maintain dominance, with rapid growth, benefiting from industrial agglomeration and population mobility. Changchun, Harbin, and Shenyang ranked among the top three, with URI values rising to 0.4217, 0.4805, and 0.4810, respectively. Conversely, resource-based cities such as Songyuan and Chaoyang exhibit lower growth rates below the average, adhering to an inverted-U trajectory from 2007 to 2023. The downward trend after 2016 may largely be precipitated by the synergetic pressures of industrial relocation and demographic outflow.

Between 2000 and 2023, high-value zones expanded steadily, concentrating in economically developed cities including Harbin, Changchun, and Dalian(Fig.6). The low-value zone contracted progressively, shifting from its 2000 concentration in most of Heilongjiang and

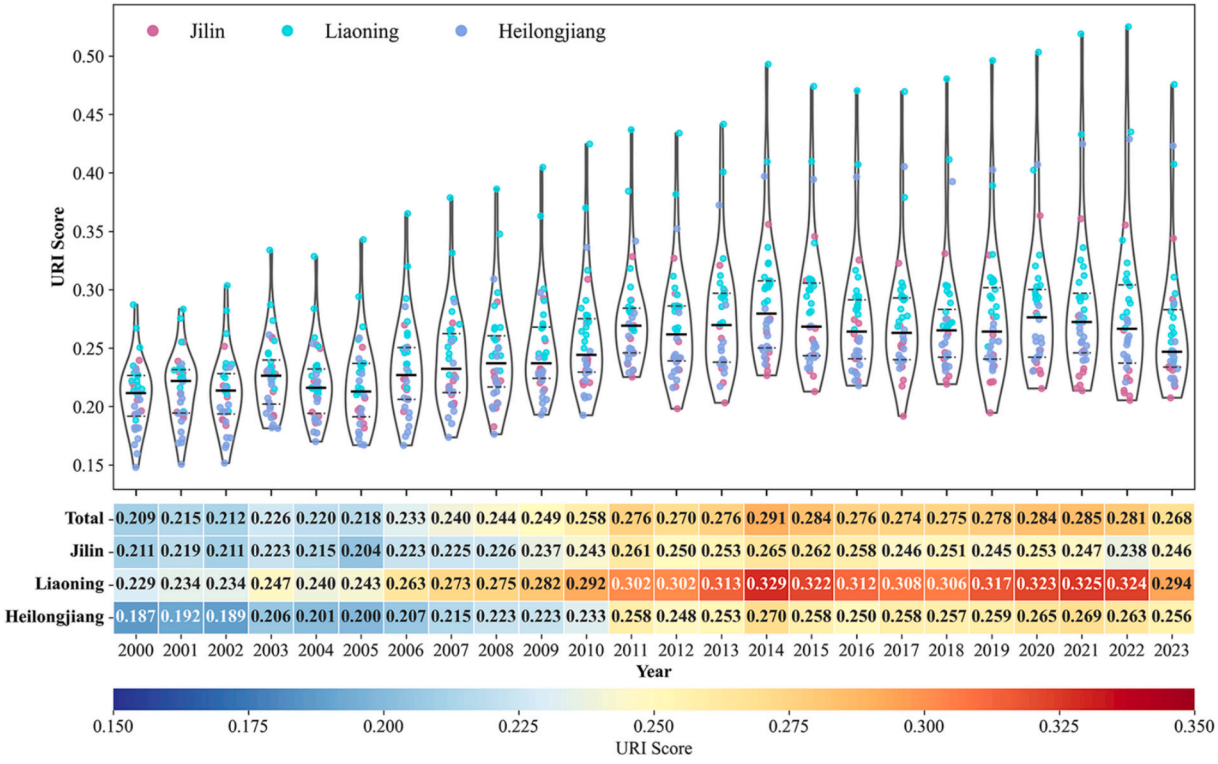

Fig. 3. Temporal changes of URI levels in different regions during 2000–2023.

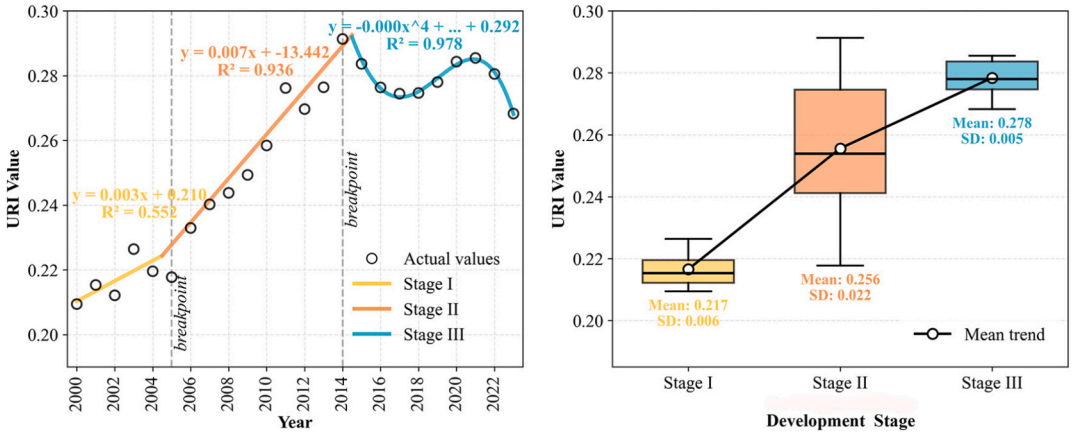

Fig. 4. Three stages of urban-rural integration development.

