International Journal of Applied Earth Observation and Geoinformation 146 (2026) 105072

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Local effects of pattern interactions in driving urbanization

Yanfang Sun [a,b,c,d], Guosheng Wu [a,b,c], Yongze Song [d,*], Haiyang Liu [d,e], Lin Wang [f], Zehua Zhang [d], Jiao Hu [d,g]

[a] College of Civil Engineering, Taiyuan University of Technology, Taiyuan, China
[b] Key Laboratory of Highway Construction & Maintenance Technology in Loess Region, Ministry of Transport, PRC, Taiyuan, China
[c] Shanxi Key Laboratory of Civil Engineering Disaster Prevention and Control, Taiyuan, China
[d] School of Design and the Built Environment, Curtin University, Perth, Australia
[e] Field Science Centre for Northern Biosphere, Graduate School of Environmental Science, Hokkaido University, Nayoro, Japan
[f] School of Architecture, Huaqiao University, Xiamen, China
[g] Key Laboratory of Poyang Lake Wetland and Watershed Research, Ministry of Education, Jiangxi Normal University, Nanchang, China

ARTICLE INFO

Keywords:
Local pattern interactions
Spatial heterogeneity
Geocomplexity
Spatial association

ABSTRACT

Spatial association and spatial interaction are fundamental to understanding geographical phenomena and regional development disparities, with broad applicability across disciplines. Existing spatial heterogeneity analysis face significant challenges in capturing pattern interactions and local variability. This study develops a local pattern interaction (LPI) model that integrates local complexity patterns or geocomplexity of spatial data, the interaction of patterns, and their locally varied power of determinants (PD). LPI is implemented in assessing the PD of local variables and pattern interactions on the spatial distributions of urbanization using statistical data, remote sensing imagery, and open geospatial data. The results show that LPI effectively identifies the local PD of interactions involving the geocomplexity patterns of urbanization-related explanatory variables. Model performance is evaluated by comparison with the optimal-parameters geographical detector (OPGD), a widely used spatial heterogeneity–based PD identification model. The model validation shows that LPI provides advantages over OPGD by capturing spatially varying interaction patterns and local effects, whereas OPGD assesses only global interaction effects. For example, the LPI-derived PD for the interaction between total retail sales and the geocomplexity pattern of tertiary-industry output averages 0.610 [0.336,0.783], indicating critical spatial variation in both local PD values and their significance, while the OPGD-derived PD yields a single global estimate of 0.537 ($p < 0.01$). This research advances theoretical understanding of spatial association and interaction, while providing an innovative analytical tool and decision-support capability for regional development, urban planning, and resource allocation.

1. Introduction

Spatial association, a core concept in geographic and spatial analysis, refers to the relationships among spatial variables within geographic space (Anselin, 2019). Spatial association identification is widely applied across various fields, including ecology, geology, public health, and environmental sciences (Ben-Moshe and Itzkovitz, 2019; Song et al., 2020; Harvey and O'Neale, 2024; Qian et al., 2024). Research on spatial association is crucial for identifying the interactive mechanisms among influencing factors in geographic space and for characterizing the interaction effects between spatial variables (Luo et al., 2025). Such studies help to reveal the formation and evolution of specific regions or phenomena (Rey et al., 2022). For instance, spatial autocorrelation analysis can be used to identify regions with relatively high or low levels of economic development, and further investigate the spatial determinants of economic disparities, such as transportation networks, infrastructure, and education levels (Anselin, 1995).

Various methods have been developed to quantify spatial association, including global indicators such as Moran's I and Geary's C (Mahato et al., 2024), and local indicators such as LISA and Getis-Ord Gi (Anselin, 1995; Chen et al., 2022). These models help identify and interpret spatial patterns. In addition, spatial regression models such as the spatial lag model (SLM) and spatial error model (SEM) have been widely used to improve the explanatory power of spatial data analysis

* Corresponding author.
E-mail address: yongze.song@curtin.edu.au (Y. Song).

https://doi.org/10.1016/j.jag.2025.105072
Received 26 August 2025; Received in revised form 3 December 2025; Accepted 29 December 2025
Available online 6 January 2026

(Anselin, 1988; Elhorst, 2010). More recently, advanced models integrating local heterogeneity and variable interactions, such as the geographically weighted regression (GWR) and the optimal parameters-based geographical detector (OPGD) have been introduced to better capture spatial dynamics in complex regional systems (Song et al., 2020; Liu et al., 2025). However, most of these methods primarily focus on the spatial distribution characteristics of single variables instead of the interactions among multiple spatial variables.

Spatial interaction is a fundamental concept for assessing the interaction effects among multiple spatial variables (Luo et al., 2025; Zhang et al., 2024). Spatial interaction reveals the mechanisms through which spatial data interact, such as the overlapping influences of human activities, the built environment, and natural systems. Understanding spatial interaction is critical for explaining regional development disparities, uneven resource allocation, and the pathways of spatial association. Classic studies, such as Tobler's First Law, highlight the importance of spatial proximity (Tobler, 1970), while subsequent research, including Hao's work in the field of new economic geography, further explores the relationship between spatial interaction and regional development (Hao et al., 2024). Spatial interaction plays a crucial role in understanding regional structures, optimizing resource allocation, and guiding the evolution of spatial configurations. By examining spatial interaction, researchers can uncover the operational mechanisms of spatial systems and identify pathways toward coordinated regional development (Liu et al., 2015).

Although spatial association and spatial interaction have been extensively studied, challenges remain in identifying their local effects, particularly when accounting for spatially varying characteristics, patterns, and interactions in the data. The local effects of spatial association refer to the localized relationships between the attributes of a specific geographic region and those of its neighboring regions, reflecting the spatial heterogeneity or uneven distribution of spatial patterns (Song and Wu, 2021). Rather than global spatial association, which captures overall spatial trends, local effects focus on the significance and patterns of spatial association at specific locations, such as clusters of high values, clusters of low values, or spatial outliers (Ren et al., 2025; Yang et al., 2025). These effects emphasize the interactions and similarities between individual local region and their surrounding areas, which may vary considerably across geographic space. Thus, the local effects of spatial association not only provide essential tools for understanding complex phenomena such as spatial clustering, spatial lag, regional disparities, and externalities, but also provide a scientific basis for addressing practical issues in urban planning, regional development, and environmental management (Wang et al., 2021).

However, while the local effects of spatial association primarily focus on the interactions between spatial data, they lack a systematic discussion of interactions between spatial patterns. A spatial pattern refers to the distribution and spatial relationships of geographic elements, reflecting the organizational structure of natural or social processes in space. Methods for describing spatial patterns can generally be categorized into three main types. The first type is spatial lag, which emphasizes the spatial dependence of variable values. The second type is spatial complexity, which focuses on the nonlinear and multiscale nature of spatial structures. The third type is spatial heterogeneity, which reveals the diversity and instability of relationships across different regions. Existing methods typically concentrate on the static relationships between single or paired variables, making it difficult to capture the complexity of multi-pattern and multidimensional interactions. This study employs the concept of pattern interaction to explore the complex interrelationships arising from the superimposed effects of different spatial variables. Pattern interaction deepens the understanding of internal heterogeneity and dynamic relationships within spatial structures and provides targeted insights and empirical evidence to support spatial decision-making and regional governance.

Spatial patterns inherently exhibit complex characteristics, such as nonlinearity, multiscale effects, and feedback mechanisms. From a nonlinear perspective, the relationships between variables within spatial systems are typically difficult to capture using linear models. Nonlinear modeling approaches, such as random forests and deep neural networks, are well-suited to uncovering these intricate interaction patterns. From a scale perspective, spatial processes typically occur simultaneously at multiple scales such as micro, meso, and macro, and patterns at different scales may interact through coupling, reinforcement, or cancellation. Multiscale analytical methods, such as multiscale geographically weighted regression (MGWR) (Vicca et al., 2023) and fractal dimension analysis, help reveal how the strength of variable effects and spatial structures vary across scales. In spatial analysis, local and global effects, while seemingly contradictory, are complementary and collectively influence spatial system dynamics. By integrating local and global effects, researchers can gain a more comprehensive understanding of the multilevel and multiscale dynamic evolution of spatial phenomena.

