frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 19 November 2025
DOI 10.3389/fenvs.2025.1697381

OPEN ACCESS

EDITED BY
Hugo Wai Leung MAK,
Hong Kong University of Science and Technology, Hong Kong SAR, China

REVIEWED BY
Zhengzheng Cao,
Henan Polytechnic University, China
Zhonghu Wu,
Guizhou University, China

*CORRESPONDENCE
Weifeng Deng,
2025102090004@whu.edu.cn

RECEIVED 02 September 2025
REVISED 24 October 2025
ACCEPTED 24 October 2025
PUBLISHED 19 November 2025

CITATION
Liang T, Zhan J, Su Y and Deng W (2025) Examining the nonlinear effects of multidimensional land use efficiency on ecological resilience using the XGBoost-SHAP and GTWR model in Guangdong province. *Front. Environ. Sci.* 13:1697381. doi: 10.3389/fenvs.2025.1697381

Examining the nonlinear effects of multidimensional land use efficiency on ecological resilience using the XGBoost-SHAP and GTWR model in Guangdong province

Tian Liang[1,2,3], Jinrui Zhan[1,2,3], Yongjun Su[1,2,3] and Weifeng Deng[4]*

[1]Guangzhou Urban Planning and Design Survey Research Institute Co., Ltd., Guangzhou, China, [2]Collaborative Innovation Center for Natural Resources Planning and Marine Technology of Guangzhou, Guangzhou, China, [3]Guangdong Enterprise Key Laboratory for Urban Sensing, Monitoring and Early Warning, Guangzhou, China, [4]School of Urban Design, Wuhan University, Wuhan, China

Understanding the complex interactions between land use efficiency (LUE) and eco-logical resilience (ER) is essential for sustainable urban development. However, existing studies have predominantly examined land use change and environmental impacts in isolation, while the nonlinear dynamics, threshold effects, and spatial heterogeneity of the LUE–ER relationship remain insufficiently explored. Moreover, limited attention has been paid to the heterogeneous roles of different LUE types—agricultural, industrial, commercial, and ecological—despite their divergent production functions and environmental externalities. Using panel data from 21 cities in Guangdong Province (2014–2022), this study investigates the spatiotemporal dynamics and interaction mechanisms of LUE and ER through an integrated XGBoost–SHAP and GTWR approach. Results show a 16.1% decline in ER across the province, mainly due to rising ecological pressure, with higher ER in the north and lower levels in the south. While industrial, commercial, and ecological LUE all declined significantly, agricultural LUE showed an increasing trend. Nonlinear and threshold effects were evident across all LUE types: agricultural, industrial, and ecological LUE significantly reduced ER once thresholds were exceeded, whereas commercial LUE enhanced ER beyond its threshold. The effects of LUE on ER were further moderated by industrial structure, green innovation, population density, urbanization, infrastructure, and government intervention. GTWR results reveal pronounced spatial heterogeneity and temporal divergence. Agricultural and industrial LUE consistently exerted negative relationship—particularly in the Pearl River Delta and eastern Guangdong—while commercial LUE evolved into a positive driver in northern and western cities. Ecological LUE shifted from a positive to a negative relationship over time. By disentangling multidimensional LUE effects and uncovering nonlinear thresholds and spatiotemporal heterogeneity, this study advances understanding of the LUE–ER nexus and provides differentiated, threshold-sensitive governance strategies for balancing land use optimization with ecological integrity in rapidly urbanizing regions.

KEYWORDS

ecological resilience, land use efficiency, XGBoost model, shapley additive explanations, guangdong province

1 Introduction

Unregulated urban land expansion has led to the global loss of more than 1.6 mil-lion square kilometers of natural land cover, threatening biodiversity, carbon storage, and the stability of ecosystem services (Wang et al., 2014; Wang and Liu, 2017; Theobald et al., 2020). In China's urban agglomerations, the pursuit of rapid urbanization—often prioritized over land use efficiency (LUE)—has emerged as a dominant development pattern since the economic reforms (Liu et al., 2021; Yang et al., 2023; Zhao et al., 2024). This inefficient trajectory has resulted in the large-scale transformation of natural ecosystems into semi-natural or fully artificial landscapes, undermining ecological structure, fragmenting habitats, and weakening ecosystem functions (Wang et al., 2016a; Wang et al., 2016b; Peng et al., 2017; Liang et al., 2024). Against this backdrop, enhancing ecological resilience (ER)—the capacity of urban ecosystems to absorb shocks, adapt to disturbances, and maintain essential functions (Holling, 1973; Dakos and Kéfi, 2022)—has become a critical policy and research priority. However, the relationship between LUE and ER remains insufficiently investigated, particularly with regard to how different dimensions of LUE can contribute to—or undermine—the resilience of ecological systems.

Existing research has extensively explored the connections between urban expansion, land-use retrieval, land resource allocation and sustainable urban development. A large body of literature has demonstrated how urban expansion leads to land conversion and functional reorganization, and how land-use efficiency plays a key mediating role in this process (Wang et al., 2019; Xie et al., 2021; Li et al., 2023; Wang et al., 2024a; b; Fan and Wei, 2025). These studies have commonly employed multi-source spatial and temporal data—such as high-resolution satellite imagery (e.g., Landsat, Sentinel), land use/land cover (LUCC) datasets, night-time light data, and urban boundary extraction techniques—to measure the scale, intensity, and spatial patterns of land expansion (Gao and O'Neill, 2020; Ul Din and Mak, 2021; Mahtta et al., 2022; Cao et al., 2024; Zhang et al., 2025). These findings consistently highlight that land-use allocation and efficiency improvements are central to mediating the relationship between urban expansion and ecological sustainability, especially for developing countries.

On one hand, improving LUE can mitigate the encroachment of ecological land, encourage compact and re-source-efficient urban forms, and alleviate human–nature conflicts (Searchinger et al., 2018; He et al., 2020; Wang et al., 2020). On the other hand, resilient ecosystems provide the ecological capacity necessary to sustain land-based development and long-term urban stability (Brand, 2009). Importantly, the LUE–ER nexus may not follow a simple linear trajectory. Moderate improvements in LUE can enhance ER by curbing sprawl and protecting ecosystem services, but excessive intensification may exceed ecosystems' regenerative capacities, leading to resource depletion, ecological fragmentation, and reduced adaptive potential (Allan et al., 2015). Whether this relationship follows a linear pattern or exhibits nonlinear dynamics with critical thresh-olds remains an open question (Li et al., 2025; Teng et al., 2025). Furthermore, traditional approaches such as system dynamics, geographical detectors, or spatial econometrics (Lee et al., 2024; Wang S. et al., 2024; Fan and Wei, 2025) often struggle to capture the complex, nonlinear, and spatially heterogeneous interactions that characterize socio-ecological systems.

Another research gap lies in the insufficient consideration of the multidimensionality of LUE. Few studies have systematically examined how different categories of land use efficiency—including agricultural, industrial, commercial, and ecological efficiency—distinctly influence ER. These land categories differ not only in spatial logics and production functions but also in environmental externalities, meaning their im-pacts on resilience are likely heterogeneous and context-dependent (Liu et al., 2021). For instance, improving agricultural land efficiency may bolster food system resilience yet degrade local ecosystems through fertilizer overuse or soil erosion (Huang et al., 2024). Enhancing commercial land efficiency may promote compact urban forms, but could also intensify ecological fragmentation and urban heat island effects (Geng et al., 2025). Similarly, industrial land efficiency may stimulate technological upgrading and resource savings, but concentrated industrial activity can generate high ecological risks. In contrast, ecological land efficiency, often reflected in the conservation and multifunctional use of green space, may directly reinforce resilience by enhancing regulating ecosystem services. Disentangling the heterogeneous, and often trade-off-laden, relationship between these LUE types and ER is essential for designing governance strategies that balance development with ecological integrity.

As China's most economically dynamic and urbanized coastal region, Guangdong Province presents a particularly valuable case for studying the LUE–ER relationship (Figure 1). Over the past 4 decades, Guangdong has undergone rapid land development, industrial restructuring, and massive urban expansion, accompanied by mounting eco-logical stress (Song et al., 2022). This dual challenge of growth and degradation makes Guangdong both a national pioneer of economic transformation and a hotspot of resilience concerns. Addressing how multidimensional LUE influences ER in such a context not only has strong regional relevance but also provides lessons for other rapidly urbanizing regions worldwide.

To fill these gaps, this study develops a multidimensional LUE evaluation frame-work encompassing agricultural, industrial, commercial, and ecological dimensions, and an ER assessment system based on the Pressure–State–Response (PSR) model.

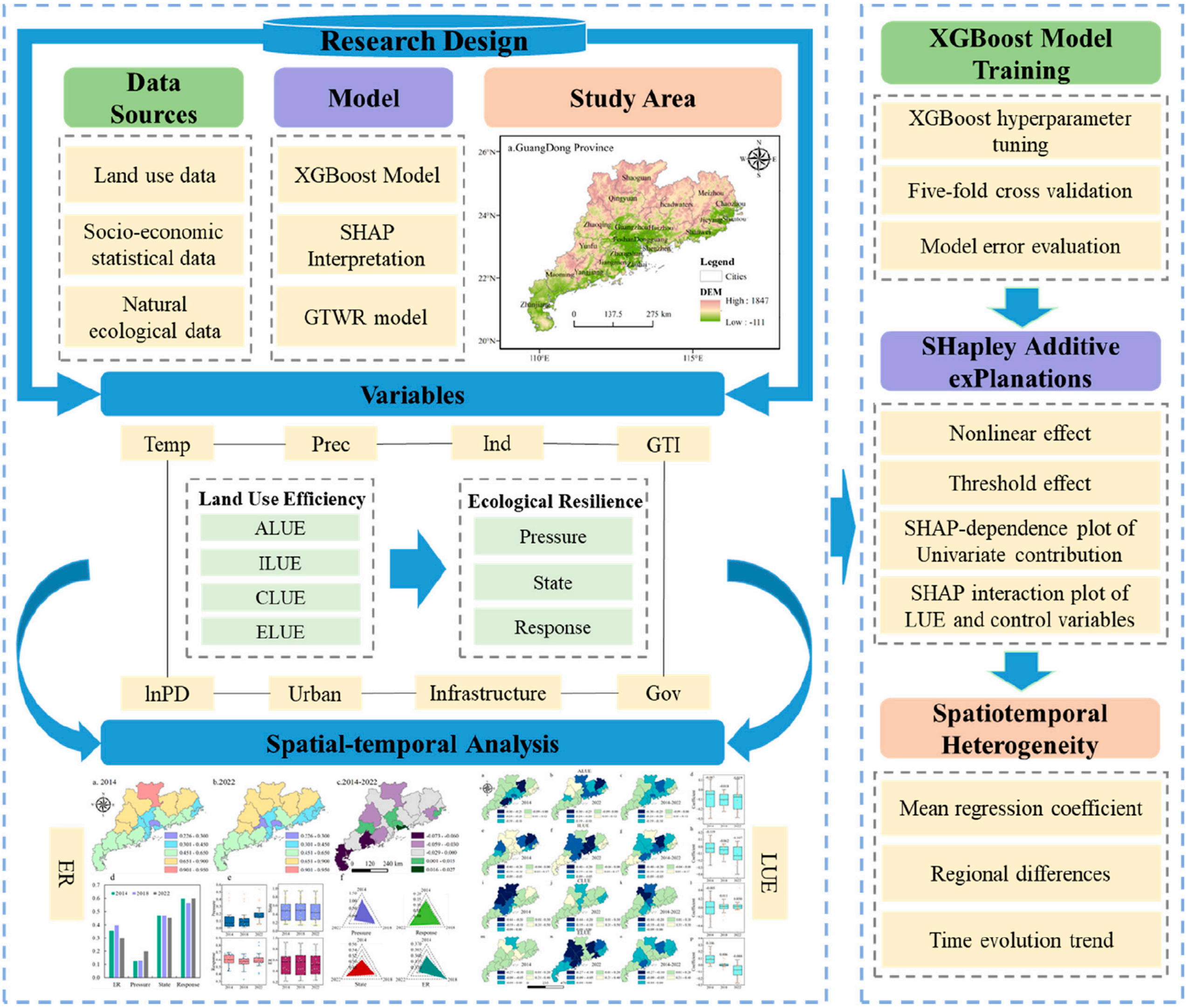

FIGURE 1
Technology roadmap.

Using data from 21 cities in Guangdong Province between 2014 and 2022, we explore the spatiotemporal evolution of both LUE and ER. To capture nonlinear effects and complex feature interactions, we employ eXtreme Gradient Boosting (XGBoost) in combination with Shapley Additive Explanations (SHAP), enabling us to identify how different LUE types influence ER and how these effects are moderated by socio-economic factors such as industrial structure, technological innovation, urbanization level, and government intervention. Furthermore, the Geographically and Temporally Weighted Regression (GTWR) model is applied to reveal spatial and temporal heterogeneity, allowing us to detect localized thresholds and divergent trajectories across the province.

This study contributes to the literature and practice in three ways: (1) by advancing a multidimensional evaluation of LUE that integrates economic, ecological, and social dimensions; (2) by identifying nonlinear dynamics, threshold effects and interaction mechanisms in the LUE–ER nexus, providing new theoretical evidence for resilience research; and (3) by mapping spatial heterogeneity across Guangdong's cities, generating policy-relevant insights for land governance and resilience-oriented planning. Collectively, these contributions aim to provide a scientific foundation and policy guidance for regulating LUE to strengthen ecological resilience in rapidly urbanizing regions.