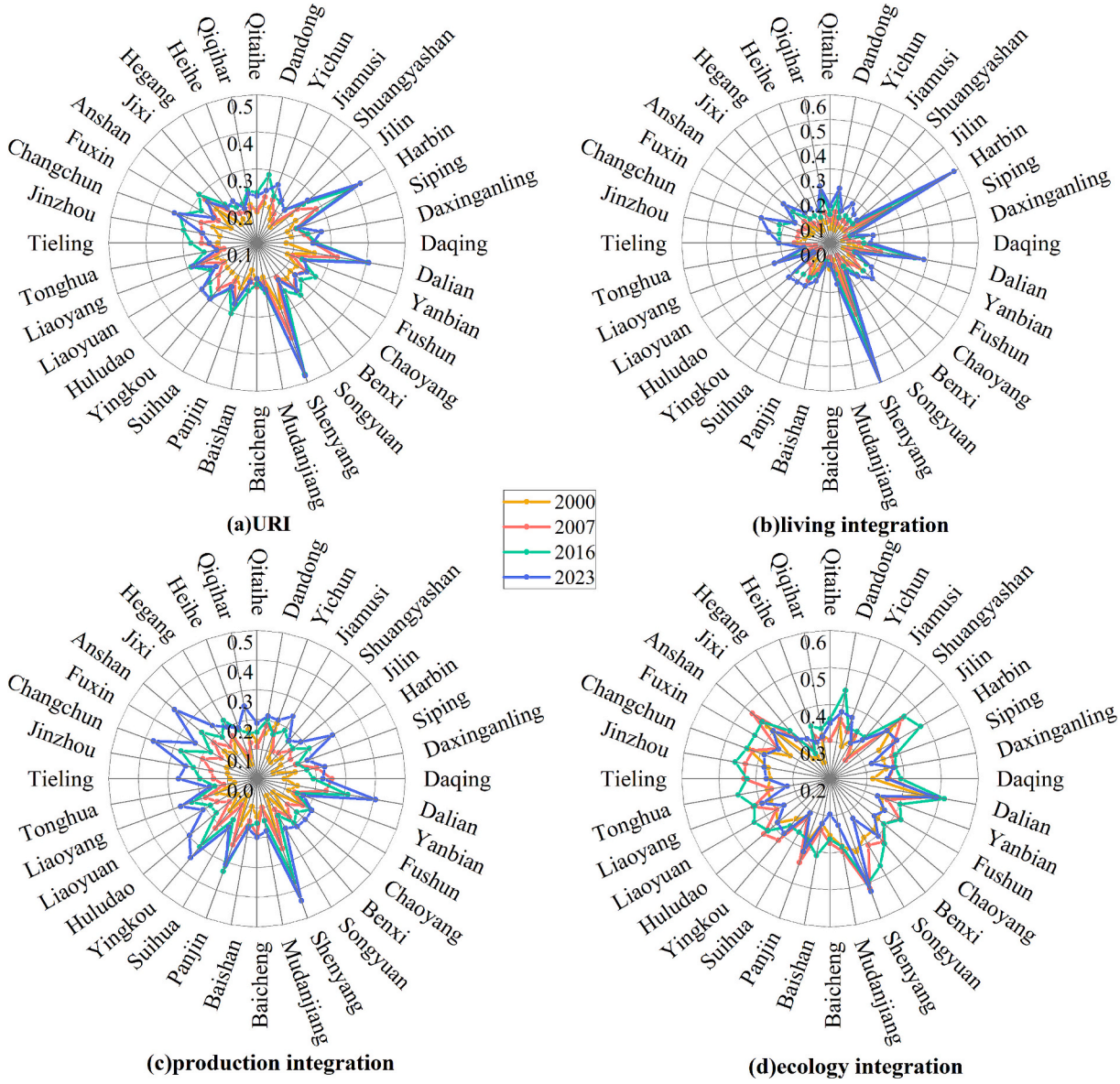

Fig. 5. The different function levels of URI in 36 cities.

eastern Jilin province to eastern Heilongjiang and Jilin province by 2023.

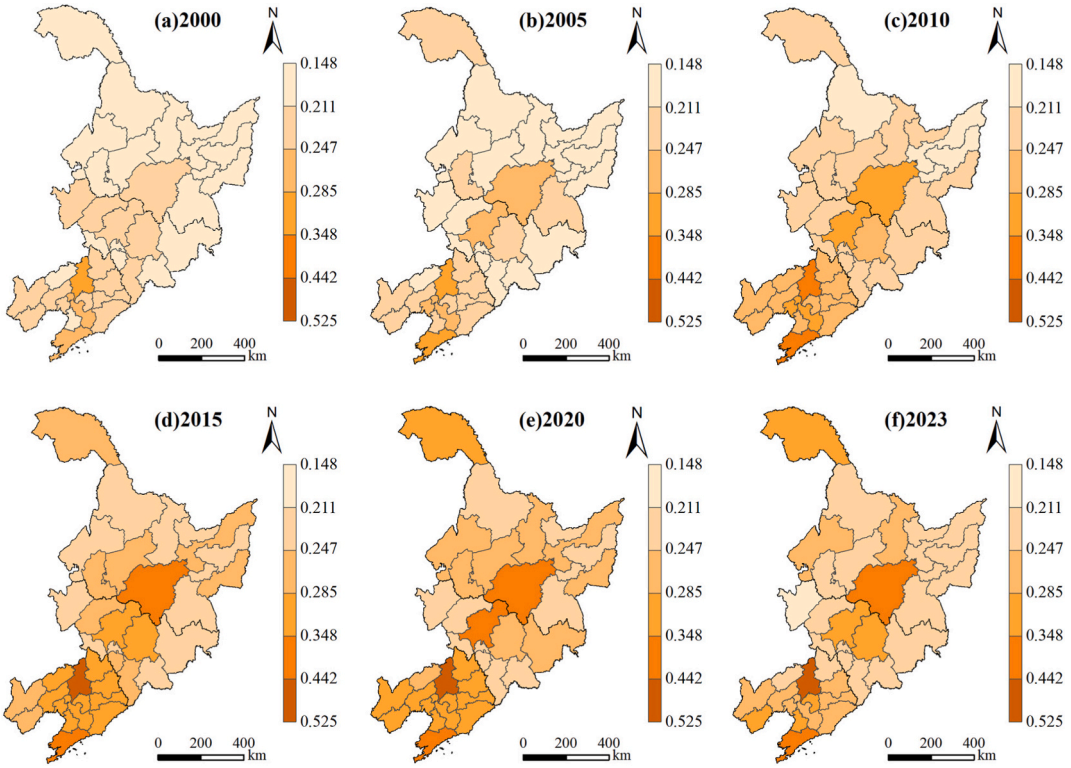

Fig. 6. Spatial patterns of URI levels in different regions during 2000–2023.

The global Moran's I passed the 1% significance test for all years (Appendix Fig.S1), thus enabling LISA clustering analysis. High-High

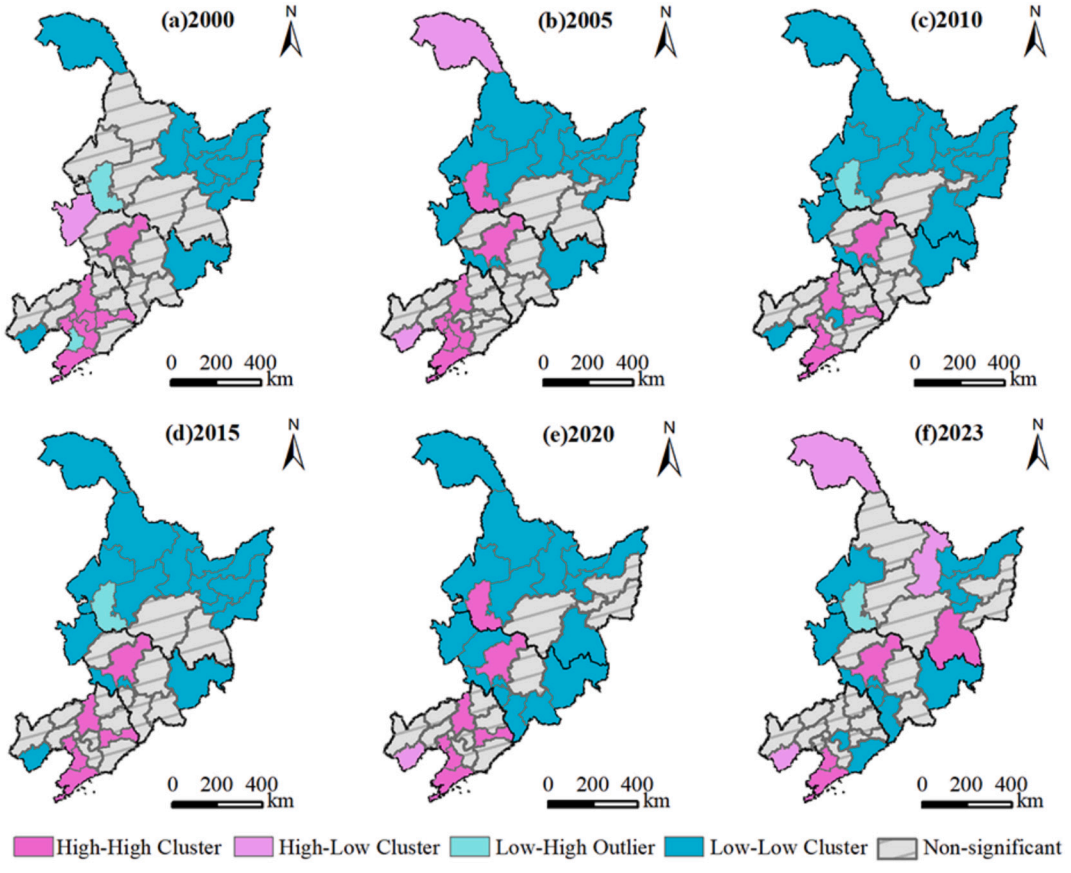

Fig. 7. Local spatial clustering of urban-rural integration in Northeast China (W2).