This study develops a local pattern interaction (LPI) model to combine local interactions and geographical patterns for spatial determinants analysis. By quantifying geographic complexity, local enhancement or weakening effects, and the interactions between patterns, LPI reveals the local spatial heterogeneity in complex spatial systems and its impact on the overall pattern, providing a more in-depth spatial analysis method. The LPI model not only focuses on each individual variable, but also emphasizes the way and degree of interaction between these variables. The LPI model specifically investigates pattern-to-pattern interactions, which can generate more complex effects on geographical processes. The LPI model incorporates both global-scale and local-scale effects, acknowledging that local manifestations typically represent environmentally contextualized expressions of broader geographic processes.

2. Local pattern interaction (LPI) model

2.1. Concept of LPI model

LPI model analyzes the interactions among local patterns in spatial data. By identifying the pattern association between a specific local region and its surrounding neighborhood, the LPI model reveals structural characteristics and mechanisms of change at a fine spatial scale. In contrast to conventional global models, the LPI model effectively characterizes spatial heterogeneity while revealing region-specific variations and their interrelationships. LPI model flexibility and general generalizability enable its use in a wide range of complex spatial analysis contexts beyond a single domain.

2.2. Calculation process

2.2.1. Geocomplexity calculation

Spatial local complexity or geocomplexity quantifies both the relationship between a region of interest and its surrounding environment, and the interactions among adjacent local regions within the target area (Zhang et al., 2023). The process of calculating geocomplexity is presented as (Zhang et al., 2023):

$$P_i = -1/mZ_i\sum_{j=1}^{m} W_{ij} \times Z_j - 1/m\sum_{j=1}^{m} W_{ij} \times Z_j \times 1/V_k\sum_{k=1}^{n} W_{jk} \times W_{ik} \times Z_k \tag{1}$$

$$P_i = -1/m \times Z_i\sum_{j=1}^{m}\left[Z_i \times Z_j + 1/V_k\sum_{k=1}^{n} Z_i \times Z_k\right] \tag{2}$$

$$G_i = P_i - min(P_i)/max(P_i) - min(P_i) \tag{3}$$

where P_i is the spatial local complexity for a location 'i' and G_i is the normalized indicator. W is a spatial adjacency matrix indicating the spatial relationship between observations. Z_i is the standardized value of the selected factor at location ‘i’, Z_j is the Z-score of the selected factor at location ‘j’, and ‘j’ is the spatial neighbor of the location ‘i’, Z_k is the Z-score of the selected factor at location ‘k’, and ‘k’ is the spatial neighbor of both location ‘j’ and ‘i’, m is the total number of spatial neighbors of location ‘i’, V_k is the number of spatial neighbors of location ‘j’ while these neighbors for location ‘j’ should be spatial neighbors of location ‘i’ at the same time.

Eq. (1) and Eq. (2) calculate the local spatial auto-correlation between the target area and all its adjacent areas by multiplying standardized variables with the weighted average of neighboring values. Simultaneously measure the spatial dependence between two adjacent values under the influence of the target area and perform a weighted average on it. The sum of these two components, taken as a negative value, yields the raw complexity score P_i. Eq. (3) is used to normalize spatial local complexity, thereby guaranteeing that all relevant values fall within the same range (0–1), which facilitates the interpretation of spatial error in traditional estimation models.

2.2.2. Local range analysis

Local range analysis aims to identify the spatial extent of heterogeneity effects in local areas and to quantify the effective radius of spatial correlation for specific variables. In this study, a semi-variate function is employed to assess the degree of local variation. The procedure involves three main steps: estimating the parameters of the empirical semi-variate function, fitting a theoretical semi-variate function model, and determining the local range. Since the true semi-variate function is not known, estimated values are used as proxy value (Olea, 2006). The empirical semi-variate function data are fitted using the exponential model, which is a commonly applied model. After fitting, the local range is defined as twice the maximum distance a at which significant spatial semi-variate function is observed. This range effectively captures local spatial variability or locally stratified heterogeneity and serves as the basis for subsequent analysis of local explanatory power of determining factors.

In this paper, we use Eq (4). to compute an unbiased estimate of the semi-variate function for a distance h:

$$\gamma(h) = 1/2n(h)\sum_{i=1}^{n(h)}[z(y_i + h) - z(y_i)]^2 \tag{4}$$

where $z(y_i)$ denotes the value of the response variable at position y_i, and $n(h)$ denotes the number of positions separated by a distance of h regions.

$$\gamma(h) = c_0 + c(1 - exp(-h/a)) \tag{5}$$

where h represents the distance. c_0 denotes the value of the semi-variance when h tends to zero, and c denotes the value of the semi-variance when the distance tends to infinity. The local extent d is calculated as (Hu et al., 2025):

$$d = 2 \times a \tag{6}$$

where a denotes the distance at which the semi-variance first reaches a value of c. The local extent d can effectively present the local spatial variability or locally stratified heterogeneity and will be used to examine the local power of determinants in subsequent steps.

2.2.3. Individual pattern deviation

The local indicator of stratified power (LISP) is an enhanced model developed based on the geographical detector and OPGD models (Wang et al., 2010; Song et al., 2020). LISP can analyze local spatial stratified association and demonstrate spatial stratified association changes across local regions (Hu et al., 2025). The core component of LISP is the local factor detector, which employs the power of determinant (PD) to assess the explanatory power of individual variables within a local spatial range. The module calculates the standard deviation across different layers by constructing geographical hierarchical variables and obtains the local ρ-value ($\rho(u)$) for each location (Wang et al., 2010; Hu et al., 2025):

$$\rho(u) = 1 - \sum_{z=1}^{M} N_Z\sigma_z^2/N\sigma^2 \tag{7}$$

where N and σ^2 represent the number of observations and the standard deviation within the local range k centered at location u. N_z is the number of observations, and σ_z^2 is the standard deviation of the observations within the geographic stratum z ($z = 1,\dots, M$) of the local range.

2.2.4. Local interaction effects

After obtaining the deviations of individual variables, this step employs a tree-based spatial discretization method to quantify the local effect of PD for interaction variables. This method constructs a hierarchical structure of interaction combinations and compares the explanatory power of single versus multiple interaction variables with respect to the local spatial structure (Luo et al., 2022):

$$\omega(u) = 1 - min(SSW_{X,D})/SST \tag{10}$$

where SST and SSW are the $N\sigma^2$ and $\sum_{z=1}^{M} N_z\sigma_z^2$ in Eq. (7), X are explanatory variables, and D refers to stratified variables. The D is computed using a tree-based spatial discretization approach (Luo et al., 2022).

2.2.5. Global improvement analysis

Global improvement analysis is a critical step in the LPI model. The core objective is to quantifying the extent to which local interactions enhance the accuracy of the global model. Comparing models with and without local effects, this analysis identifies the corrective impact of local factors on the global spatial structure.

A substantial global improvement typically indicates that local effects play a significant role in improving model accuracy and explanatory power. Global improvement analysis helps to uncover how local spatial patterns influence the overall spatial configuration. For example, certain local effects may induce substantial modifications on the global structure, thereby enabling the global model to better reflect real-world phenomena. The explanatory power of local effects and their potential to enhance model predictive performance can be assessed via global improvement analysis, which provides a scientific basis for subsequent spatial analysis. Local spatial features represent critical components in spatial modeling, since incorporating local patterns substantially enhances model performance.

2.3. Validation and heterogeneity testing

Validation and heterogeneity testing are used to evaluate the effectiveness and adaptability of LPI models to spatial data. Validation and heterogeneity testing can ensure that the constructed model not only has predictive accuracy, but also accurately captures local effects and spatial heterogeneity in the data. By comparing the predictive performance of LPI model with traditional global model, the stability and generalization ability of LPI model at different spatial scales are tested. Improvements in prediction accuracy serve as a key indicator of the success of incorporating local effects into the model. Performance comparisons among different models help determine whether the inclusion of local effects effectively enhances predictive power, particularly in the context of spatial interactions and localized patterns.

Heterogeneity testing is instrumental in identifying significant variations between different regions within the data, which is essential for understanding the interactive effects of local patterns. Detecting local heterogeneity allows for refinement of the model's local adaptability, thereby supporting robust performance across diverse spatial contexts. Model parameters can be optimized based on heterogeneity test results to enhance adaptability within specific localities.