2 Study area, methods and data sources

2.1 Overview of study area

Guangdong Province, situated along China's southern coast and bordering Hong Kong, Macau, and four inland provinces, spans latitudes 20°09′N to 25°31′N and longitudes 109°45′E to 117°20′E (Figure 2). It features a subtropical to tropical monsoon cli-mate with abundant rainfall (1,400–2,000 mm annually) and a complex topography of mountains, hills, terraces, and plains,

10.3389/fenvs.2025.1697381

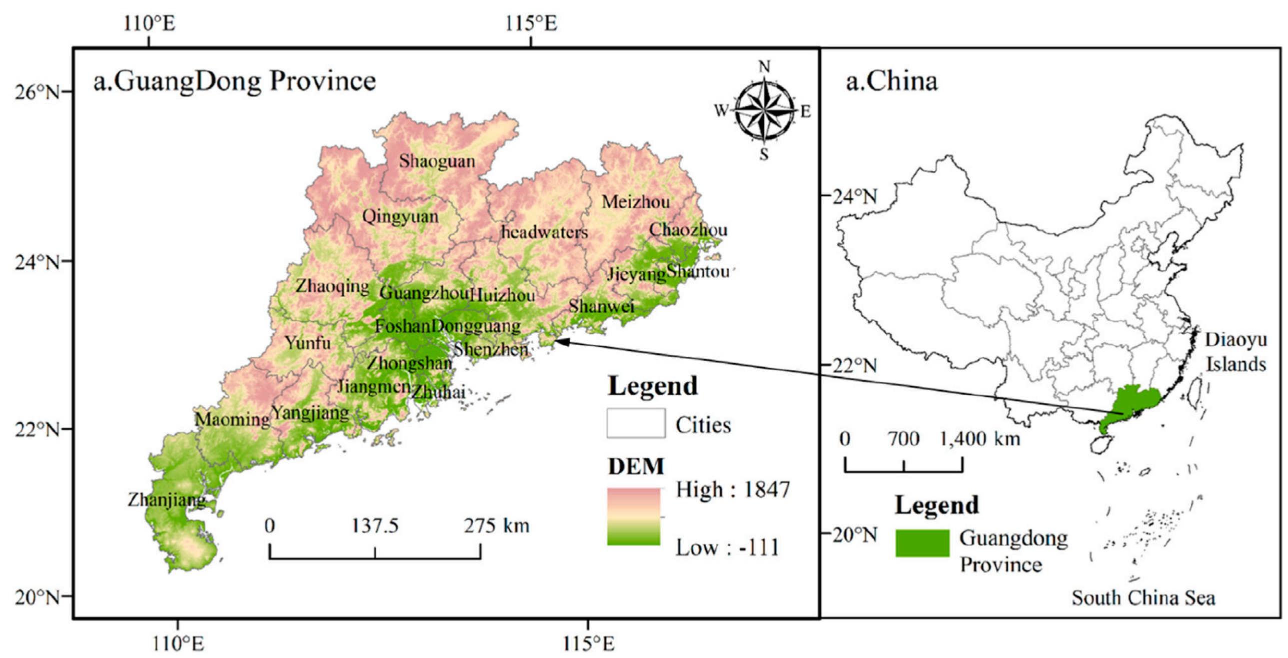

FIGURE 2
Study area.

shaped by the Pearl River system. As China's most economically developed province over the past 3 decades, Guangdong contributes nearly one-eighth of national GDP and has experienced intense urbanization, particularly in the Pearl River Delta agglomeration (Song et al., 2022). This rapid urban expansion has transformed vast areas of farmland and forest into built-up land, placing significant pressure on ecological spaces. In this study, we examine 21 prefecture-level cities across the province, including the sub-provincial cities of Guangzhou and Shenzhen, to investigate LUE and ER under conditions of sustained development stress.

2.2 Methods

The integration of the XGBoost–SHAP framework and the GTWR model in this study is motivated by the need to jointly capture nonlinear functional responses and spatial–temporal heterogeneity in the relationship between land-use efficiency (LUE) and ecological resilience (ER). Traditional econometric approaches, such as linear regression, spatial Durbin models, or panel threshold models, impose predefined functional forms and assume global parameter constancy, which may not adequately represent the complex, region-specific mechanisms driving urban ecological systems.

2.2.1 XGBoost model

eXtreme Gradient Boosting (XGBoost), developed by Chen and Guestrin (2016), is a state-of-the-art machine learning algorithm based on the Gradient Boosting Decision Tree framework. It improves predictive performance through an iterative process in which each successive tree is trained to correct the residuals of the previous one. Compared to traditional algorithms, XGBoost offers significant advantages in computational efficiency and scalability due to its optimized training procedures and support for parallel processing. Moreover, by dynamically updating the loss function throughout training, XGBoost achieves high predictive accuracy and demonstrates robust performance when applied to large-scale and complex datasets (Huang et al., 2024).

To ensure optimal model performance, hyperparameters of XGBoost were selected through a grid search combined with 10-fold cross-validation based on the lowest mean squared error (MSE) of the validation set. The main tuned parameters included the maximum tree depth (max_depth), learning rate (eta), subsampling ratio (subsample), and regularization coefficients (λ, γ). The final model configuration achieved a good balance between prediction accuracy and generalization capacity. To assess the robustness of the results, we re-estimated the model using different random seeds, repeated cross-validation, and alternative ensemble learners (Random Forest and CatBoost). The variable importance ranking and the nonlinear patterns identified by SHAP remained consistent, confirming the stability of the findings.

2.2.2 SHAP interpretation framework

To enhance the interpretability and transparency of the XGBoost model, this study applies the SHapley Additive exPlanations (SHAP) method to address its inherent "black box" nature. Grounded in cooperative game theory, SHAP assigns Shapley values to quantify the marginal contribution of each feature to the model's predictions, enabling both global and local interpretations of the relationship between predictors and outcomes (Pelegrina et al., 2023). Based on this approach, we constructed an explanatory framework to identify and assess the key drivers of ER, as detailed below:

$$\hat{y}_i = y_{base} + f\left(x_{i(ALUE)}\right) + f\left(x_{i(ILUE)}\right) + f\left(x_{i(CLUE)}\right) + f\left(x_{i(ELUE)}\right) + f\left(x_{i\,(Temp)}\right) + f\left(x_{i(Prec)}\right) + f\left(x_{i(Ind)}\right) + f\left(x_{i(GTI)}\right) + f\left(x_{i(\ln PD)}\right) + f\left(x_{i(Urban)}\right) + f\left(x_{i\,(Infrastructure)}\right) + f\left(x_{i(Gov)}\right) \tag{1}$$

In Equation 1, where x_{ij} represents the j-th feature of the i-th sample, with $i \in (1, \ldots, n)$ and $j \in \{\text{ALUE, ILUE, CLUE, ELUE}, \ldots, \text{Gov}\}$; y_{base} is the mean prediction across all samples; and $f(x_{ij})$ denotes the SHAP value attributed to the corresponding feature of that sample.

XGBoost–SHAP was selected for its advantages in modeling nonlinear, high-dimensional interactions without requiring prior assumptions about functional forms. XGBoost's gradient boosting mechanism ensures predictive robustness through iterative residual correction, while the SHAP interpretation framework provides transparent post-hoc explanations of variable importance and marginal effects. Compared with alternative ensemble methods such as Random Forest or CatBoost, XGBoost offers faster convergence, better generalization, and well-established interpretability through SHAP values—enabling a quantitative identification of thresholds and nonlinear transitions in LUE–ER linkages.

2.2.3 GTWR model

Unlike global spatial econometric models (e.g., SAR, SDM) or static GWR, GTWR allows regression coefficients to vary continuously across both space and time via Gaussian kernel weighting. By extending the traditional GWR framework to incorporate temporal variation, the GTWR model allows parameter estimates to vary simultaneously over space and time, thereby offering a more nuanced understanding of dynamic local relationships. The Geographically and Temporally Weighted Regression (GTWR) model is employed to capture the spatiotemporal heterogeneity in the effects of LUE on ER across different regions and time periods (Ou et al., 2022). The model is formally specified as follows:

$$UER_i = \beta_0(u_i, v_i, t_i) + \beta_1(u_i, v_i, t_i)ALUE_i + \beta_2(u_i, v_i, t_i)ILUE_i + \beta_3(u_i, v_i, t_i)CLUE_i + \beta_4(u_i, v_i, t_i)ELUE_i + \varepsilon_i \tag{2}$$

In Equation 2, where ER_i represents the observed value at location i; (u_i, v_i, t_i) denote the spatial and temporal coordinates of the observation; $\beta_0\ (u_i, v_i, t_i)$ is the intercept term; $\beta_1\ (u_i, v_i, t_i)$, $\beta_2\ (u_i, v_i, t_i)$, $\beta_3\ (u_i, v_i, t_i)$, and $\beta_4\ (u_i, v_i, t_i)$ is the regression coefficient of ALUE, ILUE, CLUE, ELUE for the i observation, respectively; and ε_i is the random error term.

For the GTWR estimation, both spatial and temporal weighting functions were defined using a Gaussian kernel. The spatial weight between observations i and j is given by $w_{ij} = \exp\left[-\left(d_{ij}/b_s\right)^2\right]$, where d_{ij} denotes the Euclidean distance between city centroids and b_s is the spatial bandwidth. The temporal weight is defined as $w_t = \exp\left[-\left(\left(t_i - t_j\right)/b_t\right)^2\right]$, where b_t is the temporal bandwidth. The optimal combination of spatial and temporal bandwidths was determined by minimizing the corrected Akaike Information Criterion (AICc), ensuring model parsimony and stable local parameter estimation.

2.3 Indicator selection and data source

2.3.1 ER quantification

The Pressure–State–Response (PSR) framework, initially proposed by the United Nations Environment Programme, provides a widely adopted conceptual model for examining the interactions between human activities and ecological systems. Within this framework, pressures refer to anthropogenic stressors such as pollution, resource exploitation, and land conversion; state reflects the condition and functioning of ecosystems; and response represents the institutional and societal actions taken to mitigate environmental degradation or enhance ecosystem resilience (Zhao et al., 2024; Li et al., 2023; Lee et al., 2024).

Building upon this logic, the present study develops a multi-agent, multilevel evaluation system to quantify urban ecological resilience (ER) from a dynamic socio–ecological perspective. Specifically, the pressure dimension captures the intensity of human and economic activities that exert stress on ecosystems—such as population density, land-use intensity, and industrial pollution. The state dimension measures the ecological and environmental quality of urban systems, including vegetation coverage (NDVI), *per capita* park area, water quality, and air quality indicators that collectively reflect ecosystem vitality and stability. The response dimension represents adaptive capacity and governance performance, measured by ecological investment, environmental regulation strength, and public environmental participation.

Each indicator is normalized to eliminate differences in units and magnitudes. To ensure objectivity, indicator weights are derived using the entropy method, which minimizes subjective bias and emphasizes indicators with higher informational variability. The composite ER index for each city is then calculated as the weighted sum of the three dimensions—Pressure (P), State (S), and Response (R)—yielding a bounded score between 0 and 1, where higher values denote stronger ecological resilience.

This PSR-based framework offers a systematic approach to integrating environmental pressures, ecological conditions, and governance feedbacks into a unified metric. Compared with single-dimensional ecological indices, it better captures the dynamic feedback and adaptive processes that underpin urban resilience. The specific indicators, weights, and data sources are summarized in Table 1, and detailed variable definitions and calculation formulas are provided in Supplementary Materials 1.

This study employs the entropy weight method to evaluate ER. This objective weighting approach minimizes biases associated with subjective judgment and mitigates distortions caused by extreme values in individual indicators. First, Equation 3 is applied to normalize the data based on the range of maximum and minimum values, accommodating both positive and negative indicators. Second, Equation 4 standardizes each indicator and calculates its information entropy and coefficient of variation. Finally, Equation 5 is used to derive the weight of each indicator and compute the composite ER score.

$$z_{\gamma\lambda} = \frac{c_{\gamma\lambda} - \mathrm{minc}_\lambda}{\mathrm{maxc}_\lambda - \mathrm{minc}_\lambda};\ z_{\gamma\lambda} = \frac{\mathrm{maxc}_\lambda - c_{\gamma\lambda}}{\mathrm{maxc}_\lambda - \mathrm{minc}_\lambda} \tag{3}$$

TABLE 1 Calculation indicator system of ER and data sources.