(H-H) clusters are concentrated in central Liaoning province and Changchun, establishing regional core advantages and generating significant radiation effects. This is likely attributed to innovation-driven industrial foundations, superior locational conditions, and advanced land marketization, which collectively facilitate factor mobility (Pan et al., 2023). Low-Low (L-L) clusters dominated the northern and eastern Heilongjiang province during the early period but contracted over time. Harbin exhibits statistically insignificant URI clustering despite being surrounded by L-L zones, illustrating its limited radiation capacity and poor mobility of factors. Cities in western Liaoning alternated between L-H and H-H clustering, highlighting the pronounced influence of neighboring environments on local URI (Fig.7).

5.2. Dynamic evolution of the LGUE

LGUE across 36 cities rose from 0.354 in 2000 to 0.530 in 2023, showing an overall upward trend. An initial decline to 0.084 (2000–2005) occurred predominantly in resource-dependent cities, where resource consumption and pollution emissions during construction land expansion outpaced green economic output growth. Growth subsequently accelerated from an average annual rate of 21.91% (2006–2011) to 55.86% (2012–2018) (Fig.8).

Significant turning points emerged in the fluctuations of LGUE: 2005 and 2018. Recovery after the 2005 turning point may be attributed to industrial diversification and increased green investment under the Northeast Revitalization Strategy. However, a subsequent contraction following 2018 likely relates to dual pressures from stringent

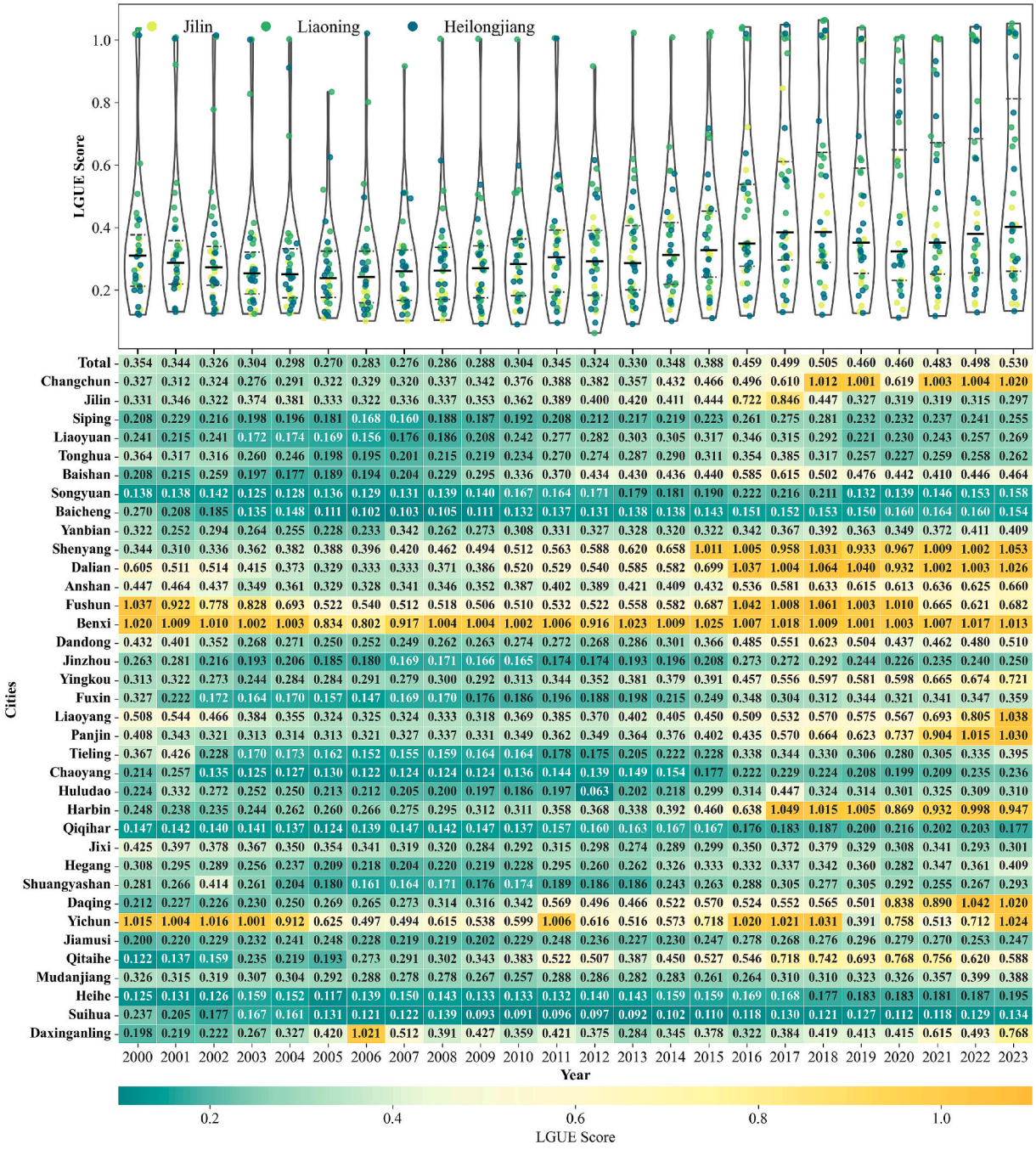

Fig. 8. Temporal changes of LGUE in different regions during 2000–2023.

environmental regulations and land productivity constraints (Zhu et al., 2025).

LGUE exhibits pronounced spatial heterogeneity (Fig.9). In 2000, high-value zones were scattered around Yichun and Dalian, while contiguous low-value clusters expanded region-wide by 2005, likely due to intensified environmental pressures from industrial expansion under the Northeast Revitalization Strategy. From 2010 to 2015, LGUE entered a period of slow growth. By 2010, central cities around Harbin reached median levels, while the low-value zone had noticeably shrunk. By 2015, cities centered around Shenyang and Dalian had formed distinct high-value clusters. High-value zones established a “concentrated-south, dispersed-north” configuration between 2020 and 2023, characterized by dense clustering in Liaoning alongside isolated nodes in Changchun and ecological functional zones such as Yichun and the Greater Khingan Range.

Global Moran's I remained consistently positive and significant throughout the study period (Appendix Fig.S2). LISA analysis reveals a polarized structure (Fig.10). H-H clusters expand from central Liaoning into the Shenyang-Dalian dual-core growth pole, while L-L clusters migrate progressively northward and eastward. In 2000 and 2005, these clusters were primarily scattered across cities like Baicheng and Mudanjiang. By 2023, northern regions such as the Greater Khingan Range and Heihe, along with eastern areas including Baishan, Yanbian, and Mudanjiang, had also been incorporated into the L-L clusters.

5.3. Spatial effect of URI on LGUE

5.3.1. Model selection and specification tests

Before estimation, variance inflation factor diagnostics confirm the absence of significant multicollinearity, with all values falling below 5 (Appendix Table S3). Benchmark tests across three spatial weight matrices show that LM_error and LM_lag tests support both SEM and SAR specifications (Table 3). The Hausman test results favor fixed effects over random effects. Both the LR test and Wald test exceed the 1% significance threshold, rejecting the null hypothesis and confirming that the SDM model provided a superior fit. Accordingly, a fixed-effects SDM model is adopted.

5.3.2. Spatial decomposition of URI effects on LGUE

Because the SDM model incorporates spatial lag terms to capture complex spatial interdependencies, local perturbations inherently trigger multi-order feedback loops across neighboring units. Consequently, the model's point estimates cannot be directly interpreted as true marginal effects. To address this, the partial derivative matrix method (LeSage and Pace, 2009) is implemented to decompose the direct and indirect effects.