3. Case: Assessing determinants of urbanization using the LPI model

3.1. Study area

In the process of rapid urbanization, the spatial distribution of urban development is no longer driven by a single factor alone, but is shaped by a complex process of interaction between multiple spatial elements. These interactions encompass not only the interrelations among economic, demographic, transportation, and ecological factors, but also the patterned co-occurrence of these elements within geographic space. Traditional urbanization studies tend to model urbanization in a linear or holistic manner, ignoring differences in the local effects of these spatial elements across regions. However, social, economic and natural conditions within regions are highly heterogeneous, and development trajectories of different localities may be influenced by the same factors acting with different intensity. Therefore, adopting an analytical approach that captures spatial heterogeneity and local interactions is crucial for a deeper understanding of the determinants of urbanization. This study employs LPI model to systematically analyze the spatial interactions among urbanization drivers and to assess the local variations in the effects of various factors across local regions in the provinces of Shanxi, Henan, and Hebei. The approach helps uncover the mechanisms of spatial pattern reinforcement and suppression, while also providing a foundation for formulating region-specific development policies.

The study area of this research encompasses the provinces of Shanxi, Henan, and Hebei, located in the central-eastern region of China. This research area is an important economic, cultural, historical and resource area in China. Shanxi Province is predominantly characterized by mountainous and hilly terrain, including major mountain ranges such as the Taihang, Lüliang, and Hengshan Mountains, with the Fen River Valley running through its center. Shanxi lies within the Yellow River Basin and constitutes the core area of the Loess Plateau, where soil erosion is particularly severe. Henan Province is mainly composed of plains, with the western region shaped by the eastern extension of the Qinling Mountains, the southern region by the Tongbai and Dabie Mountains, and the northern region bordered by the Taihang Mountains. Located in the middle and lower reaches of the Yellow River, Henan is rich in agricultural resources and is one of the cradles of traditional Chinese agrarian civilization. Hebei Province features diverse topography, including plains, mountains, plateaus, and coastal areas. Hebei Province serves as a critical component of China's Bohai Economic Rim and functions as a vital link between the northern and central economies. Shanxi's economy has traditionally been dominated by the energy sector, with a relatively homogeneous industrial structure and slow economic growth. In recent years, Shanxi province has pursued industrial transformation by promoting equipment manufacturing and the new energy sector. Henan, with a large population and one of the highest total economic outputs in the country, boasts a well-developed agricultural base, a high level of industrialization and urbanization. Henan is an important transportation hub and industrial base in the country. Hebei has a strong industrial foundation, with a significant presence of traditional industries such as steel, energy, and equipment manufacturing.

3.2. Data

To comprehensively capture the drivers of urbanization, this study collected 2022 socioeconomic indicators related to urban development levels in Shanxi, Henan, and Hebei provinces, supplemented by remote sensing and open-source map data. The main data sources include the statistical yearbooks of Shanxi (https://tjj.shanxi.gov.cn/tjsj/tjnj/nj2023/zk/indexch.htm), Henan (https://oss.henan.gov.cn/sbgt-wztipt/attachment/hntjj/hntj/lib/tjnj/2023nj/zk/indexch.htm), and Hebei (https://tjj.hebei.gov.cn/hetj/tjnj/2023/zk/indexch.htm), Google Earth Engine (GEE), and OpenStreetMap (https://www.openstreetmap.org).

3.2.1. Dependent variable data

Based on the available data, this study uses nine socioeconomic indicators related to urbanization from five dimensions: population urbanization, economic development, ecological conservation and development, urban–rural integration, and social development. The indicator names and their abbreviations are listed in Table 1. Most data were obtained from the 2022 statistical yearbooks of Shanxi, Henan, and Hebei. Missing values were supplemented using remote sensing calculations. For example, vegetation coverage rate was derived from remote sensing data on the Google Earth Engine platform, and road network density was calculated using domestic road data from OpenStreetMap.

The spatial distributions of nine urbanization indicators are shown in Fig. 1. All indicators were aggregated and mapped at the county level to guarantee that the spatial heterogeneity of urbanization drivers within the region was accurately represented. In terms of resident population, high-value areas are notably concentrated in the southern and central regions of Henan Province, the southwestern part of Shanxi Province, and the central-southern part of Hebei Province. This indicates a high degree of population agglomeration and active urbanization in these areas. Regional GDP is primarily concentrated in central Henan, resource-based cities in Shanxi, and the economic corridor near Beijing and Tianjin in Hebei, reflecting industrial concentration and the driving effect of urban agglomerations. In contrast, Per capita regional GDP is prominent in some small and medium-sized cities and in the Beijing-Tianjin-Hebei border region, indicating the variability of economic development within the region. The spatial distribution of fiscal revenue and urban residents disposable income is relatively consistent, mainly concentrated in economically active cities and regions with strong industrial bases, such as Taiyuan, Zhengzhou, and Shijiazhuang. Meanwhile, rural residents' disposable income is more dispersed, with high-value areas observed in central Henan and eastern Hebei.

The urban–rural income ratio is relatively high in the western and northern parts of Shanxi and northern Hebei, indicating pronounced urban–rural development imbalances in these regions. Vegetation coverage rate is relatively high in the southern part of Shanxi, western Henan, and mountainous areas in northern Hebei, reflecting favorable ecological conditions. In contrast, it is generally lower in densely populated and industrialized areas, likely due to urban expansion and land development. Road network density is significantly higher in urbanized regions, particularly in northeastern Henan and central-southern Hebei.

3.2.2. Explanatory variables

This study uses five socio-economic indicators from endogenous forces, market-driven forces and administrative influence aspects as explanatory variables. The names and abbreviated codes of the used indicators are shown in Table 2. The data of the indicators come from the statistical yearbook of Shanxi, Henan and Hebei provinces in 2022.

Table 1
Indicators of dependent variables for measuring urbanization across five dimensions.

Category	Variable	Code
Population urbanization	Resident population	Population
Economic development	Regional GDP	GDP
	Per capita regional GDP	PCGDP
	General public budget revenue	BudgetRevenue
	Per capita disposable income of urban households	UrbanIncome
	Per capita disposable income of rural households	RuralIncome
Ecological conservation and development	Vegetation coverage rate	Vege
Urban-rural integration	Urban-rural income ratio	UrbanRural
Social development	Road network density	Road