Variable	Target layer	Criterion layer	Indicator	Direction	Data source
Ecological Resilience	Pressure	Land occupation	Urban construction land area	–	A
		Resource consumption	Energy consumption volume	–	B
		Environmental pollution	Environmental pollution index	–	C
	State	Potential	Ecosystem service value	+	A
		Connectivity	Urban spatial compactness index	+	A
		Resilience	Normalized difference vegetation index (NDVI)	+	D
	Response	Green infrastructure	Green space ratio in built-up areas	+	E
		Resource use efficiency	Energy efficiency	–	C
		Pollution control mechanism	Centralized treatment rate of sewage	+	C

$$P_{\gamma\lambda} = \frac{z_{\gamma\lambda}}{\sum_{i=1}^{n} z_{\gamma\lambda}};\ e_\lambda = -\frac{1}{\ln n_\gamma}\sum_{\gamma=1}^{n} P_{gl}\ln P_{\gamma\lambda};\ d_\lambda = 1 - e_\lambda; \tag{4}$$

$$w_\lambda = \frac{d_{\gamma\lambda}}{\sum_{\lambda=1}^{n} d_{\gamma\lambda}};\ y = \sum z_{\gamma\lambda} w_\lambda \tag{5}$$

2.3.2 Evaluation of LUE based on super-SBM model

Traditional approaches to measuring LUE often rely on single-dimensional indicators, such as economic output per unit of land area (Cui and Wang, 2015) or *per capita* built-up area (Masini et al., 2019). Although computationally straightforward, these measures fail to capture the integrated performance of land use within multi-input–multi-output systems, limiting their applicability for evaluating complex spatial development strategies. In response, an increasing number of studies have adopted data envelopment analysis (DEA) frameworks to assess LUE more comprehensively through multidimensional indicator systems (Ferreira and Féres, 2020; Gao et al., 2020; Huang et al., 2024). To further address the heterogeneity among land functions, this study employs the super-efficiency slack-based measure (Super-SBM) model, which extends the conventional DEA approach by accounting for slack variables and allowing for cross-unit efficiency comparison even when efficiency scores exceed unity. This model is particularly suitable for evaluating urban land systems characterized by diverse input structures and output objectives, providing a robust basis for analyzing spatial disparities in LUE.

According to China's land classification standards, land use is broadly categorized into agricultural land, construction land, and unused land. Construction land is further divided into residential, industrial, and transportation-related subtypes. For analytical clarity and to align with functional land utilization patterns, this study reclassifies construction land into industrial and commercial categories, corresponding to secondary and tertiary sector activities. Ecological land, typically grouped under "unused land" in official statistics, is treated here as a distinct category to reflect its critical role in maintaining ecosystem functions and resilience. Accordingly, four types of LUE are evaluated—agricultural (ALUE), industrial (ILUE), commercial (CLUE), and ecological (ELUE)—each reflecting a specific land function within Guangdong Province.

The Super-SBM model is applied separately to each land-use category, with inputs and desirable outputs defined according to their dominant production or ecological functions. For example, ALUE considers cultivated land area, fertilizer use, and agricultural labor as inputs, with agricultural value added as the desirable output; ILUE includes industrial land, fixed asset investment, and employment as inputs, with secondary industry value added as output; CLUE uses commercial land and service employment as inputs, with tertiary industry value added as output; and ELUE treats ecological and green space area as inputs, with NDVI and NPP serving as ecological productivity outputs. All indicators are normalized to ensure comparability across cities and years.

These four LUE categories serve as representative dimensions to explore the heterogeneous mechanisms linking LUE and ER in Guangdong Province. The specific indicators and corresponding data sources are detailed in Table 2.

This study adopts the Super Slack-Based Measure (Super-SBM) model to calculate LUE. The Super-SBM model overcomes a key limitation of traditional Data Envelop-ment Analysis (DEA) methods, which cannot differentiate among decision-making units (DMUs) deemed efficient. Unlike conventional DEA models, Super-SBM permits efficiency scores greater than 1, allowing for the ranking of relatively efficient units across different regions or land use types. This capability makes it particularly well-suited for advanced evaluations involving performance comparison, spatial differentiation, and policy optimization.

$$\text{Min}\ \varphi = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{ik}}}{\frac{l}{s_1+s_2}\left(\sum_{p=1}^{s_1}\frac{\overline{y_p^d}}{y_{pk}^d} + \sum_{q=1}^{s_2}\frac{\overline{y_q^u}}{y_{qk}^u}\right)} \tag{6}$$

$$\text{Subject to}\ \begin{cases} x_{ik} \geq \sum\limits_{j=1,\neq k}^{n} x_{ij}\lambda_j - x_i \\ y_{pk}^d \leq \sum\limits_{j=1,\neq k}^{n} y_{pj}^d\lambda_j - y_p^d \\ y_{qk}^u \leq \sum\limits_{j=1,\neq k}^{n} y_{qj}^u\lambda_j - y_q^u \\ \bar{x}, \bar{y}^d, \bar{y}^u, \lambda_j \geq 0 \\ j = 1,2,\cdots,n;\ k = 1,2,\cdots,n \end{cases} \tag{7}$$

TABLE 2 LUE calculation indicator system and data sources.

Variables	Category	Index	Unit	Data source
Agricultural LUE	Input	Agricultural employment	10,000 persons	F
		Use of pesticides and fertilizers	10,000 tons	G, H, I
		Cultivated land area	1,000 ha	G, H, I
		Agricultural machinery power *per capita*	kilowatts	G, H, I
	Output	Per capita grain yield	tons	G, H, I
		Value added of primary industry	billion CNY	F
Industrial LUE	Input	Industrial land area	km^2	E
		Secondary industry employment	10,000 persons	F
	Output	Value added of secondary industry	billion CNY	F
Commercial LUE	Input	Commercial service land area	km^2	E
		Tertiary industry employment	10,000 persons	F
	Output	Value added of tertiary industry	billion CNY	F
Ecological LUE	Input	Green land area	km^2	E
		Normalized difference vegetation index	%	D
	Output	Net primary productivity of vegetation	grams/m^2	J

In Equations 6, 7, where φ represents LUE; m signifies the number of input factors, S_1 represents the number of desired output factors, S_2 represents the number of undesired output factors; x_i, y_p^d, y_q^u represent slack variables; x_{ik}, y_{pk}^d, y_{qk}^u represent the input quantity of i, desired output quantity of p, and the undesired output quantity for factor q; λ_j is the vector of weights.

2.3.3 Control variables

To mitigate potential estimation bias arising from omitted variable issues, the model incorporates a set of control variables spanning natural, economic, social, and policy dimensions (Fan and Wei, 2025; Lee et al., 2024), as detailed in Table 3.

2.4 Data source

In this study, we utilized multi-source data encompassing land use, meteorological conditions, ecological environment, and socioeconomic factors. Data sources are detailed in Table 4. A panel dataset was constructed for 21 cities in Guangdong Province, covering the period between 2014 and 2022. Missing values were addressed using standard interpolation techniques to ensure data continuity and robustness.

Table 5 presents the descriptive statistics of all variables used in the analysis. The results show substantial variation across cities and years, reflecting the spatial heterogeneity of Guangdong's socio–ecological system. ER values range from 0.226 to 0.923, indicating moderate resilience overall with noticeable disparities among cities. The four dimensions of LUE exhibit distinct efficiency levels, with ecological land generally more efficient than other land. The control variables also display reasonable variability, supporting the robustness of subsequent regression and machine learning analyses. Specifically, the Shapiro–Wilk W test was employed to examine the normality of residuals, and the results confirmed that the residuals followed an approximately normal distribution. The Variance Inflation Factor (VIF) test was employed to check for multicollinearity, and all VIF values were below 4, indicating that there were no serious multicollinearity issues between the variables.

3 Spatiotemporal evolution characteristics of ER and LUE

3.1 Spatiotemporal evolution of ER

Between 2014 and 2022, ER in Guangdong Province exhibited a clear downward trend, with the average ER score declining from 0.354 to 0.297—a cumulative decrease of approximately 16.1% (Figure 3d). This deterioration was primarily driven by a sharp rise in the ecological pressure index, which increased by over 60% during the study period. The escalation in pressure can be attributed to rapid industrialization and urbanization, particularly the continuous expansion of built-up areas and intensified human activity, which placed considerable strain on ecosystem regulatory and adaptive capacities.

Despite this overall decline, regional disparities in ER showed signs of convergence. The coefficient of variation (CV) for ecological pressure declined significantly from 1.12 in 2014 to 0.59 in 2022, indicating increasing uniformity across cities. In contrast, the CVs for ecological state and societal response remained relatively stable, ranging from 0.51 to 0.54 and 0.14 to 0.17, respectively, suggesting persistent disparities in ecosystem conditions and policy response capacities (Figures 3e,f).

Spatially, ER displays a compound pattern of "higher in the north and lower in the south" and "weaker in central, stronger in peripheral regions" (Figures 3a,b). Cities in northern Guangdong,

TABLE 3 Control variables: definitions and data sources.

Category	Variable	Notation	Measurement	Data source
Natural factors	Temperature	*Temp*	Average annual temperature	K
	Precipitation	*Prec*	Average annual temperature	K
Economic factors	Industrial structure	*Ind*	The ratio of value added in the tertiary sector to that in the secondary sector	F
	Green technological innovation	*GTI*	The number of green patent applications (log-transformed)	L
Social factors	Population density	*lnPD*	The ratio of urban population to urban area	E
	Urbanization level	*Urban*	The proportion of the urban population to the total permanent population	F
	Public infrastructure	*Infrastructure*	*per capita* road area	E
Policy factors	Government intervention	*Gov*	The ratio of local general public budget expenditure to regional GDP	F

such as Shaoguan and Qingyuan, maintain higher ER levels due to favorable ecological endowments and lower development intensity. In contrast, urban agglomerations in the Pearl River Delta—such as Guangzhou, Foshan, and Shen-zhen—exhibit lower ER values, driven by high-intensity land use and compressed ecological space.

Notably, some Pearl River Delta cities experienced ER improvements during the study period (Figure 3c). Shenzhen, Guangzhou, and Dongguan recorded respective ER increases of 8.46%, 3.32%, and 6.63%, potentially reflecting the benefits of strengthened ecological governance, green infrastructure investment, and the application of digital urban management tools. By contrast, cities in western Guangdong—such as Zhanjiang and Yangjiang—suffered more pronounced ER declines of 12.45% and 10.36%, respectively, likely due to weaker environmental protection capacity, resource-dependent industrial structures, and extensive urban expansion practices.

3.2 Spatiotemporal evolution of LUE

Between 2014 and 2022, LUE in Guangdong Province demonstrated distinct spatiotemporal patterns across four functional dimensions: agricultural, industrial, commercial, and ecological.

Agricultural LUE improved significantly, rising from 0.654 to 0.791, with regional disparities narrowing over time (Figure 4d). Spatially, it exhibited a pattern of “low in the central region, high in both eastern and western wings” (Figures 4a,b). High-efficiency zones were concentrated in western cities (e.g., Zhanjiang, Yangjiang), northern mountainous areas (e.g., Qingyuan), and eastern cities (e.g., Chaozhou, Shantou), which benefit from extensive cropland and forest resources. In contrast, the Pearl River Delta (e.g., Foshan, Huizhou, Zhuhai, Shenzhen) exhibited persistently low agricultural LUE due to rapid urbanization and farmland conversion. While agricultural LUE declined in western and northern Guangdong, it rose markedly in the east, with limited improvement in the Pearl River Delta (Figure 4c).

Industrial LUE followed a U-shaped trajectory—initially declining, then rebounding—with widening regional disparities (Figure 4h). High industrial LUE persisted in core Delta cities such as Zhongshan, Shenzhen, and Dongguan (Figures 4e,f). Non-core regions saw a decline, while the Delta experienced recovery, likely due to the transition from traditional industries to advanced manufacturing (Figure 4g).

Commercial LUE showed a fluctuating trend—declining from 0.614 in 2014 to 0.495 in 2018, then rebounding to 0.589 in 2022—driven by shifts in consumer behavior, e-commerce, and new retail formats. Spatially, higher commercial LUE appeared in eastern and western cities, reflecting efficient adaptation in non-core areas. The Pearl River Delta, however, experienced a sustained decline, suggesting a transitional mismatch between old commercial formats and emerging spatial demands. Interregional disparities in commercial LUE narrowed, indicating greater balance, likely due to infrastructure diffusion and planning efforts.

Ecological LUE followed an inverted U-shaped trend—increasing from 0.354 in 2014 to 0.397 in 2018, then falling sharply to 0.297 by 2022—with a general decline and convergence in spatial disparities (Figure 4p). The spatial pattern shifted from “high in the north, low in the south” to the reverse (Figures 4m,n). While northern Guangdong saw deterioration, the Pearl River Delta experienced notable gains (Figure 4o), possibly due to early investments in ecological restoration. However, intensified land development and shrinking ecological space have since driven down ecological LUE, posing risks of long-term functional degradation.

4 Nonlinear effects of LUE on ER

4.1 XGBoost model setting and validation

To examine the nonlinear effects of LUE on urban ER, we constructed an XGBoost regression model with ER as the dependent variable and a set of predictors including agricultural LUE (ALUE), industrial LUE (ILUE), commercial LUE (CLUE), ecological LUE (ELUE), temperature (Temp), precipitation (Prec), industrial structure (Ind), green technology innovation (GTI), population density (lnPD), urbanization level (Urban), infrastructure, and government intervention (Gov).

To mitigate overfitting and enhance generalization, the dataset was randomly divided into training (70%) and testing (30%) subsets. Model tuning was conducted using a grid-search algorithm

TABLE 4 Data source.