Generally, the impact of URI on LGUE keeps a consistent trend under different spatial weight matrices. The direct effect coefficients of URI on LGUE are 0.9923, 1.0126, and 1.2375, under W1, W2, and W3, respectively, all significant at the 1% level, confirming that URI positively affects LGUE (Table 4). The coefficients elucidate that URI has a significant indirect effect on LGUE, accounting for 68.75%(W1), 66.74% (W2), and 42.89%(W3) of the total effect, respectively. This proves that URI not only accelerates the increase of local LGUE, but also catalyzes the spatial spillover effects in neighboring regions. The possible reasons are as follows: On the one hand, the circulation of population and capital factors expands the transaction scope of the land market, promoting the construction land utilization and rural land transfer into the market, thereby optimizing the land use structure of both local and neighboring areas. On the other hand, the strengthening of industrial linkages between urban and rural areas is conducive to the government's unified environmental management, which intensifies the green transformation

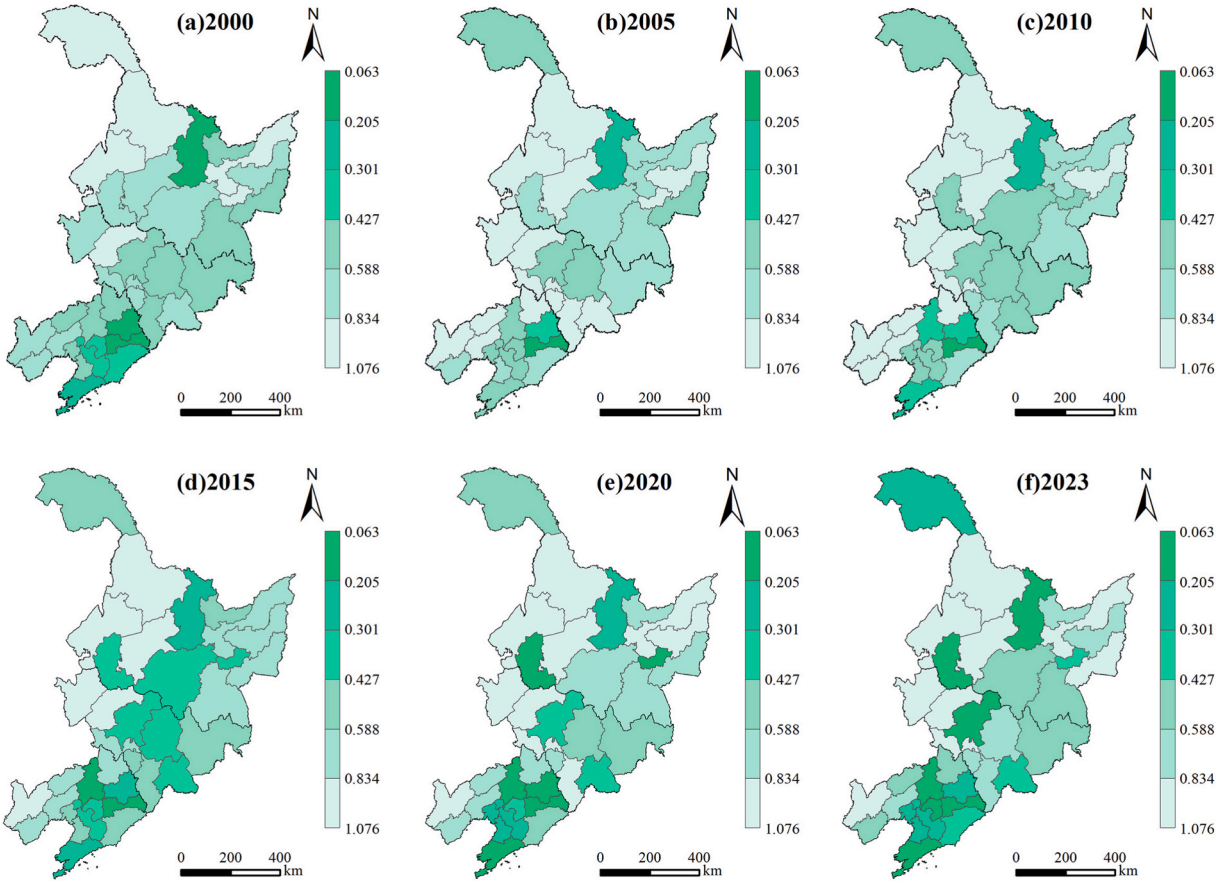

Fig. 9. Spatial patterns of LGUE in different regions during 2000–2023.

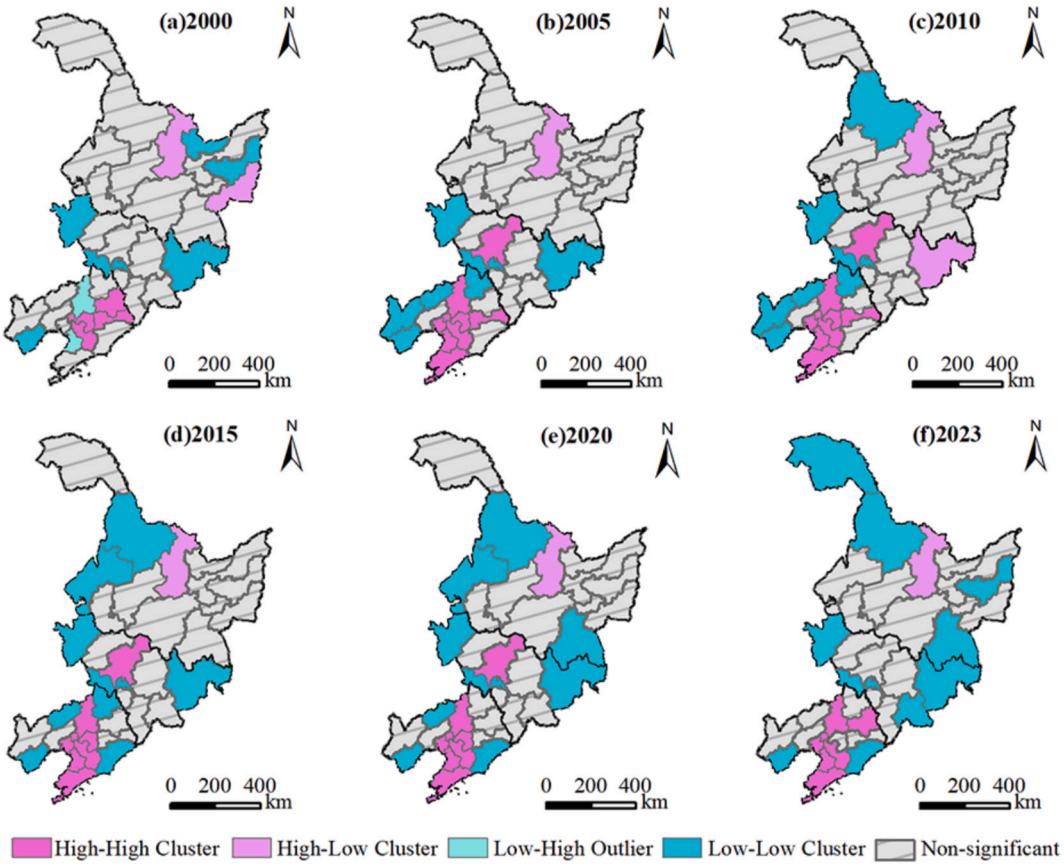

Fig. 10. Local spatial clustering of LGUE in Northeast China (W2).

Table 3
Model selection and specification tests of SDM under different spatial weight matrices.

Variables	W1	W2	W3
LM_ error	287.278(0.000)	224.007(0.000)	105.14(0.000)
Robust LM_error	54.464(0.000)	33.1(0.000)	12.415(0.000)
LM_lag	234.909(0.000)	193.097(0.000)	93.091(0.000)
Robust LM_lag	2.096(0.148)	2.19(0.139)	0.366(0.545)
LR_Lag	81.47(0.000)	71.59(0.000)	86.06(0.000)
LR_Eorror	59.58(0.000)	61(0.000)	72.02(0.000)
Wald_Lag	85.67(0.000)	74.54(0.000)	91.34(0.000)
Wald_Eorror	57.07(0.000)	57.97(0.000)	73.79(0.000)
Hausman	20.063(0.003)	20.062(0.003)	19.648(0.000)

Note: Values in parentheses represent *p*-values.

of land use.