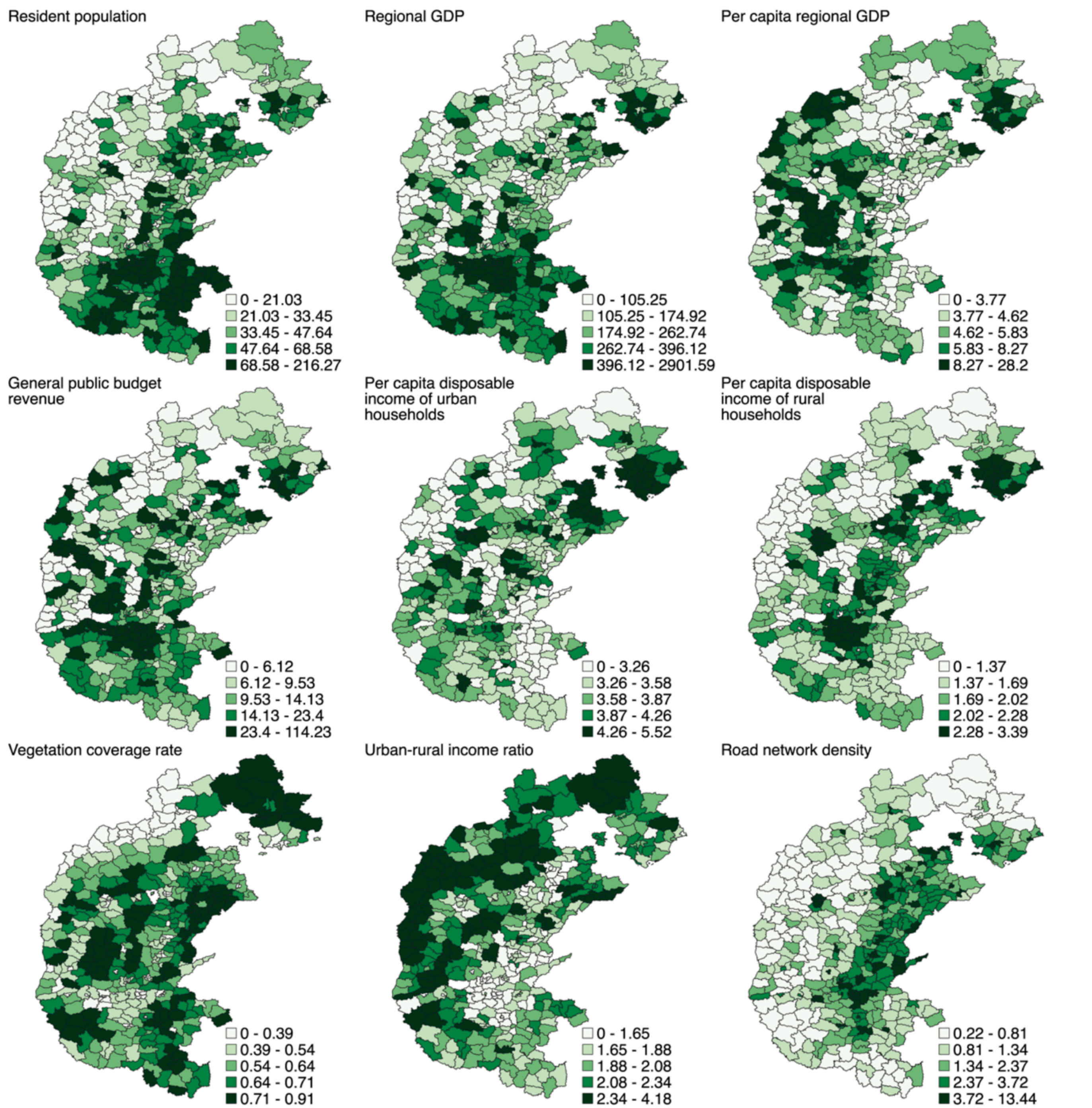

Fig. 1. Spatial distributions of urbanization-related socioeconomic indicators in the study area.

The spatial distributions of the five indicators are shown in Fig. 2. According to the distributions, the peak values of the gross output value of the primary industry are predominantly clustered in southern regions, with particularly dense agricultural activity observed in southern Henan and northeastern Hebei. The gross output value of the secondary industry exhibits distinct central-southern agglomeration patterns, particularly in central Henan, southern Shanxi, and southern Hebei, reflecting these regions' robust industrial infrastructure. The gross output value of the tertiary industry peaks in central Henan and southern Hebei, displaying strong spatial concordance with population clusters, suggesting synchronous development of service industries and urbanization. Regions with stronger consumption capacity are mainly distributed in central and southern Henan, southeastern Hebei, and several economically active urban clusters, likely influenced by a combination of population size, residents' income levels, and the urban commercial environment. Areas with higher fiscal expenditure are concentrated in southern and central Henan, central Hebei, and central Shanxi. Five explanatory variables reveal spatial imbalances in industrial structure, consumption capacity, and fiscal resource allocation both among the three provinces and within each province. Some high-value areas appear across multiple maps, indicating their advantageous positions in multiple dimensions of development.

3.3. Experiment design

This study employs LPI model to identify the key driving factors and

Table 2
Explanatory variable data indicators for explaining spatial patterns of urbanization.

Category	Variable	Code
Endogenous forces	Gross output of the primary industry	PrimaryIndustry
	Gross output of the secondary industry	SecondaryIndustry
	Gross output of the tertiary industry	TertiaryIndustry
Market-driven forces	Total retail sales of consumer goods	Retail
Administrative influence	General public budget expenditure	BudgetExpenditure

spatial interaction mechanisms in the urbanization processes of Shanxi, Henan, and Hebei provinces. The LPI-based spatial determinant identification includes: data preprocessing, local determinant analysis, and model validation.

3.3.1. Data pre-processing

The first step in data preprocessing is to deal with missing data. For missing data, records with absent values may either be removed or imputed using measures such as means or medians. Outliers can be detected and treated using standard statistical techniques. The second step is to standardize the data to eliminate the effect of the scale. Finally, data from different sources are integrated into a unified dataset to maintain data consistency and integrity.

Using entropy weighting method to weight 9 indicators in five aspects: population urbanization, economic development, ecological conservation and development, urban–rural integration, and social development. Taking the calculation of the population urbanization as an example, if there are f counties with g evaluated indicators, the index system x can be defined as follows:

$$x_{ij} = \begin{bmatrix} x_{11} & \cdots & x_{1g} \\ \vdots & \ddots & \vdots \\ x_{f1} & \cdots & x_{fg} \end{bmatrix} \tag{8}$$

where x_{ij} is the value of the j th indicator in the i th county. Standardize the values using the following equation:

$$B_j = x_j - min(x_j)/max(x_j) - min(x_j) \tag{9}$$

$$B_j = max(x_j) - x_j/max(x_j) - min(x_j) \tag{10}$$

where $B_j = [B_{1j}, B_{2j}, \cdots, B_{fj}]$ is the standardization value of indicator j and $x_j = [x_{1j}, x_{2j}, \cdots, x_{fj}]$ is the value of indicator j for all counties. Eq. (9) is the standardization for positive indicators and Eq. (10) is the standardization for negative indicators. The information entropy of indicator j is then denoted as E_j and can be obtained using the following equation:

$$E_j = -ln(g)^{-1} \sum_{i=1}^{g} p_{ij} ln(p_{ij}) \tag{11}$$

$$p_{ij} = B_{ij} / \sum_{i=1}^{g} B_{ij} \tag{12}$$

where the p_{ij} is the specific gravity value for each B_{ij}. The weight of

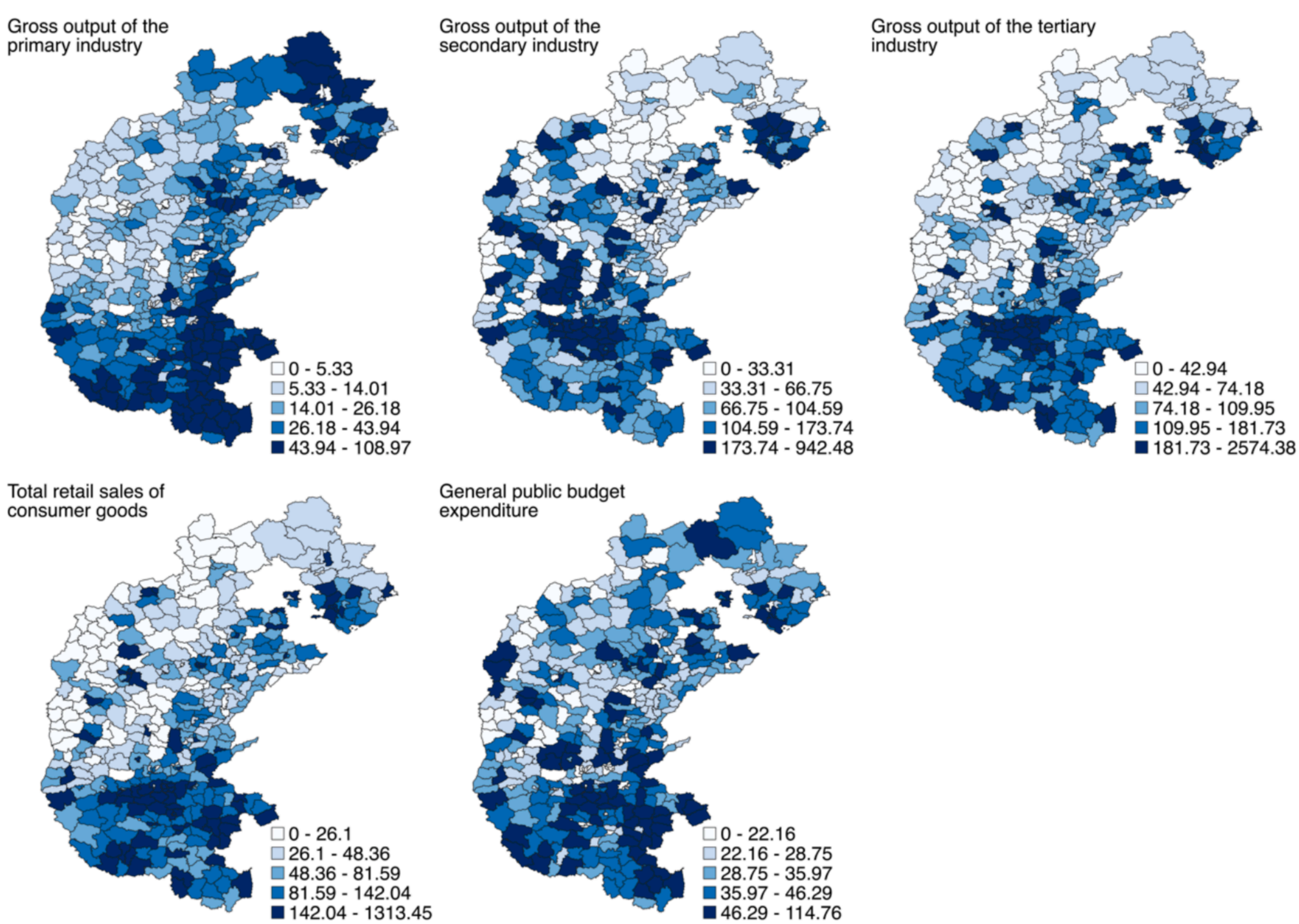

Fig. 2. Spatial distributions of urbanization explanatory variables in the research area.

indicator j can be obtained using the following equation (Ge et al., 2023):

$$T_j = 1 - E_j/g - \sum E_j (j = 1, 2, 3, \cdots, g) \quad (13)$$

3.3.2. Lpi-based spatial modeling

The first step of LPI-based spatial determinant analysis is the calculation of spatial local complexity or geocomplexity. Geocomplexity measures the structural diversity and attribute variation of a local region within its neighborhood and identifying regional heterogeneity. Local regions in highly heterogeneous environments are more likely to reflect complex spatial mechanisms. Constructing a spatial weight matrix can quantify the complexity of a region's spatial structure. High-complexity areas frequently indicate mixed functions, uneven development, or intertwined driving forces. Geocomplexity calculation facilitates the identification of areas with diverse spatial structures and frequent pattern shifts.

The second step is local interaction analysis. Local interaction analysis is used to identify the joint effects of multiple variables between local regions and their neighborhoods to reveal how different urbanization drivers collectively influence urban development in specific regions. By measuring the strength of interaction effects between variables across local regions and their neighbors, this approach can detect patterns of interaction reinforcement or mutual inhibition, thereby uncovering localized driving mechanisms in the urbanization process.

The third step is pattern interaction analysis. The core objective of pattern interaction analysis is to identify and interpret the synergistic or inhibitive spatial relationships among different urbanization drivers from a regional perspective. By quantifying the integrated interaction effects between local regions and their neighborhoods, this approach assesses whether combinations of variables exhibit spatially reinforced or weakened interaction patterns, thereby revealing the underlying structural mechanisms driving urbanization.

The final step is heterogeneity analysis. Heterogeneity analysis aims to reveal spatial differences in the intensity and mechanisms of urbanization driving factors in different regions. This step emphasizes the non-uniformity of spatial processes, reflecting how similar factors may yield divergent outcomes in different locales, or conversely, how distinct factors may lead to similar urbanization patterns.

3.3.3. Model validation

To validate the reliability of the LPI model in identifying urbanization driving mechanisms, this section conducts model validation from three dimensions: statistical accuracy, spatial consistency, and parameter sensitivity. The predictions of the LPI and OPGD models are first compared with the observed data in the 2022 provincial statistical yearbooks to assess the degree of fit of the two models in describing the trends of key variables such as population, industry, and transportation. Subsequently, spatial correlation tests are employed to evaluate the consistency between the predicted values and actual spatial distributions, thereby assessing each model's capability to reproduce spatial structural characteristics. By comparing the spatial distribution patterns generated by the LPI and OPGD models under the same explanatory variables, the sensitivity of both models in reflecting spatial associations and local variations is examined. The evaluation of spatial heterogeneity models, including LPI and OPGD, is based on the assumption that a higher PD value indicates a greater capability to explain spatial stratified heterogeneity and to identify the influence of spatial determinants. This validation approach is consistent with existing studies (e.g., Hu et al 2025; Luo et al 2023; Zhang et al 2024) and differs fundamentally from the fitness and error-based metrics such as RMSE or R^2. Finally, a model sensitivity analysis is carried out to assess the robustness of the LPI model under varying parameter settings.

Through this validation process, the performance of the LPI model across different spatial scales and data structures is systematically evaluated, providing methodological for its application in studies of urbanization driving mechanisms and enhancing the credibility of its explanatory outcomes.

4. Results

4.1. Deriving the urbanization index using entropy weighting approach

This section employs the entropy method to assign weights to five dimensions of urbanization development: population urbanization, economic development, ecological conservation and development, urban–rural integration, and social development. The results of the weight assignment are presented in Table 3. As shown in Table 3, social development has the highest weight, with population urbanization ranking second and economic development third. This indicates that social development and population urbanization are the two primary factors influencing the urbanization index, while economic development also plays a significant role that cannot be disregarded. According to Table 3, within the dimension of economic development, regional GDP and general public budget revenue are the dominant indicators, each with a weight exceeding 0.3, suggesting that macroeconomic scale has a substantial impact on the level of urbanization. In contrast, ecological conservation and development and urban–rural integration have relatively lower weights, implying that their influence on urbanization development is comparatively limited.

The spatial distribution of the urbanization index in the study area is shown in Fig. 3. Overall, urbanization in the region exhibits a spatial pattern of being higher in the southeast and lower in the northwest. Urban centers are primarily concentrated in the central, southeastern, and parts of the northeastern areas of the region. Henan Province has the highest overall level of urbanization. Notably, central Henan (e. g., Zhengzhou, Xuchang, Kaifeng) and southern Henan (e. g., Nanyang, Zhumadian) contain several dark-shaded areas, indicating a high level of urbanization. The relatively high urbanization level in Henan is closely related to its transportation infrastructure, population concentration, and the development of national-level urban agglomerations such as the Central Plains Urban Agglomeration.

Urbanization in Hebei Province is more heterogeneous. The southeastern part of the province (adjacent to the Beijing-Tianjin area), including cities such as Handan and Xingtai, shows significant urban development. In contrast, the northwestern areas, characterized by the Taihang Mountains and Bashang Plateau, exhibit lower levels of urbanization and a pronounced urban–rural disparity. Shanxi Province shows a generally lower level of urbanization, with relatively higher

Table 3
Weights of criteria and variables for calculating the urbanization index derived using the entropy weighting approach.

Criteria	Weight of criteria	Variable (direction)	Weight of variable
Population urbanization	0.259	Resident population (+)	
Economic development	0.164	Regional GDP (+)	0.327
		Per capita regional GDP (+)	0.234
		General public budget revenue (+)	0.311
		Per capita disposable income of urban households (+)	0.053
		Per capita disposable income of rural households (+)	0.076
Ecological construction and protection	0.085	Vegetation coverage rate (+)	
Urban-rural integration	0.034	Urban-rural income ratio (−)	
Social development	0.459	Road network density (+)	

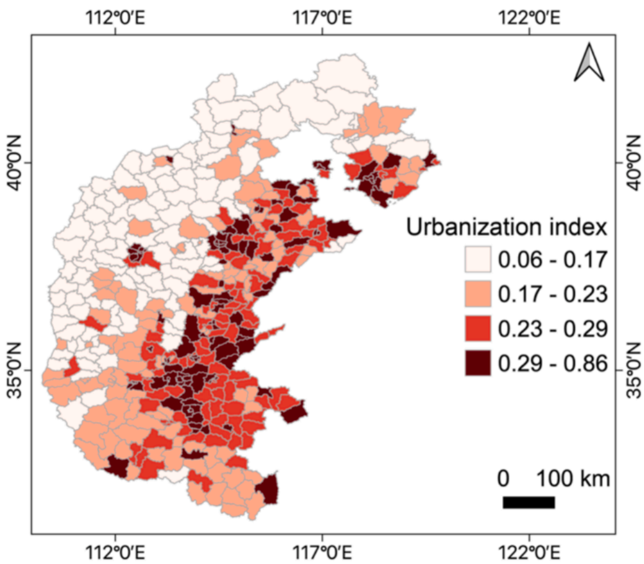

Fig. 3. Spatial distribution of the urbanization index in the study area.

urbanization observed in the southern part (e. g., Yuncheng, Jincheng), while the central, northern, and western regions remain at lower levels. The urbanization level in Shanxi is influenced by its mountainous terrain and an economy heavily reliant on energy resources, which have collectively contributed to the slower pace of urbanization in the province.