Serial number	Data source
A	Land-cover dataset of China by Yang Jie et al., Wuhan University (https://zenodo.org/)
B	Global 500 m pseudo NPP-VIIRS nighttime lights, National Earth System Science Data Center, China
C	China environmental statistics yearbook
D	Resource and Environmental Science & Data Center, Chinese Academy of Sciences (http://www.resdc.cn)
E	China urban construction statistical yearbook
F	China city statistical yearbook
G	China agriculture and forestry database
H	China rural areas, agriculture, and peasantry database
I	China regional economy database
J	NASA-EARTHDATA (https://appeears.earthdatacloud.nasa.gov/)
K	National Centers for Environmental Information (NCEI), National Oceanic and Atmospheric Administration (NOAA), United States
L	China National Intellectual Property Administration (https://www.cnipa.gov.cn/)

combined with 10-fold cross-validation, which iteratively partitioned the training data into 10 equal folds—using nine folds for model fitting and one for validation in each iteration—to identify the optimal balance between bias and variance. The final optimized hyperparameters were: *n_estimators* = 100, *max_depth* = 5, *alpha* = 0.11, *max_leaves* = 15, and *learning_rate* = 0.018.

Model performance was evaluated on both training and testing datasets using multiple metrics, including the coefficient of determination (R^2), mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). The XGBoost model achieved R^2 = 0.916, MSE = 0.003, RMSE = 0.056, and MAE = 0.048 on the training set, and R^2 = 0.829, MSE = 0.005, RMSE = 0.071, and MAE = 0.059 on the testing set. These results demonstrate strong predictive accuracy and minimal overfitting, confirming the model's generalizability. Robustness checks—including feature omission tests, hyperparameter perturbation, and controlled data noise experiments—further verified that the XGBoost–SHAP framework remained stable across different specifications, thereby ensuring the reliability of the model's interpretive outputs.

4.2 Nonlinear relationship and threshold effects

The XGBoost–SHAP combination provides a nonparametric approximation of the underlying functional relationship $f(X)$ between predictors and outcomes. To further explore the nonlinear effects of various LUE types on urban ER, SHAP dependence plots were generated (Figure 5). In each plot, the x-axis represents the value of a given feature, while the y-axis denotes its corresponding SHAP value. Each dot indicates the marginal contribution of that feature in a specific observation, enabling identification of threshold effects or turning points where the direction of influence on ER shifts. The inflection points visible on SHAP dependence plots correspond to local extrema on this estimated response surface—where the marginal effect of a given predictor changes direction. Because these patterns emerge from repeated ensemble averaging and cross-validated training, the resulting thresholds can be regarded as asymptotically stable empirical transition zones within the observed data domain.

TABLE 5 Descriptive statistics of related variables.

Variable	N	Mean	SD	Min	Max	Shapiro–Wilk W test	VIF
ER	189	0.533	0.188	0.226	0.923	0.950***	—
ALUE	189	0.728	0.221	0.330	1.506	0.971***	1.100
ILUE	189	0.521	0.199	0.153	1.174	0.967***	1.520
CLUE	189	0.565	0.190	0.217	1.259	0.947***	1.520
ELUE	189	0.357	0.330	0.029	3.003	0.771***	1.050
Temp	189	22.963	0.829	20.787	24.656	0.955***	1.280
Prec	189	0.005	0.001	0.003	0.008	0.970***	1.120
Ind	189	3.145	6.453	0.052	34.946	0.448***	1.360
GTI	189	22.978	8.038	11.862	57.676	0.893***	1.280
lnPD	189	7.902	0.727	6.006	9.491	0.985***	1.570
Urban	189	63.904	19.304	36.020	99.850	0.904***	1.530
Infrastructure	189	16.471	5.971	3.560	37.116	0.946***	1.180
Gov	189	0.177	0.072	0.070	0.399	0.907***	1.440

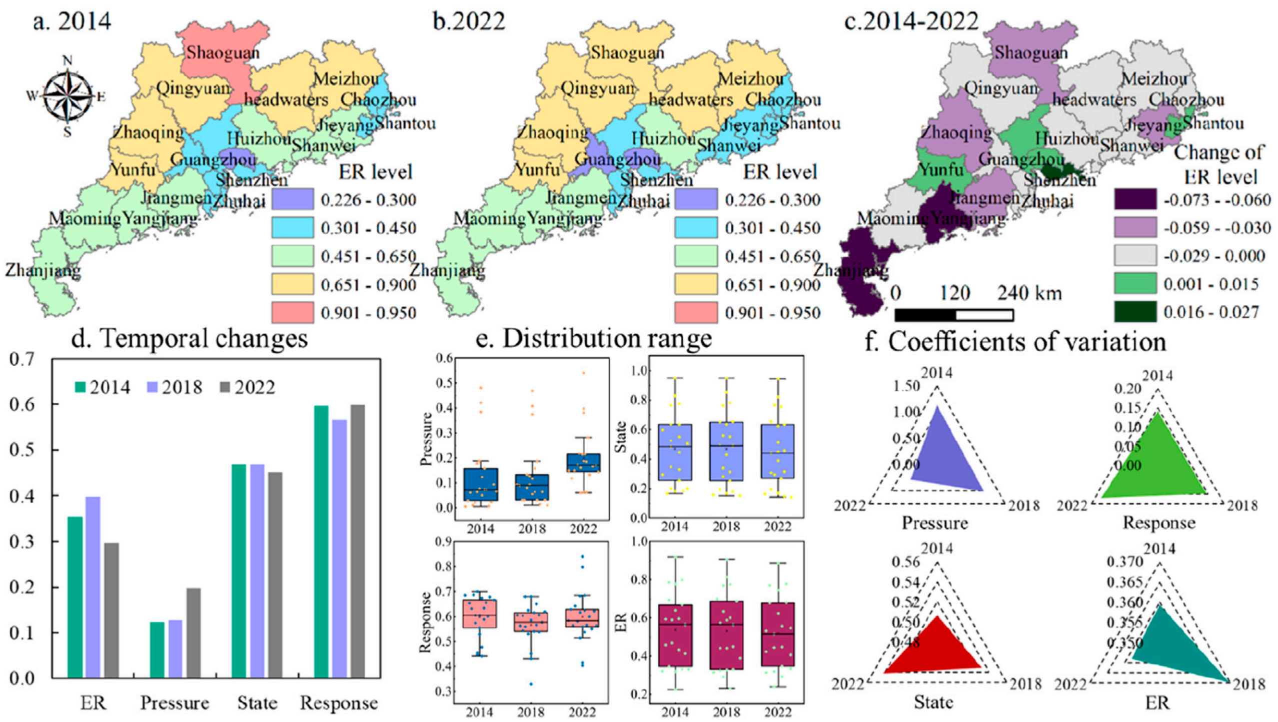

FIGURE 3
Spatio-temporal evolutionary trajectories of urban ER level in Guangdong Province. The spatial pattern of urban ER in Guangdong Province in 2014 and 2022 **(a,b)** Changes in urban ER in Guangdong Province from 2014 to 2022 **(c)** Temporal changes and distribution range in ER breakdown indicators **(d,e)** Coefficients of variation in ER and breakdown indicators **(f)**.

Figures 5a–d depict the individual effects of four LUE types. Figure 5a reveals a clear nonlinear relationship between agricultural LUE and ER: SHAP values decline as agricultural LUE increases, indicating diminishing marginal returns. When agricultural LUE remains below 0.72, its contribution to ER is positive, likely due to efficient resource use and agro-ecological protection. However, beyond this threshold, the relationship turns negative—suggesting that excessive intensification may lead to ecological degradation, biodiversity loss, or overuse of land resources.

Figure 5b demonstrates a gradient-driven threshold in industrial LUE. Below 0.66, SHAP values remain positive and stable, reflecting the benefits of efficient, moderately scaled industrial activities. Above 0.66, SHAP values decline sharply, indicating that high-efficiency zones may trigger environmental externalities such as emissions, land sealing, or infrastructure overload, thereby undermining ER despite spatial productivity gains.

Figure 5c shows that commercial LUE exhibits a clear threshold effect at 0.55. Below this value, the contribution to ER is negative, likely due to fragmented or underutilized commercial land. Once the threshold is crossed, SHAP values become positive, suggesting that well-utilized commercial land—through compact, multifunctional, and transit-oriented development—can enhance urban resilience by reducing emissions, improving accessibility, and fostering mixed land uses.

Figure 5d reveals an inverted U-shaped relationship between ecological LUE and ER. SHAP values are positive when ecological LUE is below 0.29, indicating that moderate improvements enhance ER through increased vegetation, improved microclimates, and stronger ecosystem services. However, beyond this point, the marginal contribution turns negative. This may reflect ecological overengineering or excessive concentration of ecological functions, which compromise ecosystem heterogeneity and reduce adaptive capacity.

Figures 5e,f highlights the threshold effects of climatic conditions. Moderate temperatures (<22.78 °C) and sufficient precipitation (>0.005 mm) contribute positively to ER. Beyond these thresholds, the marginal benefits either diminish or reverse—suggesting biophysical limits, where heat stress and drought increasingly suppress ecosystem resilience. These findings point to the importance of climate-sensitive spatial planning.

Figures 5g–l illustrates nonlinear effects of economic, social, and policy factors. Industrial structure exhibits a consistently negative relationship with ER, likely due to environmental pressure from industrial agglomeration. Green technology innovation displays a threshold at 6.43: below this, ER improves; beyond it, the effect reverses—possibly due to diminishing returns or uneven diffusion of innovation. Population density and urbanization level show similar inflection points at 7.83 and 49.78, respectively. Moderate urban concentration promotes ER, while over-concentration induces ecological stress. Infrastructure investment exhibits a dual-threshold pattern: ER benefits are observed within the 12.21–24.38 range, whereas both under- and overinvestment weaken resilience. Lastly, government intervention enhances ER only when exceeding 0.15, implying that minimal policy engagement is insufficient to support ecological goals.

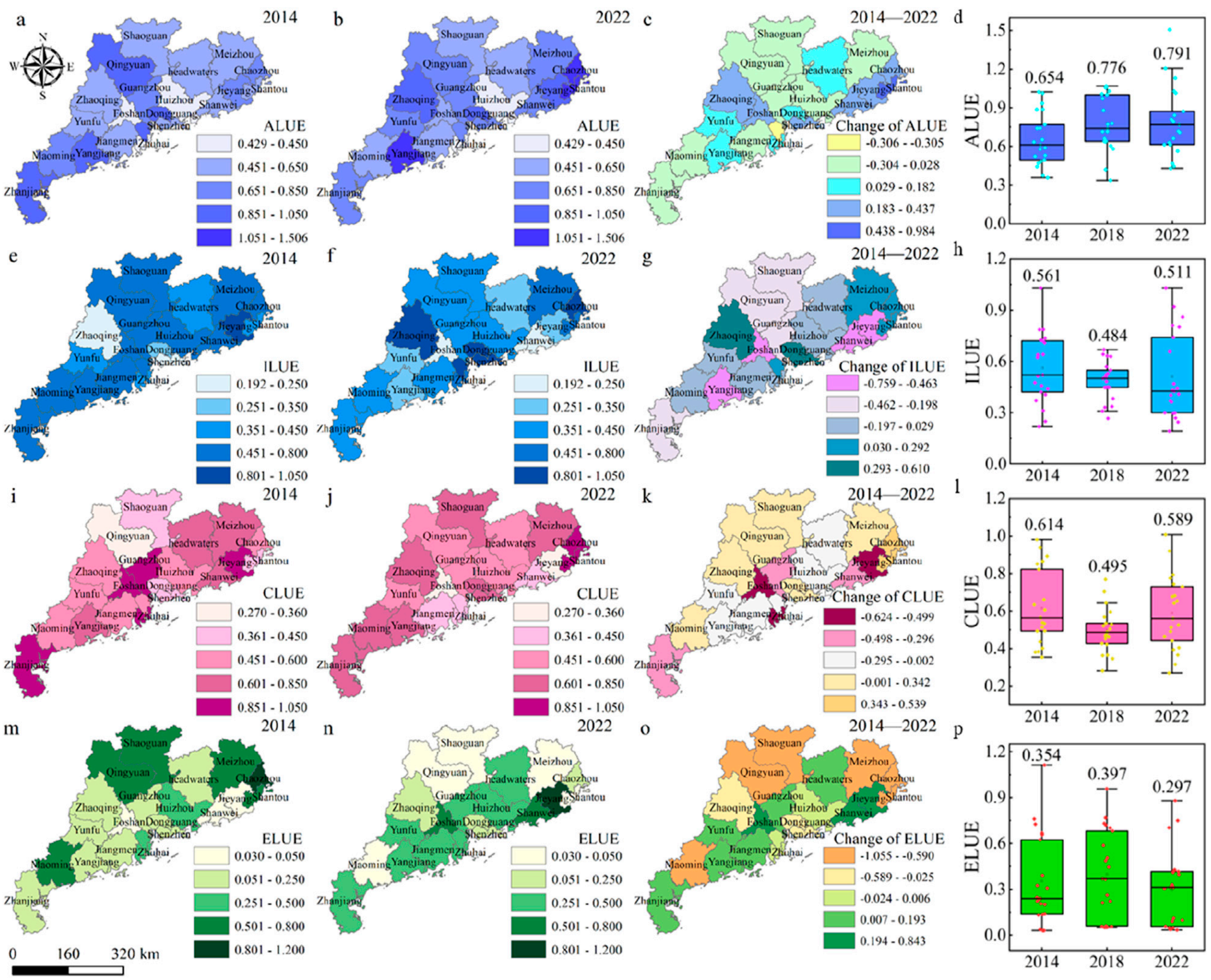

FIGURE 4
Spatiotemporal evolutionary trajectories of LUE in Guangdong Province. The spatial pattern of agriculture LUE **(a,b)** industrial LUE **(e,f)** commercial LUE **(i,j)** and ecological LUE **(m, n)** in Guangdong Province in 2014 and 2022; Changes in agricultural LUE **(e)** industrial LUE **(g)**, commercial LUE **(k)** and ecological LUE **(o)** in Guangdong Province from 2000 to 2022 **(c)** Box-plot of agricultural LUE **(d)** industrial LUE **(h)** commercial LUE **(l)** and ecological LUE **(p)** in Guangdong Province from 2014 to 2022.