5.4. Heterogeneity analysis

5.4.1. Heterogeneity of different URI development stages

Based on integrating government policies with the chronological development stages of URI (Fig.4), the influence of URI on LGUE is analyzed across three distinct intervals: the fluctuation period (2000–2005), the rapid growth period (2006–2014), and the slow growth period (2015–2023).

The direct effect of URI on LGUE exhibits a phased diminishing trend (Table 5). Coefficients peaked above 2.3 ($p < 0.01$) between 2000 and 2005. It declined to approximately 1.9 during the rapid growth period (2006–2014). Although the mobility factors strengthened, it was insufficient to resolve the Northeast's challenges of slow industrial transformation, potentially hindering the utilization of land resources (Zhu et al., 2025). A further decline to around 1.4 during the slow growth period (2015–2023) coincided with intensifying urban shrinkage and reduced urban-rural mobility (Jin et al., 2026), which may weaken URI's effect on LGUE. Indirect spillover effects remain predominantly

Table 4
Results of spatial effects under alternative spatial weight matrices.

Variable	W1			W2			W3		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
URI	0.9923***	2.1827***	3.1750***	1.0126***	2.0318***	3.0444***	1.2375***	0.9293**	2.1668***
Control variables	Yes			Yes			Yes		
W × explanatory variables	Yes			Yes			Yes		
City fixed effect	Yes			Yes			Yes		
Time fixed effect	Yes			Yes			Yes		
Number	864			864			864		
R^2	0.239			0.233			0.216		

Note: *, **, and *** indicate the significance at the confidence levels of 10%, 5%, and 1%, respectively.

Table 5
Grouping regression results based on different URI development stages.

Variable	W1		W2		W3	
	Direct effect	Indirect Effect	Direct effect	Indirect Effect	Direct effect	Indirect Effect
2000–2005 URI	3.6726 ***	−2.1801	2.3109 ***	2.1704 **	3.4794 ***	−0.1610
2006–2014 URI	1.9780 ***	−1.2475 *	1.9239 ***	−1.2710	1.9780 ***	−1.2475
2015–2023 URI	1.3957 **	−0.1365	1.4220 **	−0.5161	1.3957 **	−0.1365
Number (2000–2005)	216		216		216	
Number (2006–2014)	324		324		324	
Number (2015–2023)	324		324		324	
Control variables	Yes		Yes		Yes	
W × explanatory variables	Yes		Yes		Yes	
City fixed effect	Yes		Yes		Yes	
Time fixed effect	Yes		Yes		Yes	

Note: *, **, and *** indicate the significance at the confidence levels of 10%, 5%, and 1%, separately.

insignificant across all phases, indicating that the spatial diffusion of URI benefits constitutes a protracted shaping process with limited short-term visibility.

5.4.2. Heterogeneity of different city types

The northeastern region of China represents a quintessential concentration of resource-based cities. Based on the *National Plan for Sustainable Development of Resource-Based Cities (2013–2020)*, the cities can be divided into two types: non-resource-based cities (Group 1) and resource-based cities (Group 2).

The results show that the direct effect coefficients of URI on LGUE are 0.9943 (W1), 0.8296 (W2), and 0.9209 (W3), demonstrating that URI has a positive contribution to the local LGUE in non-resource-based cities. In stark contrast, these coefficients turn negative for resource-based cities, with only the estimate under W1 achieving statistical significance. This reveals that URI hinders the LGUE improvement in these cities to some degree. The spillover effect coefficients for the resource-based group are statistically significant, and their absolute magnitudes surpass those of the direct effect coefficients, suggesting suppressive interconnections of URI brought to LGUE (Table 6).

5.5. Nonlinear effects of URI on LGUE

5.5.1. Preliminary analysis and model evaluation

Before model training, Pearson correlation analysis was performed to evaluate the risk of multicollinearity among the twelve independent variables, preventing model overfitting. The correlation coefficients among all features are below 0.65, suggesting no severe multicollinearity was present. This ensures that each feature maintains a reasonable degree of explanatory power, and all variables are retained for subsequent modeling (Appendix Fig.S3).

A competitive assessment was conducted by six machine learning models based on a comparative evaluation of four key metrics, namely R^2, root mean square error (RMSE), and mean absolute error (MAE), across both the training and test sets. TabPFN demonstrates superior predictive robustness and generalization capability, achieving the highest test set R^2 (0.902) while maintaining the lowest error levels (MAE = 0.0403, RMSE = 0.0730), outperforming other models (Fig.11). Accordingly, the TabPFN model was selected to further investigate the nonlinear relationship across different subsystems of how URI influences LGUE.

After a comprehensive evaluation of all models under identical experimental conditions (utilizing the same random seed), we conducted a sample-size sensitivity analysis to verify the robustness of the TabPFN model against input perturbations (Appendix Fig.S4 & Table S4). By incrementally increasing the training set ratio from 10% to 100%, TabPFN consistently maintained the highest R^2 values compared to the linear model and the four ensemble models, underscoring its superior predictive performance.

5.5.2. Indicator importance analysis

Based on the regression results, the SHAP algorithm was applied to rank the importance of 12 secondary features across subsystems, and the proportion of each feature's mean absolute SHAP value relative to the cumulative SHAP value was calculated (See Fig.12).

Production functional integration dominates LGUE, contributing 57.4% cumulatively (Fig.12a, d). Among these, labor ranks first (23.6%), underscoring the urban-rural human capital circulation as the

Table 6
Grouping regression results based on different city types.

Variable	W1		W2		W3	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
Group1	0.9943***	9.7266	0.8296**	8.2158	0.9209**	−3.0150*
Group2	−0.2561*	−1.3487**	−0.3750	−0.9934*	0.1217	−2.1275***
Number (Group1)	360		360		360	
Number (Group2)	504		504		504	
Control variables	Yes		Yes		Yes	
W × explanatory variables	Yes		Yes		Yes	
City fixed effect	Yes		Yes		Yes	
Time fixed effect	Yes		Yes		Yes	

Note: *, **, and *** indicate the significance at the confidence levels of 10%, 5%, and 1%, separately.