4.2. Lpi-based pattern determinants analysis

The spatial distributions of geocomplexity patterns of urbanization explanatory variables are shown in Fig. 4. The gross output value of the primary industry is primarily concentrated in most areas of Henan Province and the northeastern part of Hebei Province, with abundant agricultural resources, concentrated arable land, and a strong foundation for agricultural production. The corresponding geocomplexity map shows relatively high geocomplexity values in central Henan and parts of eastern and northern Hebei, indicating a high degree of local heterogeneity in the spatial distribution of agriculture, influenced by natural conditions, agricultural structure, and other factors. The spatial distribution of the gross output value of the secondary industry is relatively dispersed, with higher values observed in industrial clusters, suggesting that these regions are dominant in industrial development. The geocomplexity of industry is notably high in central Shanxi, southwestern Henan, and northeastern Hebei, reflecting a more intricate spatial configuration of industrial development in these areas. The gross output value of the tertiary industry and the total retail sales of consumer goods are significantly concentrated in provincial capital cities and their surrounding areas. The corresponding GC values are particularly prominent on the peripheries of these urban centers, highlighting the spatial differentiation of urban functional zones. Public fiscal budget expenditure is relatively evenly distributed overall, but certain regions exhibit high geocomplexity, which may be associated with policy orientation and functional allocations. In summary, the geocomplexity of the variables is jointly driven by multiple factors, including natural conditions, industrial structure, urban hierarchy, and policy investment. Urban peripheries and industrial clusters are the regions where

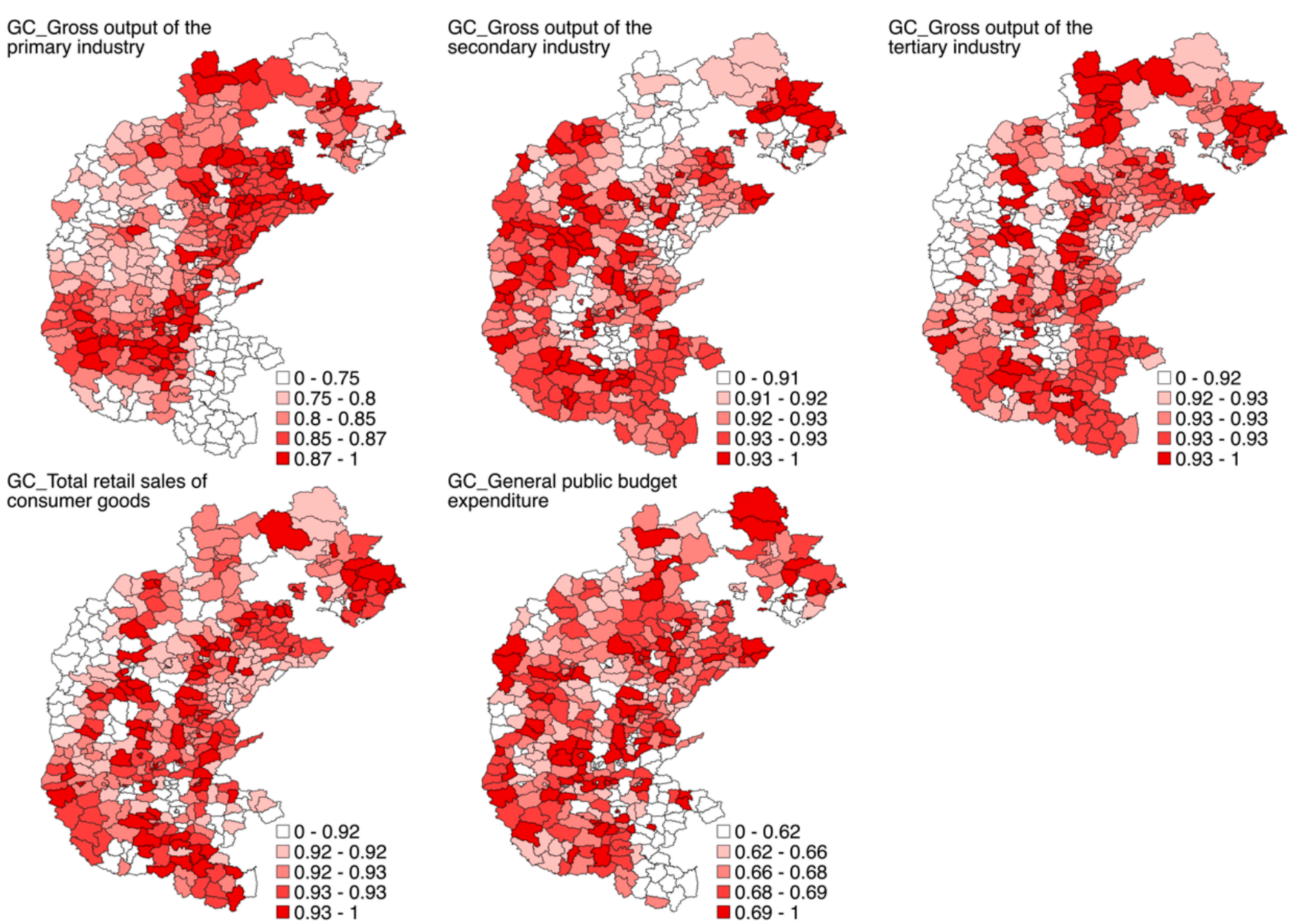

Fig. 4. Spatial distributions of the geocomplexity patterns of urbanization explanatory variables.

geocomplexity is relatively high.

To demonstrate how urbanization-driving factors influence the geocomplexity of regional spatial structures across different value levels, distribution trend curves were constructed to depict the nonlinear relationships between each explanatory variable and its geocomplexity pattern (Fig. 5). Results show that when the variable values are low, the geocomplexity values are generally high, indicating the varied relationships between spatial data and the geocomplexity patterns. The geocomplexity value gradually decreases, reflecting a more concentrated spatial structure in high-value areas, as the variable value increases. Among these indicators, the output values of the primary, secondary, and tertiary sectors, along with total retail consumer goods sales, demonstrate distinct high-value stabilization patterns, whereas public financial expenditures exhibit a fluctuating downward trajectory.

To determine the scope of local spatial analysis, this study developed a semi-variance model to identify the critical range of spatial correlation of urbanization variables, which is shown in Fig. 6. As shown in Fig. 6, the exponential model fit yields a range value of 99.28 km, indicating a local stratified heterogeneity range of 198.56 km. This local spatial analysis scope provides a critical spatial scale reference for setting local neighborhoods in subsequent modules of the LPI model.