Collectively, these results highlight the policy significance of threshold-aware governance. The identified values function as empirical reference ranges guiding differentiated land-use management. Rather than pursuing ever-higher efficiency, cities should aim to optimize within the threshold range—encouraging underperforming areas to improve efficiency while guiding highly developed regions toward ecological restoration and balanced resource use. Such evidence-based thresholds provide quantitative support for adaptive, region-specific land-use and resilience strategies under China's dual-carbon and sustainable-urban-development goals.

4.3 Interaction effects between LUE and socioeconomic factors

To further elucidate how different types of LUE interact with key socioeconomic factors to influence urban ER, Figure 6 presents SHAP interaction plots capturing joint effects across multiple dimensions. Each subplot displays how the marginal contribution of an LUE dimension to ER changes under varying levels of another variable. The color gradient indicates the magnitude of the interacting variable, and the curved line traces the combined marginal effect.

Agricultural LUE and industrial structure exhibit a pronounced U-shaped interaction (Figure 6a): both low and high levels of agricultural LUE synergize positively with industrial upgrading to enhance ER. However, at moderate levels of agricultural LUE, the interaction becomes negative—suggesting that mismatches between land intensification and industrial transformation may result in ecological overuse or degradation. Similarly, the interaction between agricultural LUE and population density reveals a "double-edged sword" pattern (Figure 6c): in low-density areas, the synergy enhances ER, likely due to lower ecological stress, while in high-density contexts, intensified land pressure undermines the regulatory functions of agroecosystems. Interactions with green

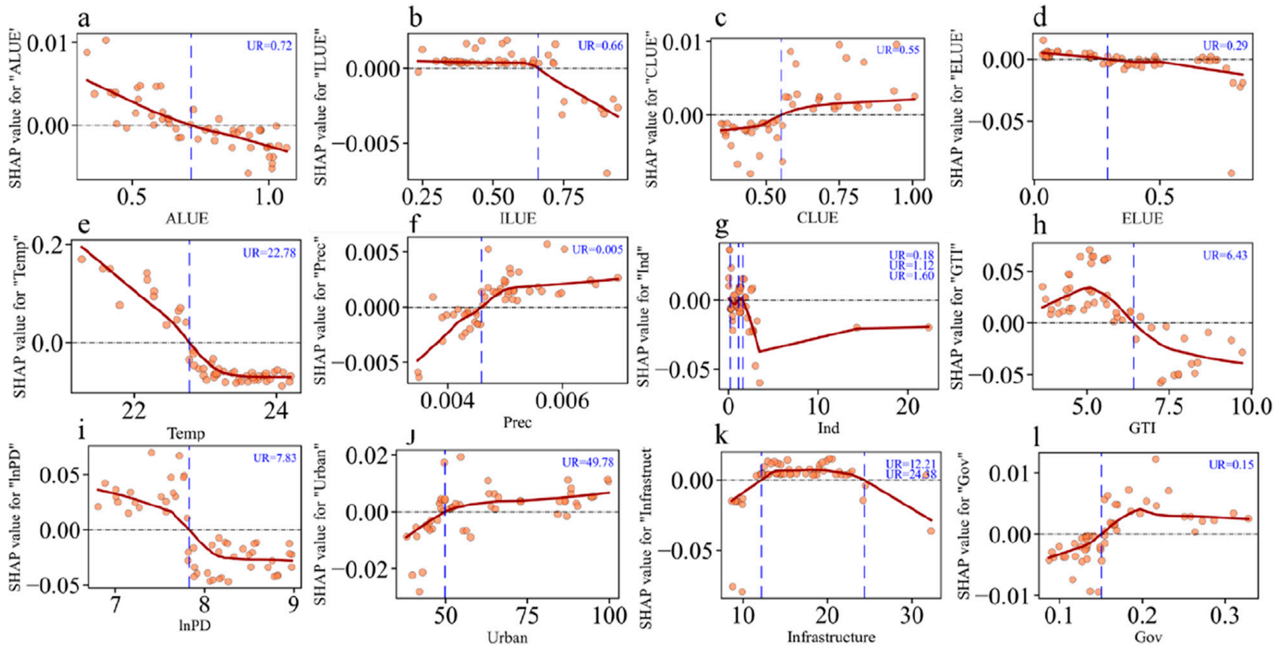

FIGURE 5
SHAP-dependence plot of univariate contribution of ALUE **(a)**, ILUE **(b)**, CLUE **(c)**, EL-UE **(d)**, Temp **(e)**, Prec **(f)**, Ind **(g)**, GTI **(h)**, lnPD **(i)**, Urban **(j)**, Infrastructure **(k)** and Gov **(l)** for ER. Note: The notation "UR" denotes the upper-range threshold value derived from SHAP dependence analysis. It marks the empirical point at which the marginal impact of a predictor on ER changes its sign or intensity, reflecting a critical transition in the land–ecosystem interaction.

technology innovation, urbanization, infrastructure, and government intervention (Figures 6b,d,e) generally amplify agricultural LUE's positive contribution to ER. However, once agricultural LUE exceeds a critical threshold, its joint benefits diminish or even reverse, reflecting ecological saturation or mismanagement under intensified land use.

In contrast, industrial LUE and industrial structure exhibit more nuanced interactions (Figure 6g). In areas with a monostructural industrial base, high industrial LUE may aggravate environmental pressure due to production rigidity and governance inefficiencies, leading to negative ER outcomes. As industrial structures diversify and upgrade, the ecological benefits of efficient industrial land become increasingly prominent, suggesting that structural transformation is key to unlocking industrial land's ecological potential. However, interaction effects between industrial LUE and green technology innovation or population density are relatively weak (Figures 6h,i), implying that these drivers have yet to fully integrate into industrial ecological upgrading strategies. Meanwhile, interactions with urbanization, infrastructure, and government intervention (Figures 6j–l) often exert suppressive effects on ER. In contexts of weak planning or insufficient administrative oversight, high industrial LUE may correlate with ecological decline, forming a classic "efficiency–pollution paradox."

The interaction between commercial LUE and industrial structure follows an inverted U-shaped trajectory (Figure 6m). At moderate commercial LUE levels, synergy with optimized industrial structures enhances ER—possibly due to spatial compactness and mixed-use efficiencies. However, overall effects remain largely suppressive, suggesting ecological trade-offs in over-commercialized spaces. Interactions between commercial LUE and green technology innovation, population density, and urbanization generally strengthen ER contributions as these factors increase (Figures 6n–p), indicating that commercial land becomes more ecologically functional when embedded in innovation-driven, dense, and urbanized environments. Yet, under low commercial LUE, these synergies may collapse, reversing their beneficial effects. Interaction effects with infrastructure and government intervention are relatively weak (Figures 6q,r), suggesting limited integration of ecological policy or public investment in commercial land governance.

Ecological LUE and industrial structure display a U-shaped interaction (Figure 6s): strong synergy at low and high ecological LUE levels, but weak interaction at mid-range values—potentially due to fragmented ecological networks or transitional governance inefficiencies. The interaction with green technology innovation (Figure 6t) reveals a "reversal effect": innovation supports ER when ecological LUE is low, but becomes redundant or counterproductive at high LUE levels, possibly due to diminishing marginal returns or over-engineered green spaces. The interaction with population density is negligible (Figure 6u), implying a degree of resilience in ecological land to demographic pressures. However, under elevated urbanization and government intervention, ecological LUE's positive effects on ER are significantly diminished (Figures 6v,x), pointing to potential inefficiencies in top-down planning or ecological space compression. Notably, interaction with infrastructure exhibits an inverse U-shaped pattern (Figure 6w), suggesting that moderate infrastructure investment best supports ecological

10.3389/fenvs.2025.1697381

land functions, while underinvestment or overdevelopment weakens them.

5 Spatiotemporal heterogeneity in the relationship between LUE and ER

To assess how LUE influences ER across space and time, we applied a Geographically and Temporally Weighted Regression (GTWR) model. This model captured the dynamic and region-specific effects of four LUE dimensions—agricultural, industrial, commercial, and ecological—on ER. Diagnostic tests confirmed the model's reliability, with R^2 and adjusted R^2 consistently exceeding 0.80, and all variance inflation factors (VIFs) below 10, indicating minimal multicollinearity. Regression coefficients were visualized in ArcGIS (Figure 7), revealing pronounced spatiotemporal heterogeneity in both the direction and magnitude of LUE–ER relationship, shaped by regional development paths and ecological contexts.

The average coefficient for agricultural LUE increased from −0.087 in 2014 to −0.019 in 2022 (Figure 7d), indicating a gradually weakening negative relationship with ER. This trend may reflect the growing adoption of green, intensive, and eco-agriculture practices, which have reduced the ecological disruption historically associated with agricultural intensification. However, agricultural LUE remained negatively correlated with ER overall, suggesting that risks of resource depletion, soil degradation, and agro-ecosystem fragmentation persist under high-efficiency regimes. Spatially, the most negative effects shifted from the Pearl River Delta in 2014 to eastern Guangdong by 2022 (Figures 7a–c). These shifts likely reflect intensified land-use conflicts in peri-urban zones where agricultural expansion encroaches on ecological land. In contrast, western and northern Guangdong exhibited weaker negative effects or near-neutral impacts, possibly due to lower land development intensity and better ecological baselines.

Industrial LUE consistently exerted a strong negative effect on ER, with average coefficients of −0.119, −0.062, and −0.107 in 2014, 2018, and 2022, respectively (Figure 7h). Although the negative effect weakened slightly around 2018—potentially due to early industrial upgrading—industrial LUE remained a major suppressor of ER. This likely reflects the ecological cost of spatially concentrated industrial activity, particularly in regions with persistent dependence on high-emission and resource-intensive sectors. The spatial pattern of negative relationship expanded from eastern Guangdong in 2014 to encompass the Pearl River Delta and northern Guangdong by 2022 (Figures 7e–g), highlighting the ecological stress associated with the spread of industrial agglomeration. However, western Guangdong showed relatively weaker effects, and in some cities, industrial LUE even had a slightly positive relationship on ER—possibly due to the region's lower industrial density and greater ecological buffering capacity.

In contrast, commercial LUE transitioned from having a weak negative effect on ER to a positive one, with its average regression coefficient rising from −0.005 in 2014 to 0.050 in 2022 (Figure 7l). This shift likely reflects improvements in spatial compactness, resource integration, and mixed-use commercial planning. Northern Guangdong and the Pearl River Delta shifted from predominantly negative to increasingly positive coefficients over time (Figures 7i–k), indicating that commercial land is being used more efficiently and sustainably in these urbanized regions. Nonetheless, some cities—such as Shaoguan, Guangzhou, and areas in the Chaoshan region—still exhibited negative effects by 2022, suggesting that issues such as spatial fragmentation and functional redundancy continue to hamper ER. In contrast, commercial LUE had a more consistently positive relationship in western and eastern Guangdong, where urban development pressure is moderate, and spatial conflicts between commercial and ecological land are less pronounced.

The effects of ecological LUE on ER reversed over time, with average coefficients declining from 0.106 in 2014 to −0.088 in 2022 (Figure 7p). Initially, improvements in ecological land use—such as optimizing green infrastructure and enhancing ecosystem service delivery—contributed positively to ER. However, by 2022, this relationship had turned negative in many cities. This suggests that ecological land, while being used more "efficiently," is also increasingly marginalized or functionally overloaded, resulting in ecological space compression and reduced systemic resilience. In 2014, most cities (except Shaoguan) exhibited positive coefficients, indicating general benefits from ecological LUE (Figures 7m–o). By 2022, however, negative relationship emerged in western and eastern Guangdong, suggesting that development pressures have begun to erode ecological land's protective functions. This reversal exemplifies an emerging "efficiency paradox", where the pursuit of LUE—without sufficient attention to ecological thresholds—ultimately undermines ecological stability and long-term resilience.

6 Discussion

6.1 Interpretation of results and theoretical contributions

6.1.1 Natural and human factors jointly shape the spatial variability of ER and LUE in Guangdong province

The observed 16.1% decline in ER across Guangdong Province from 2014 to 2022 reflects intensifying tensions between rapid urbanization and ecosystem integrity. The sharp rise in the ecological pressure index—primarily driven by accelerated land development and industrial activity—suggests that unchecked expansion and resource extraction are eroding ecosystems' adaptive capacity (Fan and Wei, 2025; Wang S. et al., 2024). While the ecological state and societal response dimensions remained relatively stable, the marked convergence in ecological pressure levels implies that urban-induced ecological stress is becoming a structural challenge across regions, particularly in fast-growing city clusters.