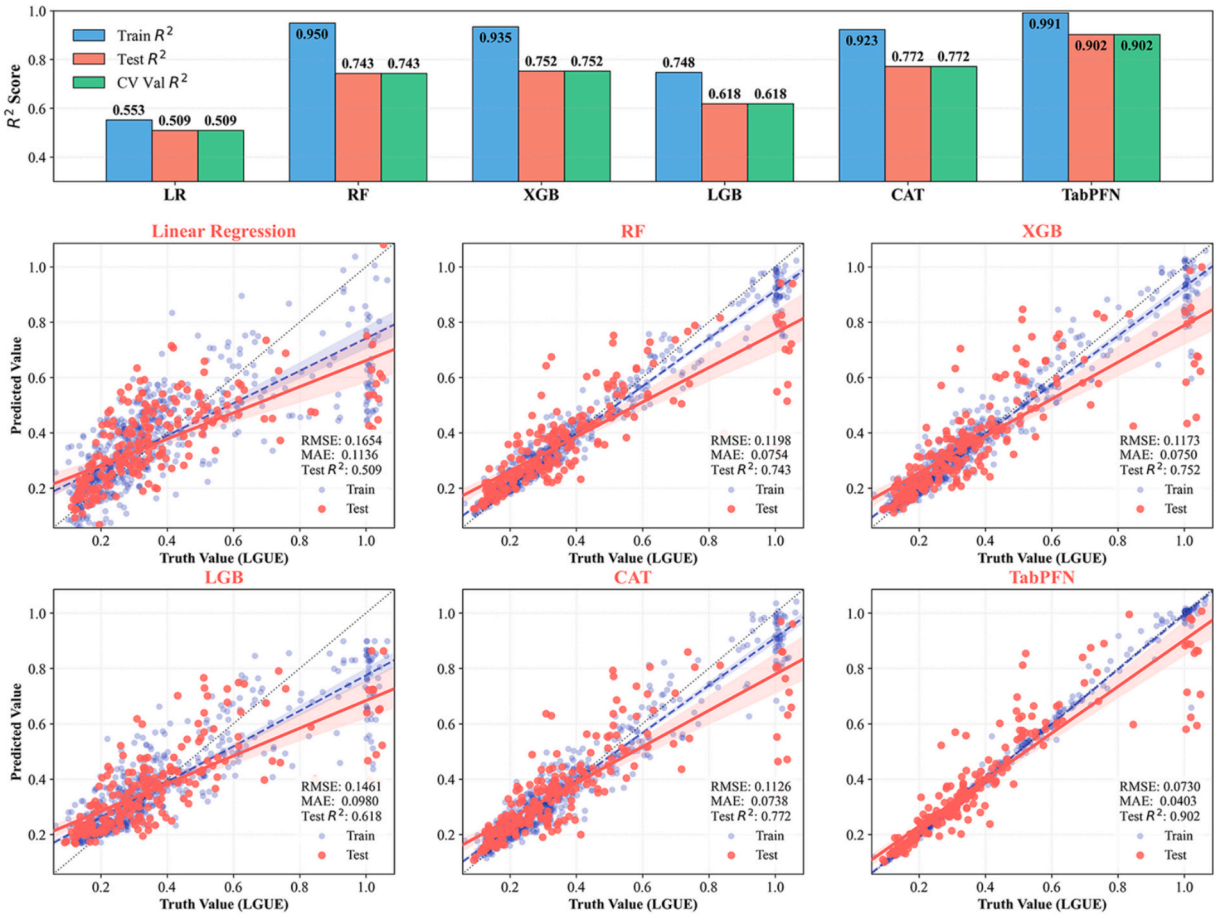

Fig. 11. Comparison and goodness-of-fit analysis of six machine learning models.

core driving force for improving LGUE, followed by capital allocation and production structure. Furthermore, urban-rural ecological function also proves critical, as evidenced by the greening level achieving a contribution rate of 16.6%. These results illustrate the pivotal role of urban-rural factor integration in both production and ecological functions for land green use.

To further investigate whether regional heterogeneity exists in the effects of URI subsystems, separate regression analyses were conducted for cities of different development types.

Non-resource-based cities (Fig.12b, e) exhibit a "production-ecology" dual-driver pattern, with contributions of 44.6% and 39.6%, respectively. While labor retains top ranking, energy utilization demonstrates a comparable contribution of 20.6%, far exceeding that observed in resource-based cities. As these cities predominantly serve as regional economic centers with high industrial agglomeration, they exhibit substantial energy consumption, which exerts a considerable influence on LGUE. Consequently, energy structure optimization is identified as a key leverage point for LGUE improvement in such cities (Zhao et al., 2023b), alongside technological advancement and asset allocation.

Resource-based cities (Fig.12c,f): Production functional integration plays a primary role in enhancing LGUE. Notably, production structure ranks second (14.1%), markedly higher than in non-resource-based cities, reflecting the importance of rational factor allocation and industrial structural upgrading for green land use in resource-dependent economies (Li et al., 2024b). It is worth noting that living functional integration records the highest proportional contribution (18%), with public services and social welfare playing particularly prominent roles. This proves the necessity of improving urban-rural public service systems in economically lagging regions, as such improvements provide essential human and social capital support for efficient land use (Zhou and Lu, 2023).

5.5.3. *Threshold effect analysis*

To further explore the nonlinear relationships between URI and LGUE, GAM models were employed to fit the SHAP response curves of the two most important factors within each URI subsystem (additional details on the identified thresholds are provided in Appendix Table S5).

At the regional level (Fig.13a-f), the fitted curve for labor mobility exhibits a monotonically increasing trend, generating a positive effect on LGUE once the value exceeds 0.0191. Capital allocation follows a fluctuating downward trajectory, turning negative above 0.0043, highlighting the importance of a well-balanced capital allocation structure for LGUE. Within the ecological function, both the greening level and energy utilization curves exhibit monotonically increasing trends, affirming the importance of urban-rural ecological functional connectivity.

Non-resource-based cities (Fig.13g-l): the labor mobility curve initially declines gradually, but the SHAP value rises sharply after reaching the inflection point at approximately 0.015, with the rate of increase decelerating beyond an inflection point near 0.03. The fluctuation pattern of the capital allocation curve exhibits an L-shaped trend, which is similar to the regional level, suggesting that capital misallocation is negatively associated with land green use even in economically advanced cities. When the value of social welfare exceeds 0.0137, its contribution turns positive, and the curve subsequently fluctuates upward, indicating that the improvement in welfare provision has a positive impact on LGUE. The GAM curves for both greening level and energy use display an initial phase of accelerated growth followed by a gradual stabilization. This demonstrates that the improvement of the

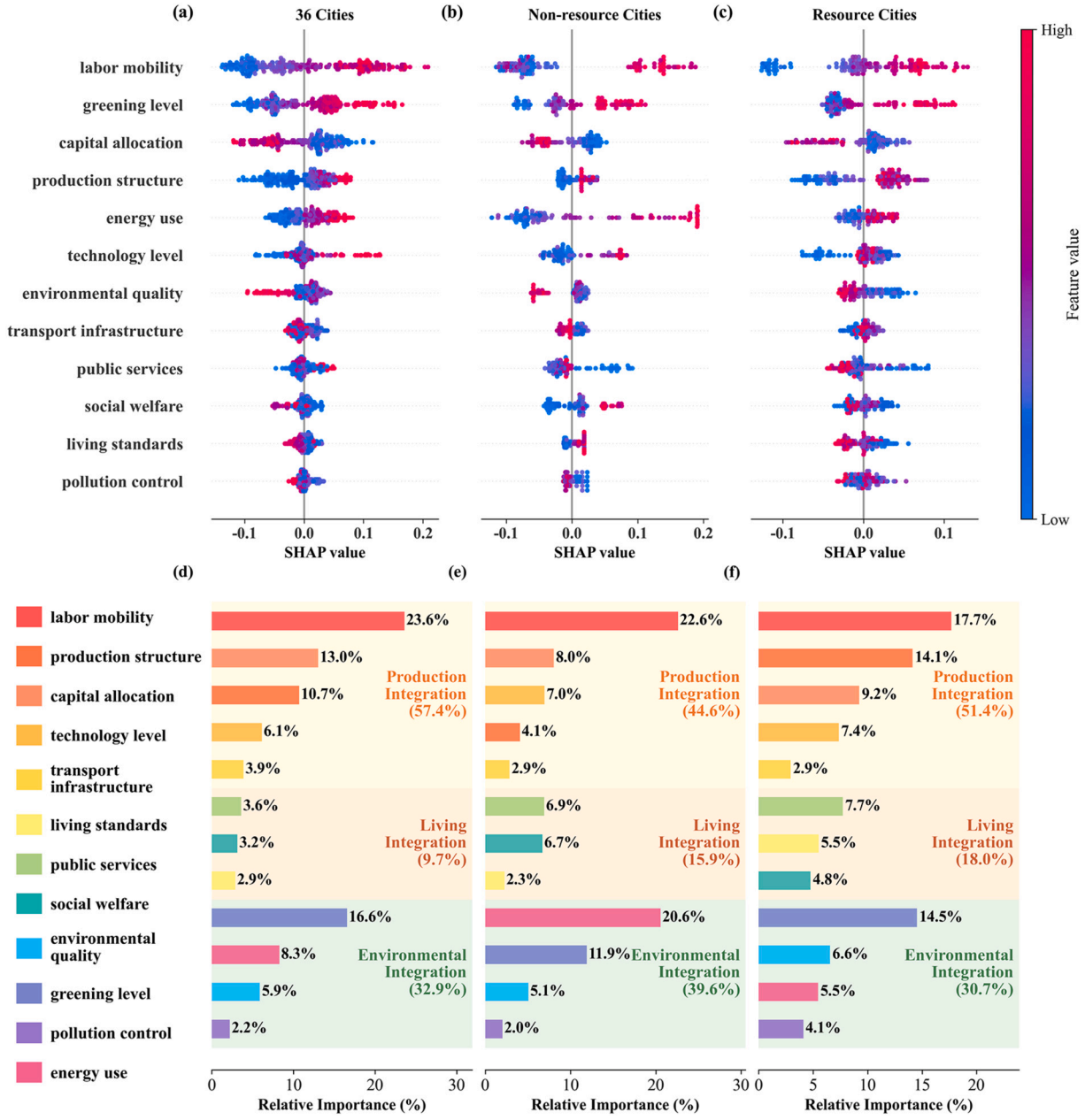

Fig. 12. (a to c depict the contribution values of 12 secondary features to LGUE, where red dots represent high feature values and blue dots represent low feature values; negative values along the x-axis indicate adverse effects while positive values indicate beneficial effects; d–f represent the relative importance of features belonging to the production, living, and ecological subsystems with respect to LGUE).

greening environment and the upgrading of the energy utilization structure in urban and rural areas hold immense potential for the enhancement of LGUE.