The PD values for each explanatory variable are calculated within the local spatial range to evaluate their local explanatory power for urbanization. The spatial distributions of PD values for the five variables, together with their statistical significance, are shown in Fig. 7, revealing critical regional variance in the dominant factors shaping urbanization patterns. The gross output value of the tertiary industry exhibits the highest PD values in most regions, with a high level of statistical significance, indicating that the tertiary industry is a key driver of urban spatial structure, particularly prominent in central cities

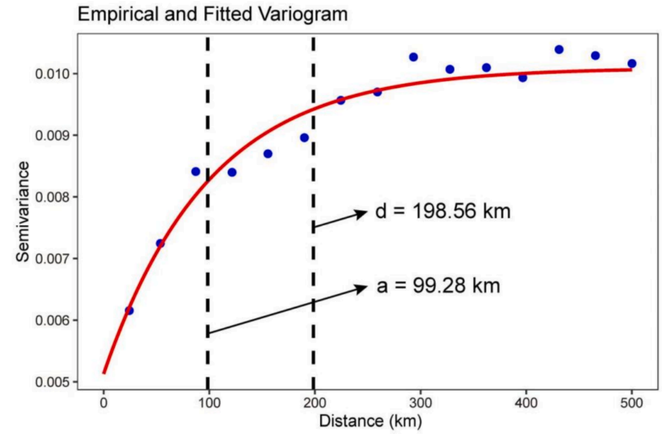

Fig. 6. The process and outcome of the range for examining local heterogeneity.

and economically active areas. Similarly, the total retail sales of consumer goods show strong explanatory power in areas with a high degree of urbanization, suggesting that consumption activity is an important driving force of urban development. In northern Hebei and central Shanxi, the gross output value of the secondary industry shows high PD values and a relatively high level of significance across most areas. In contrast, the gross output value of primary industry and general public budget expenditure exhibit relatively low influence in most regions, with statistically significant areas being sparsely distributed. The gross output value of primary industry and general public budget expenditure

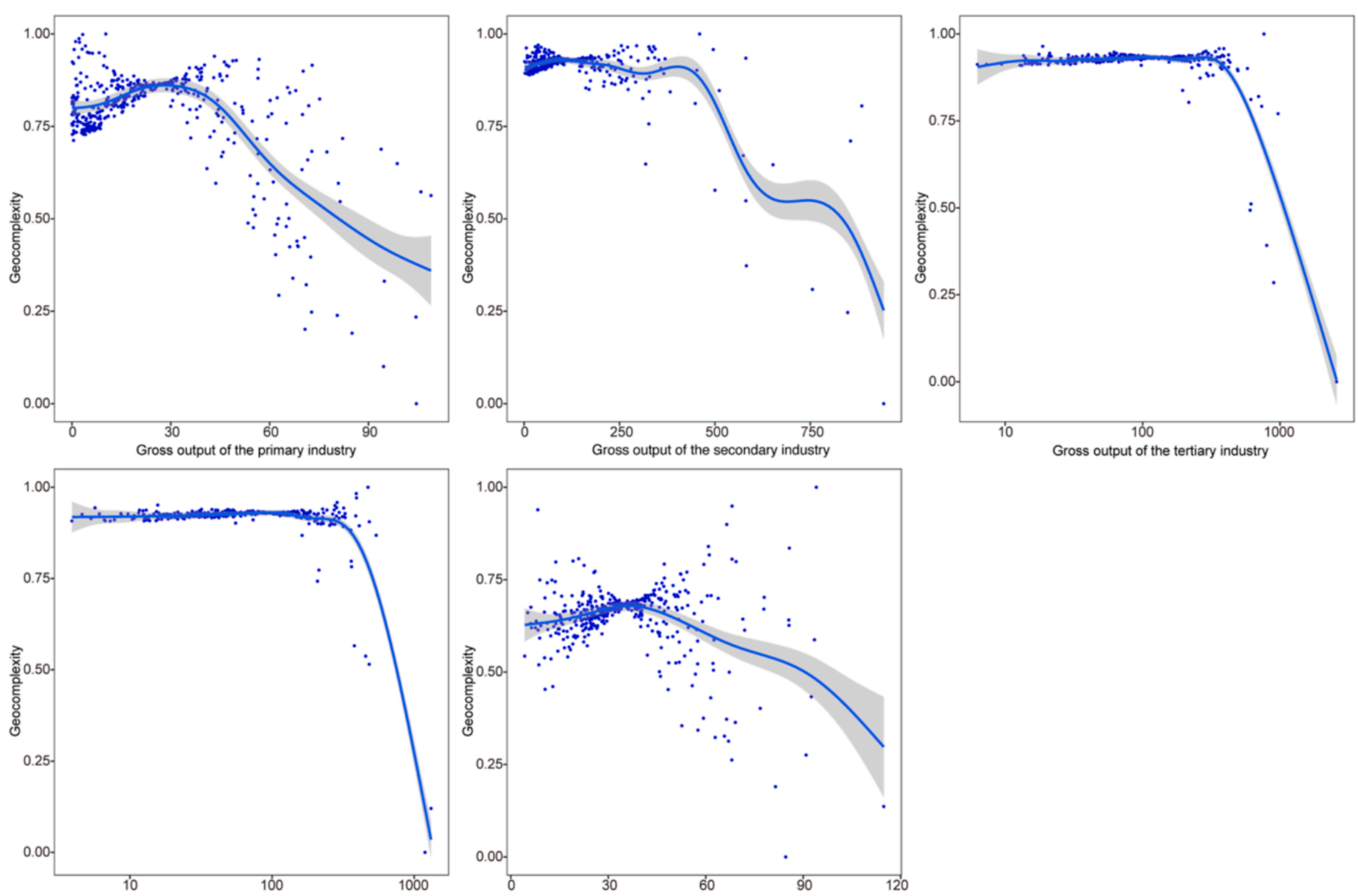

Fig. 5. A comparison of statistical distribution trends of explanatory variables and their geocomplexity patterns.

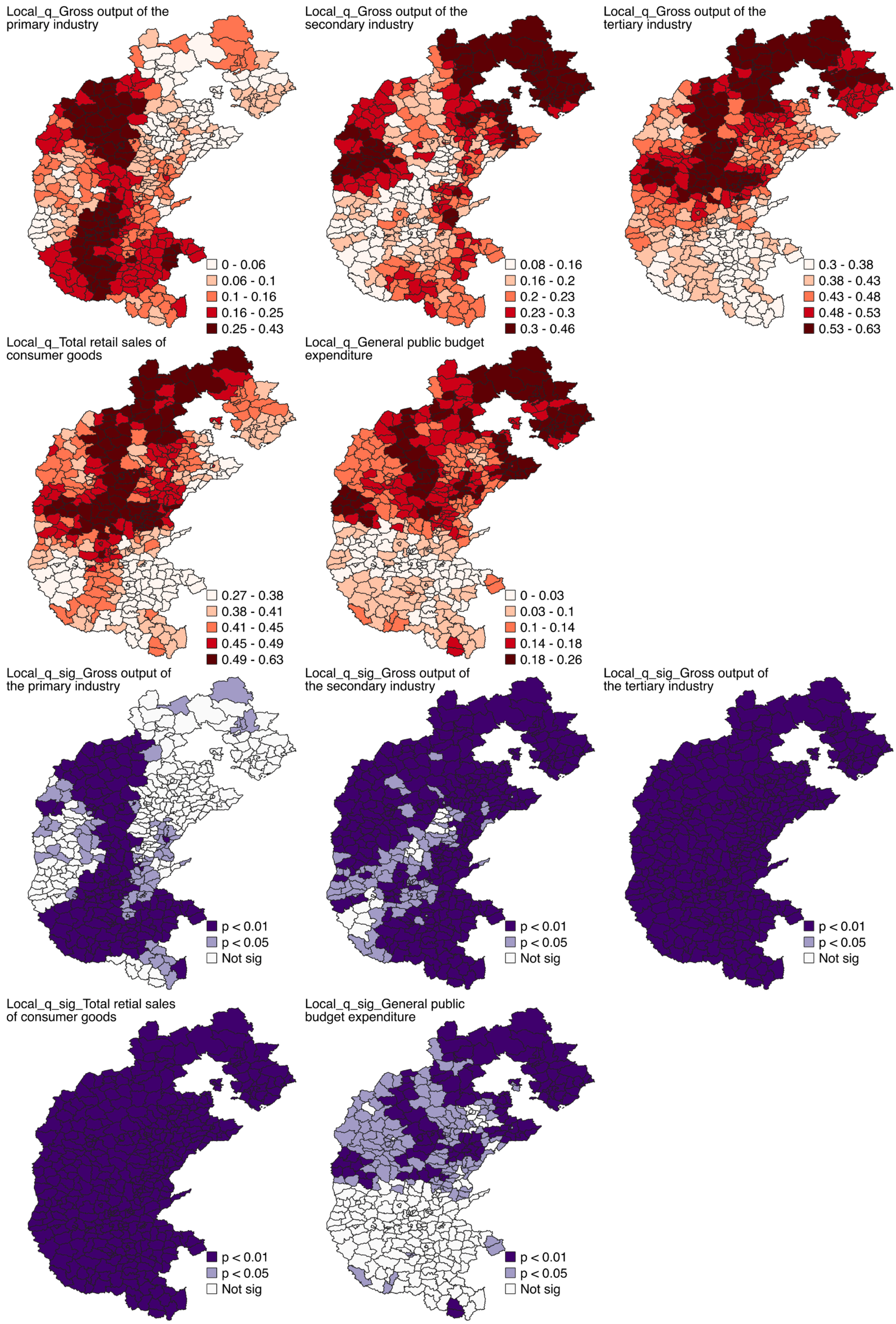

Fig. 7. Spatial distributions of the power of determinants (PD) of variables and their significance levels.

have limited overall dominance in shaping urbanization patterns, they may yield localized influence in certain areas.