Spatially, ER presented a dual-gradient pattern—higher in the northern and peripheral regions, and lower in the densely populated urban cores of the south and center. This pattern underscores the vulnerability of highly urbanized areas with constrained ecological space and intensive land use. However, improvements observed in megacities such as Shenzhen and Guangzhou suggest that resilience decline is not an inevitable consequence of urban growth. Targeted interventions—such as green infrastructure investment, digital

10.3389/fenvs.2025.1697381

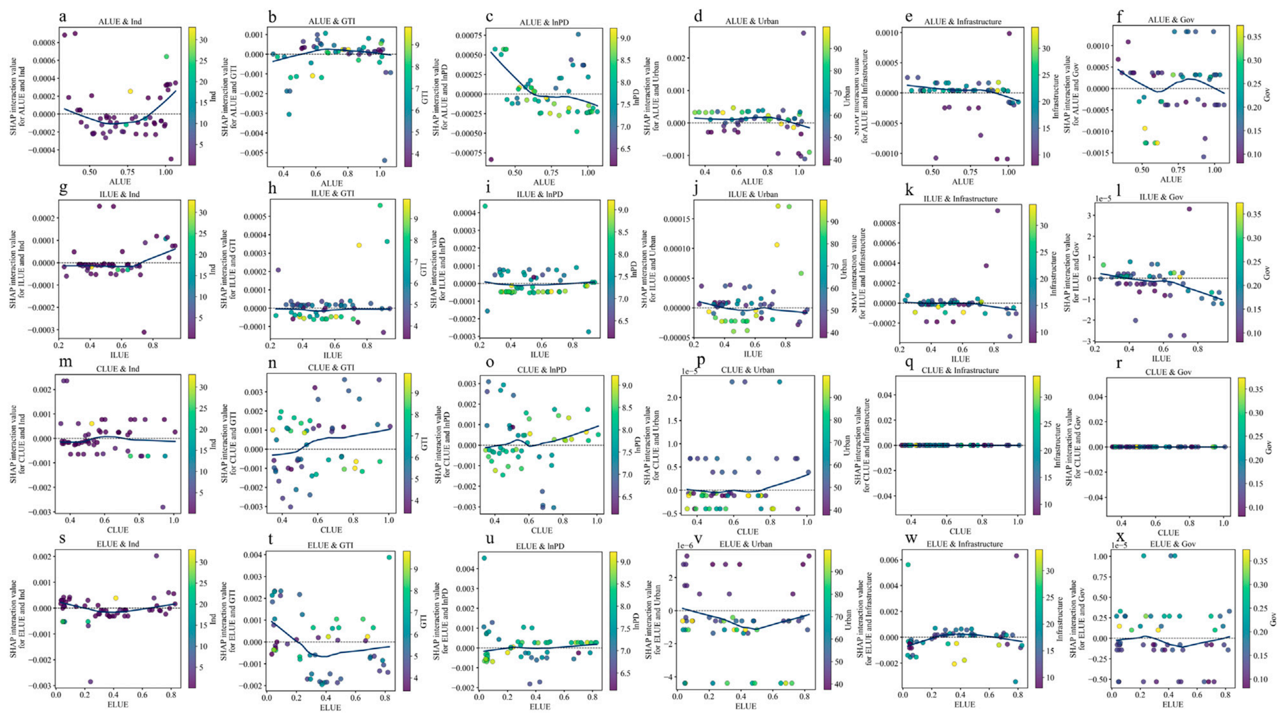

FIGURE 6
SHAP interaction plot of agricultural LUE **(a–f)** industrial LUE **(g–l)** commercial LUE **(m–r)** and ecological LUE **(s–x)** and control variables for ER.

governance platforms, and regulatory innovation—appear to have enhanced adaptive capacity in these high-density contexts, consistent with recent arguments that technological and institutional innovations can partially mitigate ecological stress in complex urban systems. In contrast, the continued ER deterioration in western Guangdong highlights the limitations of current ecological governance in resource-dependent and underdeveloped areas. Insufficient policy enforcement, underinvestment in green infrastructure, and the persistence of extensive land development practices likely contribute to this negative trajectory. These findings call for regionally differentiated resilience strategies: fragile ecological zones require urgent restoration and conservation measures, while urban cores demand sustained innovation and governance reform to sustain resilience under pressure.

The spatiotemporal evolution of LUE across four functional land types reveals differentiated trajectories shaped by development intensity, ecological constraints, and structural transformation. Agricultural LUE exhibited a consistent upward trend, especially in eastern Guangdong, supported by favorable biophysical conditions and cropland optimization. However, stagnation in the Pearl River Delta underscores the enduring ecological trade-offs of urban expansion, where arable land is continuously converted for industrial and residential uses. This pattern echoes the "peri-urban paradox," where land intensification in core regions often occurs at the expense of ecological and food system stability.

Industrial LUE followed a U-shaped trajectory—initially declining due to disruptions from structural adjustment, then rebounding in advanced cities such as Shenzhen and Dongguan amid high-tech industrial upgrading. This pattern supports the theory of "creative destruction," in which short-term losses in efficiency are offset by long-term gains through technological innovation and structural transition. However, outside of these innovation hubs, the recovery remains uneven, and intensive industrial land use continues to impose sustained ecological stress.

Commercial LUE displayed a fluctuating trend, mirroring the spatial and structural reconfiguration of retail activity in response to digital commerce and shifting consumption patterns. Declines in commercial LUE in core urban areas likely reflect spatial mismatches during the transition from traditional retail formats to platform-based economies, whereas improvements in non-core regions may indicate the "latecomer advantage" of leapfrogging outdated spatial structures.

Ecological LUE exhibited an inverted U-shaped pattern—initially rising with investment in ecological infrastructure, then declining markedly after 2018. This trend illustrates an "efficiency paradox": efforts to maximize ecological land output may lead to functional degradation when green space is over-engineered or excessively fragmented. The erosion of ecological capacity in previously robust areas such as northern Guangdong suggests that efficiency gains are not always synonymous with sustainability. In contrast, temporary improvements in the Pearl River Delta likely reflect policy-driven ecological engineering efforts that have yet to translate into long-term resilience.

Collectively, the divergent trajectories of the four LUE dimensions highlight the complexity of navigating the trade-offs between efficiency and ecological sustainability. These findings underscore the need for integrated, function-specific land governance approaches that reconcile productivity with environmental stewardship. Tailored interventions—responsive to local development stages, ecological baselines, and land use

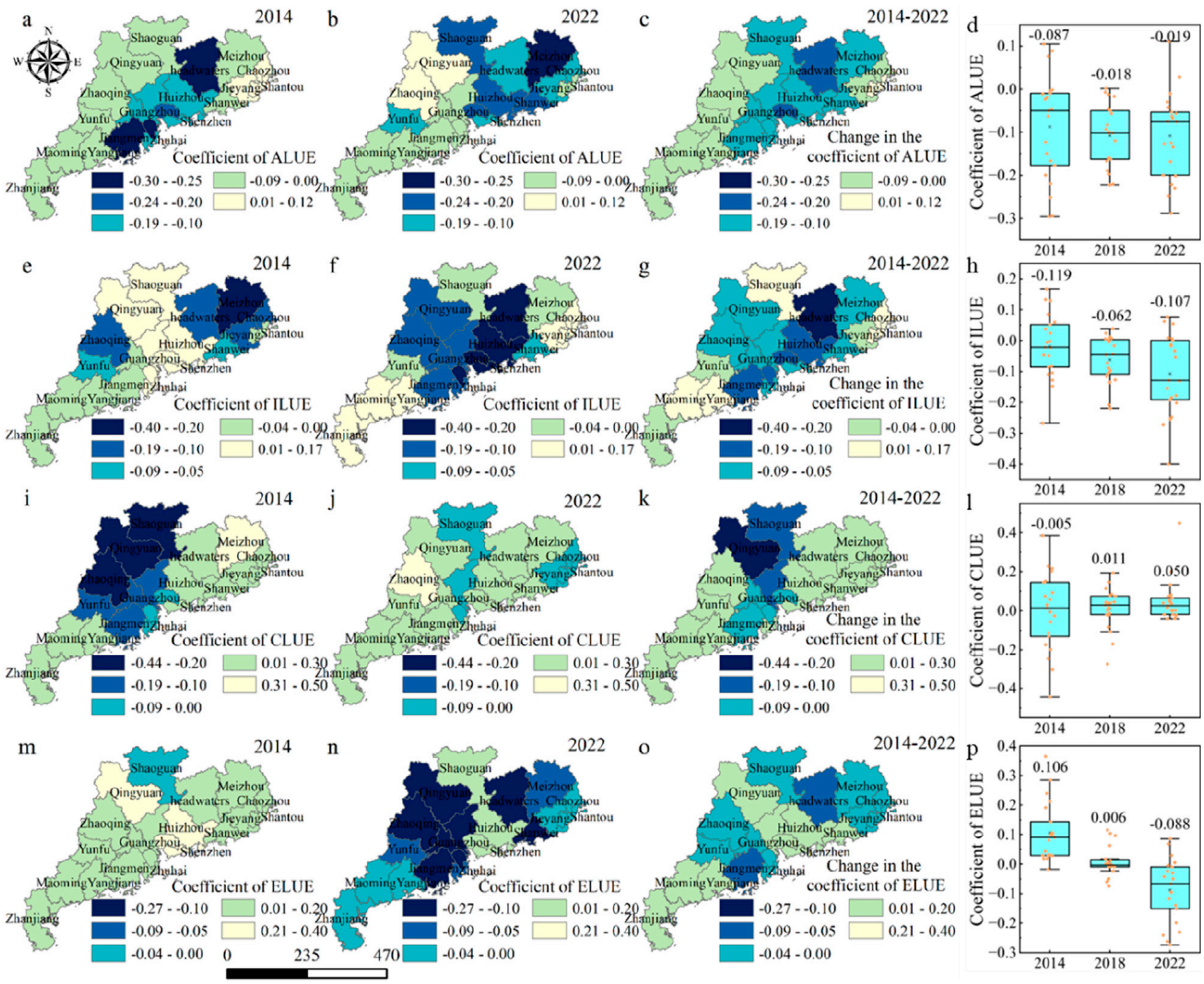

FIGURE 7
Spatiotemporal Variation in Regression Coefficients of agricultural LUE **(a–d)** industrial LUE **(e–h)** commercial LUE **(i–l)** and ecological LUE **(m–p)** in the GTWR Model for Guangdong Province, 2014–2022.

conflicts—are essential to achieving spatially adaptive and coordinated transitions toward sustainable land systems.

6.1.2 A nonlinear relationship between LUE and ER

The nonlinear and threshold effects identified in this study offer critical insights into how different types of LUE interact with urban ER in complex and often counterintuitive ways. Agricultural LUE exhibits a classical diminishing marginal return pattern: improvements below the 0.72 threshold contribute positively to ER by promoting resource conservation and maintaining agro-ecological stability. However, once this threshold is exceeded, agricultural intensification imposes ecological overload, consistent with previous studies linking excessive land exploitation to biodiversity loss and ecosystem degradation. This underscores the imperative for agricultural modernization to operate within ecological carrying capacities in order to sustain long-term resilience.

Industrial LUE displays a sharper and more abrupt turning point, with a steep decline in its contribution to ER beyond the 0.66 threshold. This reflects the inherent duality of industrial intensification: while initial improvements enhance spatial efficiency and productivity, excessive concentration of industrial activity results in elevated emissions, land surface sealing, and infrastructural stress—all of which impair ecosystem function. This pattern resonates with the concept of the urban ecological paradox, where surface-level efficiency gains obscure underlying ecological trade-offs unless mitigated by stringent green governance and systemic technological innovation.

Commercial LUE, in contrast, shows a positive nonlinear shift beyond the 0.55 threshold, suggesting that spatially efficient commercial land use—typically characterized by mixed-use development, transit-oriented planning, and compact urban form—can significantly enhance ER. Such land configurations reduce commuting distances, promote public transportation use, and enable low-carbon lifestyles, thereby functioning as catalysts for urban sustainability. These findings align with the emerging consensus that commercial spatial efficiency, when strategically leveraged, serves as a key enabler of resilient urban systems.

Ecological LUE presents a more counterintuitive dynamic, with an inverted threshold effect: values below 0.29 positively influence ER, while higher levels are associated with declining contributions. This contradicts conventional assumptions that more efficient use of green space necessarily enhances resilience. Instead, it points to a variant of the efficiency paradox in ecological land planning—where the over-concentration of ecological functions or excessive artificial interventions compromise ecological heterogeneity, reduce redundancy, and undermine adaptive capacity. These outcomes highlight that ecological functionality depends not merely on the quantity or efficiency of green space, but also on maintaining balanced, diverse, and context-sensitive ecological designs.

Taken together, these findings advance theoretical understandings of urban ER by emphasizing the necessity of incorporating nonlinear and threshold-sensitive mechanisms into both research and practice. They demonstrate that the ecological benefits of land use optimization are not universal but contingent—bounded by ecological thresholds, spatial configuration, and institutional capacities. In this light, sustainable urban resilience demands not only LUE, but also strategic moderation, contextual adaptation, and integrative governance that aligns ecological objectives with socio-technical realities.

6.1.3 A interaction relationship between LUE and socioeconomic factors for ER

The interaction analysis reinforces the conclusion that the ecological consequences of LUE are not shaped by LUE alone, but are highly contingent upon surrounding socioeconomic contexts. SHAP-based results uncover widespread nonlinearities, threshold effects, and synergy–suppression dynamics, indicating that the relationship between LUE and ER is deeply embedded within local industrial structure, innovation capacity, demographic characteristics, and governance regimes.