For resource-based cities (Fig.13m-r): Compared to non-resource-based cities, the production structure has a more profound impact on LGUE, with the fitted curve following an inverted U-shaped curve. Its critical threshold value is identified at 0.0054. As the production structure optimizes within the value range from 0.0054 to 0.007, its positive contribution to LGUE has an accelerated upward trend. The trend for greening level is similar to this in non-resource-based cities, prompting LGUE when it is better than the threshold value of 0.0396. Notably, environmental quality significantly contributes to affecting LGUE in resource-based cities, with the curve exhibiting a monotonically decreasing trend, likely because the considerable fiscal burden of environmental governance suppresses short-term economic output, generating a net negative influence on LGUE when the value is greater than 0.0472.

6. Discussion

6.1. The effect of URI on LGUE: spatial spillover and nonlinear relationship

Empirical results confirm that URI exerts a positive direct effect on LGUE, driven by adjustments in factor mobility ratios and spatial functional structures. Despite an upward trajectory in both URI and LGUE across the study area from 2000 to 2023, overall LGUE remained below levels observed in economically developed southern regions (He et al., 2020; Xu et al., 2025). This discrepancy may be attributed to economic developmental lag in Northeast China compared to eastern coastal regions, precipitated by synergetic pressures, specifically sustained labor outflow and stagnant industrial restructuring (He and Song,

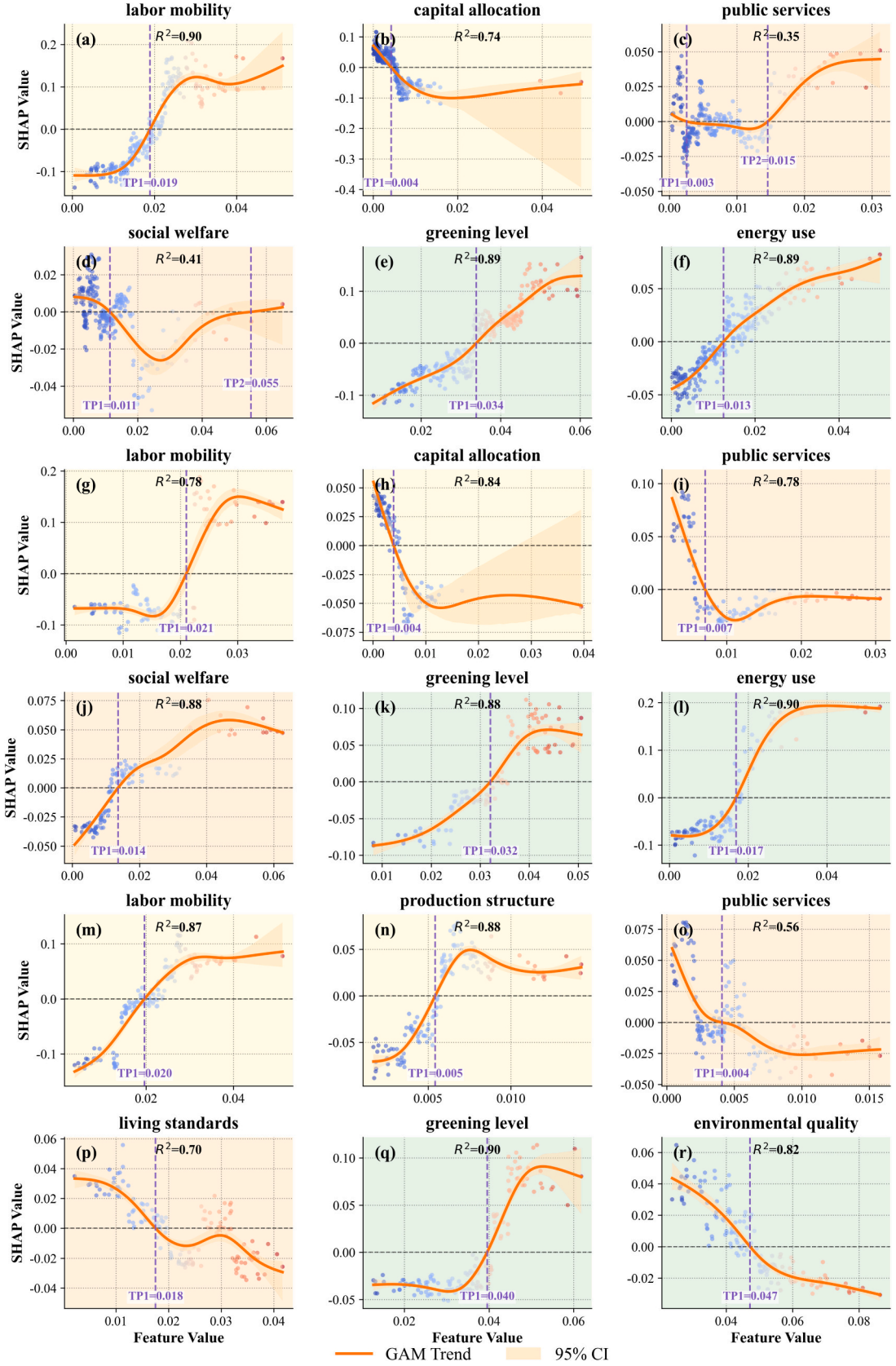

Fig. 13. Threshold effects of the first two factors in the three subsystems integrating urban-rural production, living, and ecological functions across different regions (a–f represent scatter plots of critical threshold points for characteristic elements in 36 cities; g–l represent non-resource-based cities; m–r represent resource-based cities. Note: GAM trend denotes fitted curve.)

2023). A more theoretically consequential finding is that spillover coefficients exceed direct effects, indicating that the dividends of URI are more substantially harvested by neighboring cities than by the city itself. During the dismantling of urban-rural barriers, the direct benefits generated by the flow of factors of production are unlikely to offset the potential costs incurred by local cities due to structural adjustments in the short term; Consequently, neighboring regions might potentially emerge as indirect beneficiaries, which is consistent with the process of optimal restructuring within the production framework.

This study employs the TabPFN-SHAP model to reveal the nonlinear relationships of multiple factors within the URI system and LGUE. The threshold regression unveils a dual mechanism of "critical threshold constraints" and "structural misallocation". Specifically, labor mobility is the primary influential factor, following a fluctuating upward trend, where its positive impact on LGUE increased significantly once reaching a certain threshold value. This underscores that incipient population flows lack the critical scale to effectively dismantle the entrenched urban-rural dual structure. This finding resonates with Zou et al. (2022), who concluded the effect of labor transfer on land eco-efficiency is initially negative and only turns positive later, reinforcing the premise that early stages of mobility fail to yield immediate green benefits. Conversely, capital allocation exhibits a threshold constraint, suggesting that once the identified threshold is exceeded, fiscal and industrial resources may be disproportionately diverted into carbon-intensive sectors, thereby crowding out green investments and weakening their positive contribution to LGUE(Bai et al., 2024; Zhou et al., 2022).

6.2. Divergent feedback of urban resource endowments on land green use efficiency

The heterogeneity analysis reveals that the association between URI and LGUE differs across city types. Resource-based and non-resource-based cities exhibit distinct patterns in the effects of URI on LGUE, indicating that the effects of URI are context-dependent rather than uniform. Such differences may be related to variations in resource endowments, industrial structures, and development conditions across cities.

Non-resource-based cities exemplify a "proactive synergy" paradigm. Leveraging diversified industrial bases and robust market mechanisms, these urban cores drive LGUE through active spatial spillovers. Coastal cities anchored by Dalian leverage their advantages in foreign capital and technological support to channel productive factors into rural areas via industrial parks, facilitating the entry of rural collective construction land into market circulation and accelerating the transition toward intensive utilization (Zhu et al., 2025). Ecological conservation policies have simultaneously constrained development intensity in sensitive zones such as coastal wetlands, redirecting land use toward green transformation (Wang et al., 2026). In inland cities, URI optimizes land functional layouts through industrial coordination(Huang et al., 2024): Changchun and Shenyang have dispersed automotive and equipment manufacturing supply chains into surrounding counties, alleviating land pressure in urban cores while activating idle and collectively-owned construction land in peri-urban townships.

In contrast, resource-based cities remain trapped in a development structure where rigid resource dependency engenders a "walled-off" dilemma against urban-rural factor mobility. In mature resource-based cities, capital and labor are fixed in the original industry, resulting in sluggish factor circulation and homogeneous land use structures (He et al., 2017). Declining resource-based cities, such as Liaoyuan and Hegang, confront the compounded challenges of resource depletion and environmental contamination; fiscal restraint in these economically lagging cities has stalled shantytown redevelopment and remediation of industrial wastelands (Gao and Ryan, 2021). This indirectly displaced pollution burdens onto rural areas, hindering the transition toward green land use (Zhang et al., 2023). Even in regenerative cities, such as Panjin and Anshan, that actively pursue large-scale land reclamation and spatial repurposing to resolve legacy land-use contradictions, the ecological and economic dividends of such structural overhauls are constrained by substantial time lags. Ultimately, across all resource-dependent typologies, the fragile economic linkages and asymmetric functional complementarity between urban and rural areas remain the primary bottlenecks for LGUE enhancement (Wang et al., 2024; Zhan et al., 2023).

6.3. Policy implications

This study confirms that URI exerts spatially heterogeneous and nonlinearly threshold-dependent effects on LGUE, necessitating place-sensitive governance strategies (Sorensen, 2000) that transcend administrative boundaries and translate urban-rural integration from a policy objective into an endogenous driver of green development.

First, non-resource-based core cities should strengthen their radiative capacity over surrounding regions. Through vertically integrated industrial chains, this mechanism converts the "siphon effect" of urban cores into a "trickle-down effect" for their hinterlands. Drawing on the successful collaborative governance model of Germany's Ruhr region (Arora and Schroeder, 2022), these cities should establish vertically integrated supply chains and cross-jurisdictional planning authorities. This strategic alignment will systematically convert urban "siphon effects" into regional "trickle-down" dividends, thereby effectively overcoming administrative fragmentation.

Second, based on the finding that indirect effects consistently exceed direct effects, the government can leverage the Harbin-Dalian High-Speed Railway and the Binzhou-Binshui rail corridor to establish a cross-shaped green development axis, thereby strengthening spatial linkages across development gradients. Economically advanced cities should anchor green innovation, clean production, and circular economy systems. And peripherally located cities, such as Yichun, Hegang, and Daxing'anling, require targeted industrial transformation and institutional innovation. Specifically, provincial fiscal transfer payments and integrated land remediation programs can catalyze inter-regional factor mobility, alleviating path dependencies on extractive resource exploitation.

6.4. Research applicability and limitations

This study embeds URI and LGUE within a systematic analytical framework of "spatiotemporal evolution-effect decomposition-heterogeneity-threshold relationships," supplementing novel perspectives and integrated methods to quantify their complex interdependencies. Key contributions include:(1) Existing studies predominantly construct URI indicator systems along discrete social, environmental, economic, and spatial dimensions (Liu et al., 2024a; Niu et al., 2023), overlooking functional-level dynamics within urban-rural territorial systems. Adopting a production-living-ecology function perspective more precisely captures integrative processes across factor allocation, human settlement, and ecological environment, thereby enriching the theoretical foundations and evaluative scope of URI. (2) Prior LGUE assessments typically focus on single land categories at either the urban or cultivated land scale. By simultaneously incorporating multiple land-type inputs, including arable land area and urban built-up area, this study constructs a more comprehensive and internally consistent measurement framework. (3) The multidimensional role of interactions within urban-rural systems is frequently overshadowed by a prevailing focus on the aggregate impact of URI on LGUE. This study disaggregates its influence into production, living, and ecological functional subsystems, examining their respective nonlinear effects on LGUE alongside threshold analysis of secondary-level drivers. This decomposed approach yields deeper structural insights into the URI-LGUE relationship.

The framework retains broad transferability beyond China. Regions sharing structural analogies with northeastern China, including

Jharkhand in India, northern Vietnam, and Ukraine (Zhu et al., 2025), confront similar trajectories of heavy industry dependence, institutional rigidity, and urban-rural imbalance. Elucidating the nonlinear dual mechanisms linking urban-rural integration to land use efficiency thus provides transferable theoretical references and empirical insights for reconciling economic development with ecological restoration in industrial transition regions globally.

Several limitations warrant acknowledgment. First, the analysis focuses on spatial spillover effects and nonlinear relationships without establishing causal mechanisms. Future research could incorporate mediation effect models or DID approaches to trace the causal chain from policy intervention to efficiency improvement through mediating pathways such as technological innovation and industrial transformation. Second, the study examines the unidirectional influence of URI on LGUE, leaving potential bidirectional feedback and endogeneity concerns unaddressed. Subsequent work should employ simultaneous equation models or identify credible instrumental variables to rigorously establish causal identification between the two constructs.

7. Conclusion

URI constitutes a pivotal gateway to reducing the income gap and promoting high-quality development. The deep integration of urban and rural areas profoundly influences LGUE. This study develops a comprehensive framework to reveal the spatial and nonlinear effects of URI on LGUE across 36 prefecture-level cities in northeastern China (2000−2023). Key findings are as follows:

(1) Over the study period, URI and LGUE in northeastern China followed a phased upward trajectory. They exhibited strong positive spatial correlation, with high-value clusters concentrated along the Harbin-Dalian Railway corridor and persistently low-value zones at provincial borders and peripheral areas.

(2) URI exerts a significant positive effect on local LGUE, while its spillover coefficient exceeds the direct effect, highlighting the crucial role of regional spatial connectivity. Spatial spillover effects fail to exhibit statistical significance when heterogeneity is analyzed by city types, indicating the effect is regionally systematic.

(3) The nonlinear analysis reveals that the production integration (57.4%) contributes most to LGUE, while the living integration(9.7%) accounts for the least. Among the subsystems, labor mobility, capital allocation, and greening level play pivotal roles. Marked variations in drivers were exhibited across different city types. Non-resource-based cities were deeply influenced by energy consumption, while resource-based cities were more contingent upon production structure.

(4) Threshold regression results indicate that within the production integration, labor mobility on LGUE transitions from negative to positive once exceeding 0.0191, whereas capital allocation turns negative upon reaching the critical threshold of 0.0043. In the ecological integration, both greening level and energy utilization exhibit monotonically increasing impact curves. Within the living integration, the fitted curve for social welfare maintains a consistent monotonically increasing trend, suggesting that more robust welfare security systems enhance human capital contributions to LGUE.

CRediT authorship contribution statement

Xiaowan Meng: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yanjun Zhang:** Writing – review & editing, Supervision. **Wentong Jia:** Investigation, Data curation. **Yuefen Li:** Project administration, Funding acquisition.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2026.115102.

Data availability

Data will be made available on request.

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