Agricultural LUE exhibits a pronounced U-shaped interaction with industrial structure and a “double-edged sword” relationship with population density. These findings suggest that both traditional low-efficiency agriculture and high-efficiency green farming systems can bolster ER, yet transitional zones with moderate LUE levels often experience ecological degradation. This is likely due to a mismatch between land intensification and industrial adaptation, as well as unsustainable exploitation of land resources. In densely populated areas, elevated land stress and intensified landscape fragmentation further compromise ecological regulatory functions. Although interactions with green technology innovation, urbanization, infrastructure, and government intervention tend to enhance the ecological benefits of agricultural LUE, such synergies exhibit diminishing marginal returns. Beyond a critical efficiency threshold, agricultural over-intensification leads to declining ER—reflecting an “over-efficiency trap” where ecological systems become strained by attempts to maximize land productivity.

Industrial LUE remains constrained by a persistent “efficiency–pollution” paradox. While increased land efficiency can contribute to compact industrial layouts and reduced per-unit land consumption, positive ecological outcomes are contingent on concurrent structural upgrading toward cleaner, innovation-driven industries. Weak interaction effects with green technology innovation and population density imply a lag in the ecological modernization of the industrial sector. Moreover, in contexts characterized by weak governance or spatial mismanagement, increases in industrial LUE often coincide with environmental degradation—underscoring the failure of current policy mechanisms to effectively internalize ecological externalities associated with industrial land use.

Commercial LUE offers comparatively more optimistic dynamics. Its interaction with industrial structure follows an inverted U-shape, suggesting optimal ecological outcomes at intermediate efficiency levels—likely a result of balanced, compact, and multifunctional spatial development. Positive synergies with innovation, urbanization, and population density indicate that commercial land, when planned with ecological considerations, can play a supportive role in enhancing urban resilience. However, the limited interactions with infrastructure investment and government intervention reveal a missed opportunity to embed ecological objectives within commercial spatial planning and public investment strategies.

Ecological LUE demonstrates strong nonlinearities and pronounced context dependence. While moderate improvements in ecological LUE can enhance ER—through optimized green space use and ecosystem service delivery—excessive intensification, particularly under conditions of rapid urbanization and weak ecological governance, leads to diminishing or even negative returns. The “reversal effect” observed in conjunction with green innovation implies a saturation point beyond which additional inputs no longer yield resilience gains and may instead degrade ecological functionality, particularly in artificially engineered green spaces. These findings call for a fundamental rethinking of how ecological land is utilized, managed, and integrated within broader urban systems.

In summary, these results highlight the necessity of context-sensitive, differentiated land use strategies. Policymakers must prioritize the alignment of LUE improvements with broader industrial transformation goals, ensure the effective integration of green innovation into land planning processes, and preempt ecological overloading in high-density urban areas. A one-size-fits-all approach to land use optimization is insufficient; instead, adaptive governance frameworks that account for spatial heterogeneity, systemic thresholds, and ecological feedbacks are essential to fostering resilient and sustainable urban systems.

6.1.4 Spatiotemporal heterogeneity effect of LUE on ER

The GTWR results underscore the pronounced spatiotemporal heterogeneity in how different types of LUE influence ER, reflecting the regionally divergent development trajectories, land-use configurations, and ecological baselines across Guangdong Province. These findings reaffirm that the relationship between LUE and ER is not only nonlinear, but also highly context-dependent, varying considerably across both space and time.

Agricultural LUE maintained a persistently negative correlation with ER throughout the study period, although its detrimental relationship gradually weakened between 2014 and 2022. This temporal attenuation may be attributed to the increasing adoption of green and ecological agriculture practices, which have partially mitigated the environmental externalities traditionally associated with land intensification. Nevertheless, the

10.3389/fenvs.2025.1697381

sustained negative association highlights the ecological fragility of peri-urban agricultural zones, where spatial coupling between urban development and farmland leads to land encroachment, habitat fragmentation, and biodiversity loss. Spatially, eastern Guangdong—characterized by intensive agricultural activity—exhibited the most severe negative effects, reinforcing the notion that efficiency gains in agriculture, absent strong ecological safeguards, may accelerate ER deterioration.

In contrast, industrial LUE exerted a consistently strong negative relationship with ER across the entire study period, with only marginal temporal fluctuations. This suggests that improvements in industrial land efficiency have not translated into ecological benefits, likely due to the continued dominance of high-emission, resource-intensive industries. The spatial expansion of negative regression coefficients—from eastern Guangdong into the Pearl River Delta and northern cities—signals that while industrial agglomeration may enhance economic productivity, it simultaneously escalates ecological stress when not accompanied by green transformation measures. Conversely, western regions with relatively low levels of industrialization exhibited neutral or even slightly positive associations, suggesting that early-stage industrial regions may still pursue efficiency improvements without exceeding ecological carrying capacities.

The effect of commercial LUE on ER demonstrated a notable temporal improvement, shifting from marginally negative to consistently positive over the study period. This evolution likely reflects the transformation of commercial land use patterns—from dispersed, low-density developments toward compact, multifunctional, and transit-oriented configurations aligned with low-carbon urban planning principles. The increasingly positive coefficients observed in both the Pearl River Delta and northern Guangdong support the view that well-optimized commercial spaces can enhance urban adaptability and systemic resilience. However, localized negative effects in cities such as Shaoguan and Guangzhou caution that issues such as functional redundancy, spatial congestion, or overbuilt commercial infrastructure may still compromise ER, even in the presence of high commercial LUE.

Perhaps most strikingly, ecological LUE underwent a reversal from a positive to a negative correlation with ER—an empirical manifestation of the "efficiency paradox." While initial improvements in ecological land efficiency enhanced ER by maximizing green space functionality and ecosystem service provision, mounting development pressures in later years led to the spatial compression, artificial modification, and functional simplification of ecological land. The emergence of negative coefficients in 2022 across both western and eastern Guangdong indicates that beyond a critical threshold, efficiency-driven ecological planning may inadvertently erode ecological connectivity, heterogeneity, and regenerative capacity—thereby undermining long-term resilience.

Collectively, these spatiotemporal divergences illustrate the limitations of uniform LUE enhancement strategies. Attempts to universally increase LUE without regard to regional context may yield unintended ecological trade-offs. Instead, the findings advocate for differentiated land governance frameworks tailored to local development intensity, industrial structure, and ecological vulnerability. Moreover, LUE improvements should be strategically integrated with ecological redline protections, biodiversity conservation targets, and resilience-oriented spatial planning to ensure that land use optimization contributes not only to productivity, but also to the sustained health and integrity of urban ecosystems.

6.1.5 Theoretical contributions

The empirical results of this study also resonate with and extend several established theories concerning the relationship between economic development and ecological conservation. First, the nonlinear and threshold-dependent patterns observed between land-use efficiency (LUE) and ecological resilience (ER) are broadly consistent with the Environmental Kuznets Curve (EKC) hypothesis, which posits that environmental quality initially deteriorates but subsequently improves as economies transition from extensive to intensive growth. The turning points identified in agricultural, industrial, and commercial LUE (0.72, 0.66, and 0.55, respectively) reflect such stage-dependent dynamics—where efficiency gains eventually generate negative ecological feedbacks once industrial or spatial intensification exceeds the system's carrying capacity.

Second, the finding that moderate technological and managerial upgrading can offset ecological pressures supports the Porter Hypothesis, emphasizing that innovation-driven and regulation-induced efficiency improvements can yield "win–win" outcomes for both productivity and environmental performance. The observed positive effects of green technology innovation (GTI) and policy intervention (Gov) on ER confirm that well-designed governance and innovation frameworks can decouple economic growth from ecological degradation.

Finally, the study's emphasis on optimizing rather than maximizing LUE aligns with the Ecological Modernization and Coupling Coordination paradigms, which advocate for synergistic evolution between economic and ecological systems. These theoretical connections underscore that sustainable urban development requires not linear expansion of land-use efficiency, but context-sensitive, adaptive governance that internalizes ecological limits while leveraging technological progress.

6.2 Policy recommendations

The findings of this study underscore the need for differentiated, threshold-sensitive, and context-aware land governance to reconcile LUE with ER in rapidly urbanizing regions such as Guangdong Province. Translating these results into actionable policy, several targeted recommendations can be made.

6.2.1 Adopt region- and land-type-specific management frameworks

The pronounced spatial heterogeneity in the LUE–ER relationship demonstrates the inadequacy of uniform policies. Policymakers should formulate zonal management strategies that differentiate between ecological hinterlands, transitional urban–rural zones, and high-density urban cores. In ecologically fragile western and peripheral regions, priority should be given to low-impact agriculture, ecological restoration, and restrictions on extractive land-use practices. In rapidly urbanizing cores such as the Pearl River Delta, local governments should promote institutional innovation, green infrastructure investment, and digital land governance platforms that can monitor ecological performance in real time. By tailoring land-use controls to regional ecological functions and development intensity, governments can better align economic growth with resilience objectives.

6.2.2 Institutionalize ecological threshold management in planning and regulation

The identified nonlinearities and critical efficiency thresholds—such as 0.72 for agricultural land and 0.66 for industrial land—demonstrate that crossing functional limits can trigger ecological degradation. Policymakers can operationalize these findings by: Integrating threshold-based indicators into land-use zoning and ecological red-line planning; Establishing dynamic monitoring systems using satellite and big data to track changes in LUE and ER; Introducing adaptive zoning mechanisms that automatically tighten or relax land-use intensity based on real-time ecological feedback; and Embedding carrying-capacity assessments into environmental impact evaluations. Such mechanisms convert empirical research thresholds into actionable governance tools, enabling evidence-based control of land intensification.

6.2.3 Strengthen synergy between land-use efficiency, innovation, and governance capacity

The study shows that the ecological effects of LUE depend strongly on the surrounding socioeconomic context—especially industrial upgrading, green-technology innovation (GTI), and institutional quality. Policymakers should therefore pursue cross-sectoral coordination through: Linking land-use planning with industrial and innovation policies to encourage cleaner production and low-carbon urban design; Providing fiscal incentives and subsidies for green industrial transformation; Expanding environmental governance capacity, including stricter performance evaluation systems for local officials based on ecological outcomes. This integrated approach ensures that improvements in LUE yield genuine ecological benefits rather than trade-offs.

6.2.4 Redefine "ecological efficiency" to address the green space paradox

While ecological land is conventionally viewed as beneficial, the study's finding of a threshold at 0.29 suggests that over-optimization or excessive artificialization can undermine resilience. Policymakers should therefore move beyond quantitative expansion and prioritize: The development of multifunctional, biodiverse, and interconnected green infrastructure; Incorporation of nature-based solutions and ecosystem-service networks into urban renewal; Establishment of monitoring frameworks that evaluate not only green area ratios but also landscape diversity and connectivity. These measures would help balance ecological productivity with functional heterogeneity, strengthening long-term adaptive capacity.

6.2.5 Build a data-driven decision-support system for resilient land governance

Finally, governments should institutionalize a data platform integrating LUE, ER, and environmental indicators to support dynamic evaluation and early warning. The system could provide threshold alerts when land intensification approaches critical levels, guiding planning authorities to adjust zoning, investment, or restoration priorities. This mechanism would translate the study's analytical framework into a practical governance instrument for resilience-oriented decision-making. Together, these policy pathways demonstrate how the study's quantitative results—particularly the threshold values and spatial heterogeneity patterns—can inform precise, adaptive, and evidence-based land-use decisions under China's dual-carbon and sustainable urban development agendas.

6.3 Limitations and future research

While this study provides new insights into the nonlinear, threshold-dependent, and spatially heterogeneous relationships between land-use efficiency (LUE) and ecological resilience (ER), several limitations should be acknowledged.

First, the temporal and spatial scope of the data constrains interpretation. The analysis ends in 2022, prior to the implementation of the "Green and Beautiful Guangdong" policy (2023). Subsequent ecological restoration and spatial governance measures may reshape the LUE–ER relationship. Future studies incorporating post-2023 data could therefore assess how institutional interventions modify land–ecosystem dynamics.

Second, although the XGBoost–SHAP framework effectively captures nonlinearities, the thresholds it identifies represent empirical transition ranges rather than statistically discrete or universally transferable breakpoints. These values reflect the socio-ecological context of Guangdong Province and should not be generalized without recalibration. Future research could apply Bayesian or bootstrap-based uncertainty estimation to derive confidence intervals and enhance the interpretive robustness of threshold inference.

Third, the indicator systems for both LUE and ER remain simplified. The Super-SBM model omits undesirable outputs such as industrial emissions or agricultural non-point pollution due to data constraints, while the ER index relies on proxy variables that do not fully capture ecological processes like biodiversity, connectivity, or adaptive capacity. Future research could employ higher-resolution, multi-source datasets and dynamic modeling approaches to refine indicator accuracy.

Last, this study focuses on Guangdong Province—a highly urbanized and economically developed region—and that the identified LUE–ER thresholds and spatial associations may not directly apply to less developed or rural areas with different ecological and institutional conditions. To strengthen transferability, we suggest that future research undertake cross-provincial or comparative studies to test whether similar nonlinear relationships and threshold effects emerge under varying levels of urbanization and governance.

7 Conclusion

This study demonstrates that the relationship between LUE and ER in Guangdong Province is highly nonlinear, spatially heterogeneous, and context-dependent, shaped by intricate interactions among ecological, socioeconomic, and institutional factors. From 2014 to 2022, the province experienced a 16.1% decline in ER, signaling intensifying ecological stress amid rapid urbanization and industrial expansion.

The trajectories of different LUE types diverge markedly. Agricultural and industrial LUE exhibit critical threshold effects, beyond which further efficiency gains generate diminishing or even negative returns for ER—underscoring the ecological risks of over-intensification. In contrast, commercial LUE demonstrates positive potential, especially when embedded within compact, multifunctional spatial configurations aligned with low-carbon urban development. Ecological LUE, however, reveals a notable "efficiency paradox": efforts to maximize ecological land use may inadvertently reduce system adaptability, compromise ecological functions, and fragment green space networks when exceeding optimal levels.

Moreover, the relationship between LUE and ER are strongly conditioned by local socioeconomic environments, including industrial structure, population density, innovation capacity, and governance quality. The geographically and temporally weighted regression (GTWR) results highlight pronounced spatiotemporal heterogeneity, revealing that the same type of LUE can yield divergent ecological outcomes depending on local contexts and development trajectories.

These findings challenge the validity of one-size-fits-all land use strategies and highlight the urgency of adopting differentiated, threshold-sensitive, and resilience-oriented land governance frameworks. Enhancing urban ER in rapidly transforming regions such as Guangdong requires contextualized land use planning, targeted investment in green and adaptive infrastructure, and the integration of ecological thresholds into spatial decision-making processes. Only by aligning land efficiency improvements with the ecological carrying capacity and institutional readiness of each locality can long-term urban sustainability and resilience be meaningfully achieved.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

TL: Conceptualization, Formal Analysis, Funding acquisition, Writing – original draft. JZ: Funding acquisition, Validation, Methodology, Writing – review and editing, Supervision. YS: Software, Resources, Writing – review and editing, Project administration, Funding acquisition. WD: Formal Analysis, Visualization, Conceptualization, Writing – review and editing.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was funded by Collaborative Innovation Center for Natural Resources Planning and Marine Technology of Guangzhou (No.2023B04J0301, No.2025B04J0031), and National Natural Science Foundation of China (No.42371207). We would like to thank the support of academic specialty group for urban sensing in Chinese Society of Urban Planning.

Conflict of interest

Authors TL, JZ, and YS were employed by Guangzhou Urban Planning and Design Survey Research Institute Co., Ltd.

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

Generative AI statement

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

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

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2025.1697381/full#supplementary-material

References

Allan, E., Manning, P., Alt, F., Binkenstein, J., Blaser, S., Blüthgen, N., et al. (2015). Land use intensification alters ecosystem multifunctionality *via* loss of biodiversity and changes to functional composition. *Ecol. Lett.* 18 (8), 834–843. doi:10.1111/ele.12469

Brand, F. (2009). Critical natural capital revisited: ecological resilience and sustainable development. *Ecol. eco-nomics* 68 (3), 605–612. doi:10.1016/j.ecolecon.2008.09.013

Cao, X., Wang, H., Zhang, B., Liu, J., and Yang, J. (2024). Sustainable management of land use patterns and water allocation for coordinated multidimensional development. *J. Clean. Prod.* 457, 142412. doi:10.1016/j.jclepro.2024.142412

Chen, T., and Guestrin, C. (2016). "Xgboost: a scalable tree boosting system," in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, 785–794.

Cui, X., and Wang, X. (2015). Urban land use change and its effect on social metabolism: an empirical study in shanghai. *Habitat Int.* 49, 251–259. doi:10.1016/j.habitatint.2015.05.018

Dakos, V., and Kéfi, S. (2022). Ecological resilience: what to measure and how. *Environ. Res. Lett.* 17 (4), 043003. doi:10.1088/1748-9326/ac5767

Fan, Y., and Wei, G. (2025). Assessment of ecological resilience and its response mechanism to land spatial structure conflicts in China's southeast coastal areas. *Ecol. Indic.* 170, 112980. doi:10.1016/j.ecolind.2024.112980

Ferreira, M. D. P., and Féres, J. G. (2020). Farm size and land use efficiency in the Brazilian amazon. *Land use policy* 99, 104901. doi:10.1016/j.landusepol.2020.104901

Gao, J., and O'Neill, B. C. (2020). Mapping global urban land for the 21st century with data-driven simulations and shared socioeconomic pathways. *Nat. Commun.* 11 (1), 2302. doi:10.1038/s41467-020-15788-7

Gao, X., Zhang, A., and Sun, Z. (2020). How regional economic integration influence on urban land use efficiency? A case study of wuhan metropolitan area, China. *Land Use Policy* 90, 104329. doi:10.1016/j.landusepol.2019.104329

Geng, Y., Li, X., and Chen, J. (2025). Integration of land use resilience and efficiency in China: analysis of spatial patterns, differential impacts on SDGs, and adaptive management strategies. *Appl. Geogr.* 175, 103490. doi:10.1016/j.apgeog.2024.103490

He, S., Yu, S., Li, G., and Zhang, J. (2020). Exploring the influence of urban form on land-use efficiency from a spatiotemporal heterogeneity perspective: evidence from 336 Chinese cities. *Land use policy* 95, 104576. doi:10.1016/j.landusepol.2020.104576

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annu. Rev. Ecol. Syst.* 4, 1–23. doi:10.1146/annurev.es.04.110173.000245

Huang, J., Han, W., Zhang, Z., Ning, S., and Zhang, X. (2024). The decoupling relationship between land use efficiency and carbon emissions in China: an analysis using the socio-ecological systems (SES) framework. *Land Use Policy* 138, 107055. doi:10.1016/j.landusepol.2024.107055

Lee, C. C., Yan, J., and Li, T. (2024). Ecological resilience of city clusters in the middle reaches of yangtze river. *J. Clean. Prod.* 443, 141082. doi:10.1016/j.jclepro.2024.141082

Li, Y., Liu, W., Feng, Q., Zhu, M., Yang, L., Zhang, J., et al. (2023). The role of land use change in affecting ecosystem services and the ecological security pattern of the hexi regions, northwest China. *Sci. Total Environ.* 855, 158940. doi:10.1016/j.scitotenv.2022.158940

Li, X. L., Ren, Z. Y., Cao, Z. Z., and Ren, H. (2025). Study on coal drawing parameters of deeply buried hard coal seams based on PFC. *Sci. Rep.* 15 (1), 21934. doi:10.1038/s41598-025-08154-4

Liang, J. Y., Wang, S. J., Liao, Y. T., and Feng, K. S. (2024). Carbon emissions embodied in investment: assessing emissions reduction responsibility through multi-regional input-output analysis. *Appl. Energy* 358, 122558. doi:10.1016/j.apenergy.2023.122558

Liu, J., Hou, X., Wang, Z., and Shen, Y. (2021). Study the effect of industrial structure optimization on urban land-use efficiency in China. *Land Use Policy* 105, 105390. doi:10.1016/j.landusepol.2021.105390

Mahtta, R., Fragkias, M., Güneralp, B., Mahendra, A., Reba, M., Wentz, E. A., et al. (2022). Urban land expansion: the role of population and economic growth for 300+ cities. *Npj Urban Sustain.* 2 (1), 5. doi:10.1038/s42949-022-00048-y

Masini, E., Tomao, A., Barbati, A., Corona, P., Serra, P., and Salvati, L. (2019). Urban growth, land-use efficiency and local socioeconomic context: a comparative analysis of 417 metropolitan regions in Europe. *Environ. Manag.* 63 (3), 322–337. doi:10.1007/s00267-018-1119-1

Ou, C., Li, F., Zhang, J., Hu, Y., Chen, X., Kong, S., et al. (2022). Multiple driving factors and hierarchical management of PM2. 5: evidence from Chinese central urban agglomerations using machine learning model and GTWR. *Urban Clim.* 46, 101327. doi:10.1016/j.uclim.2022.101327

Pelegrina, G. D., Duarte, L. T., and Grabisch, M. (2023). A k-additive choquet integral-based approach to approximate the SHAP values for local interpretability in machine learning. *Artif. Intell.* 325, 104014. doi:10.1016/j.artint.2023.104014

Peng, J., Liu, Y., Li, T., and Wu, J. (2017). Regional ecosystem health response to rural land use change: a case study in lijiang city, China. *Ecol. Indic.* 72, 399–410. doi:10.1016/j.ecolind.2016.08.024

Searchinger, T. D., Wirsenius, S., Beringer, T., and Dumas, P. (2018). Assessing the efficiency of changes in land use for mitigating climate change. *Nature* 564 (7735), 249–253. doi:10.1038/s41586-018-0757-z

Song, C., Yang, J., Wu, F., Xiao, X., Xia, J., and Li, X. (2022). Response characteristics and influencing factors of carbon emissions and land surface temperature in Guangdong province, China. *Urban Clim.* 46, 101330. doi:10.1016/j.uclim.2022.101330

Teng, T., Chen, Y., Wang, Y., and Qiao, X. (2025). *In situ* nuclear magnetic resonance observation of pore fractures and permeability evolution in rock and coal under triaxial compression. *J. Energy Eng.* 151 (4), 04025036. doi:10.1061/jleed9.eyeng-6054

Theobald, D. M., Kennedy, C., Chen, B., Oakleaf, J., Baruch-Mordo, S., and Kiesecker, J. (2020). Earth transformed: detailed mapping of global human modification from 1990 to 2017. *Earth Syst. Sci. Data* 12 (3), 1953–1972. doi:10.5194/essd-12-1953-2020

Ul Din, S., and Mak, H. W. L. (2021). Retrieval of land-use/land cover change (LUCC) maps and urban expansion dynamics of hyderabad, Pakistan *via* landsat datasets and support vector machine framework. *Remote Sens.* 13 (16), 3337. doi:10.3390/rs13163337

Wang, S., and Liu, X. (2017). China's city-level energy-related CO2 emissions: spatiotemporal patterns and driving forces. *Appl. Energy* 200, 204–214. doi:10.1016/j.apenergy.2017.05.085

Wang, S., Fang, C., Guan, X., Pang, B., and Ma, H. (2014). Urbanisation, energy consumption, and carbon dioxide emissions in China: a panel data analysis of China's provinces. *Appl. Energy* 136, 738–749. doi:10.1016/j.apenergy.2014.09.059

Wang, S., Fang, C., and Wang, Y. (2016a). Spatiotemporal variations of energy-related CO2 emissions in China and its influencing factors: an empirical analysis based on provincial panel data. *Renew. Renew. Sustain. Energy Rev.* 55, 505–515. doi:10.1016/j.rser.2015.10.140

Wang, S., Li, Q., Fang, C., and Zhou, C. (2016b). The relationship between economic growth, energy consumption, and CO2 emissions: empirical evidence from China. *Sci. Total Environ.* 542, 360–371. doi:10.1016/j.scitotenv.2015.10.027

Wang, S., Fang, C., Sun, L., Su, Y., Chen, X., Zhou, C., et al. (2019). Decarbonizing China's urban agglomerations. *Ann. Am. Assoc. Geogr.* 109 (1), 266–285. doi:10.1080/24694452.2018.1484683

Wang, S., Gao, S., Huang, Y., and Shi, C. (2020). Spatiotemporal evolution of urban carbon emission performance in China and prediction of future trends. *J. Geogr. Sci.* 30 (5), 757–774. doi:10.1007/s11442-020-1754-3

Wang, J. Y., Shan, Y. L., Cui, C., Zhao, C. Y., Meng, J., and Wang, S. J. (2024a). Investigating the fast energy-related carbon emissions growth in African countries and its drivers. *Appl. Energy* 357, 122494. doi:10.1016/j.apenergy.2023.122494

Wang, S. J., Zhou, S. J., Wu, R., Feng, K. S., and Hubacek, K. (2024b). Interregional flows of embodied carbon storage As-sociated with land-use change in China. *Ann. Am. Assoc. Geogr.* 114 (7), 1526–1545. doi:10.1080/24694452.2024.2356849

Wang, S., Chen, X., Xie, R., Liu, K., Wang, J., Liu, X., et al. (2024c). Demand-side insights for steering human appropriation of net primary productivity within planetary boundaries. *One Earth* 7 (4), 650–662. doi:10.1016/j.oneear.2024.02.010

Xie, X., Fang, B., Xu, H., He, S., and Li, X. (2021). Study on the coordinated relationship between urban land use efficiency and ecosystem health in China. *Land use policy* 102, 105235. doi:10.1016/j.landusepol.2020.105235

Yang, C., Li, Q. Q., Wang, X. Q., Cui, A. H., Chen, J. Y., Liu, H. Z., et al. (2023). "Human expansion-induced biodiversity crisis over Asia from 2000 to 2020,", 6. *Research*, 0226. doi:10.34133/research.0226

Zhang, Y., Lin, Y., Zheng, G., Liu, Y., Sukiennik, N., Xu, F., et al. (2025). MetaCity: data-Driven sustainable development of complex cities. *Innovation* 6 (2), 100775. doi:10.1016/j.xinn.2024.100775

Zhao, Y., Zhang, M. L., Liu, Z. Q., Ma, J. B., Yang, F., Guo, H. M., et al. (2024). "How human activities affect groundwater storage,", 7. *Research*, 0369. doi:10.34133/research.0369