The PD values of their geocomplexity patterns were calculated within a localized spatial scope, and the spatial distributions with corresponding significance tests are calculated. Fig. 8 shows each variable's explanatory power in shaping its geocomplexity patterns, along with the corresponding distribution of significance levels. The geocomplexity of the gross output value of the tertiary industries and secondary industries is strongly dominated by their respective variables, particularly in core cities and industrial clusters, where local PD values are notably high and statistically significant in most areas. In contrast, the geocomplexity of the gross output value of primary industry and general public budget expenditure show relatively low explanatory power and limited statistical significance, with the spatial distribution of geocomplexity failing to pass significance tests in the majority of regions. The explanatory power of the geocomplexity of the total retail

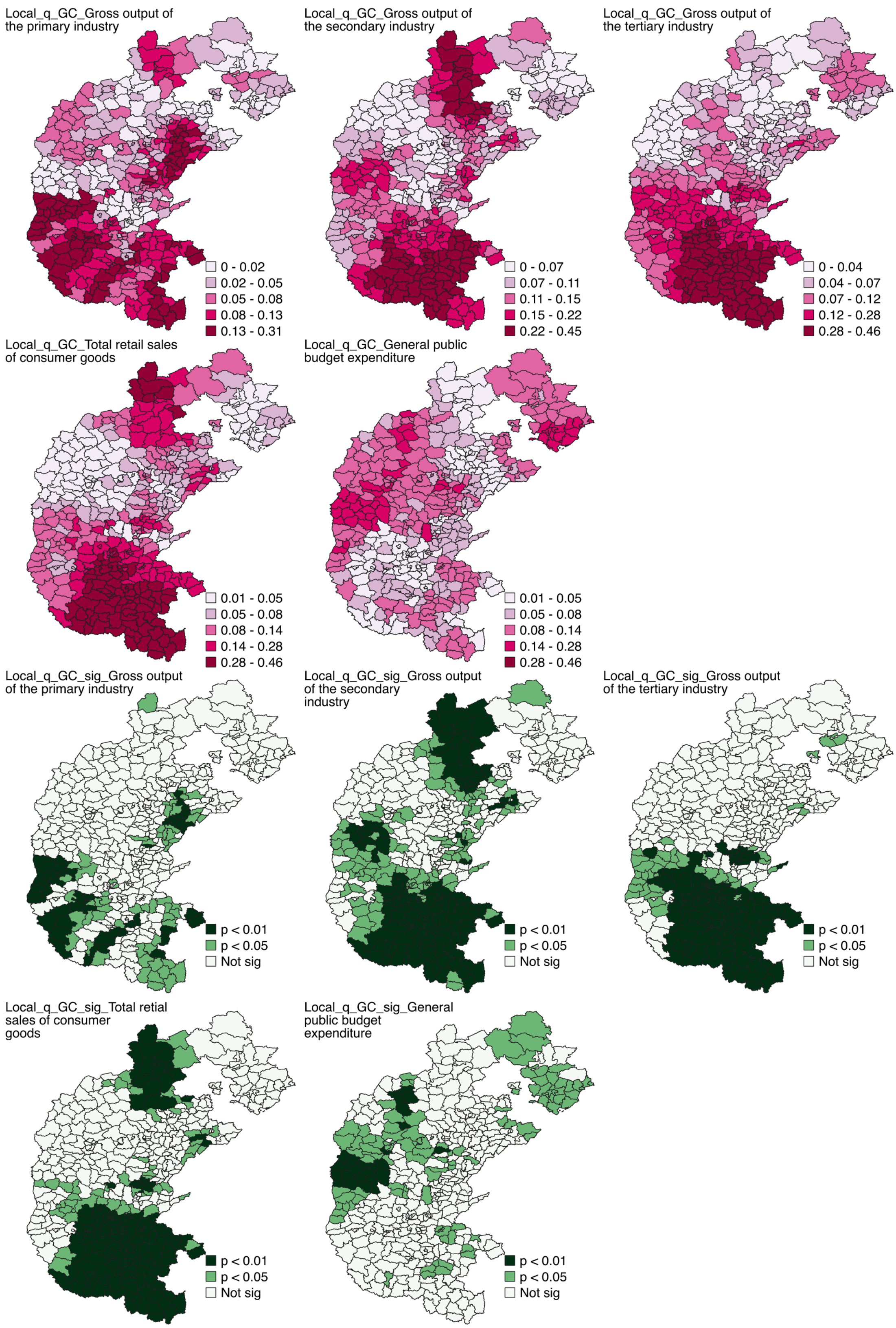

Fig. 8. Spatial distributions of the power of determinants (PD) of variables' geocomplexity pattens and their significance levels.

sales of consumer goods variable lies somewhere in between, reaching significance levels in some regions, although its PD value is intermediate overall. Most regions have significant performance, but the significance regions of different variables vary significantly. Highlighting the advantages of the LPI model in capturing local complex relationships and spatial heterogeneity.

Fig. 9 presents the types and relationships of interactions between variables, revealing whether the combined effects of two variables are mutually enhanced or weakened, or independent. Interactions between variables can be categorized into various types, and in this study, only nonlinear enhancement and bivariate enhancement are discussed. Nonlinear enhancement refers to cases in which the combined effect of two variables exceeds the simple sum of their individual effects when acting independently. Bivariate enhancement refers to instances where the joint effect of two variables is greater than that of each variable alone but less than the sum of their independent effects. The interaction strength map demonstrates the interaction strength of the two variables, with color intensity indicating the degree of interaction, ranging from 48 % to 86 %.

As shown in the Fig. 9, the overall bivariate interaction strength is relatively high in Shanxi Province, indicating a strong explanatory power of the five used variables on urbanization levels. In contrast, some regions within Hebei and Henan provinces exhibit relatively weaker explanatory power. The variable interaction maps depict the influence of variables at the county level and across spatial locations within the study area, as well as the ways in which these variables combine to produce joint effects. The total of ten explanatory variables, which comprise five core variables and their five corresponding geocomplexity variables, yields 45 possible pairwise interaction combinations. Based on the active combinations of these interactions, the affected regions can be classified into three categories: the first category involves interactions between two core variables, such as the interaction between the gross output value of the primary industry and secondary industry, as illustrated in the interaction maps. The second category involves interactions between variables and variable geocomplexity, for example, between the gross output value of the primary industry and the geocomplexity of the gross output value of the tertiary industry, or between the gross output value of the primary industry and the geocomplexity of total retail sales of consumer goods. The third category involves the interactions between the complexities of two different variables, such as the interaction between the geocomplexity of the gross output value of the primary industry and tertiary industry output. According to Fig. 9, the first type of interaction accounts for 41.72 %, the second type of interaction accounts for 56.69 %, while the third type of interaction is extremely rare.

4.3. Model validation

The performance of the LPI model is evaluated by comparing it with the OPGD model, which calculates the global PD values of each explanatory variable and their interaction terms to assess their explanatory power for urbanization patterns (Fig. 10). The OPGD-based outcomes show that the gross output of the tertiary industry has the highest PD value (0.483), indicating that the gross output of the tertiary industry is the most important single variable in explaining the regional urbanization spatial pattern at the global scale. The PD value of the total retail sales of consumer goods is 0.438, suggesting that consumption vitality and market size have a decisive influence on urban spatial structure. The PD value of gross output of secondary industry is 0.196, which is at a moderate level, indicating that the total output value of the secondary industry has a significant influence in certain regions, but its effect is not as strong as that of gross output of the tertiary industry and total retail sales of consumer goods. The PD values for the gross output of the primary industry and general public budget expenditure are 0.113 and

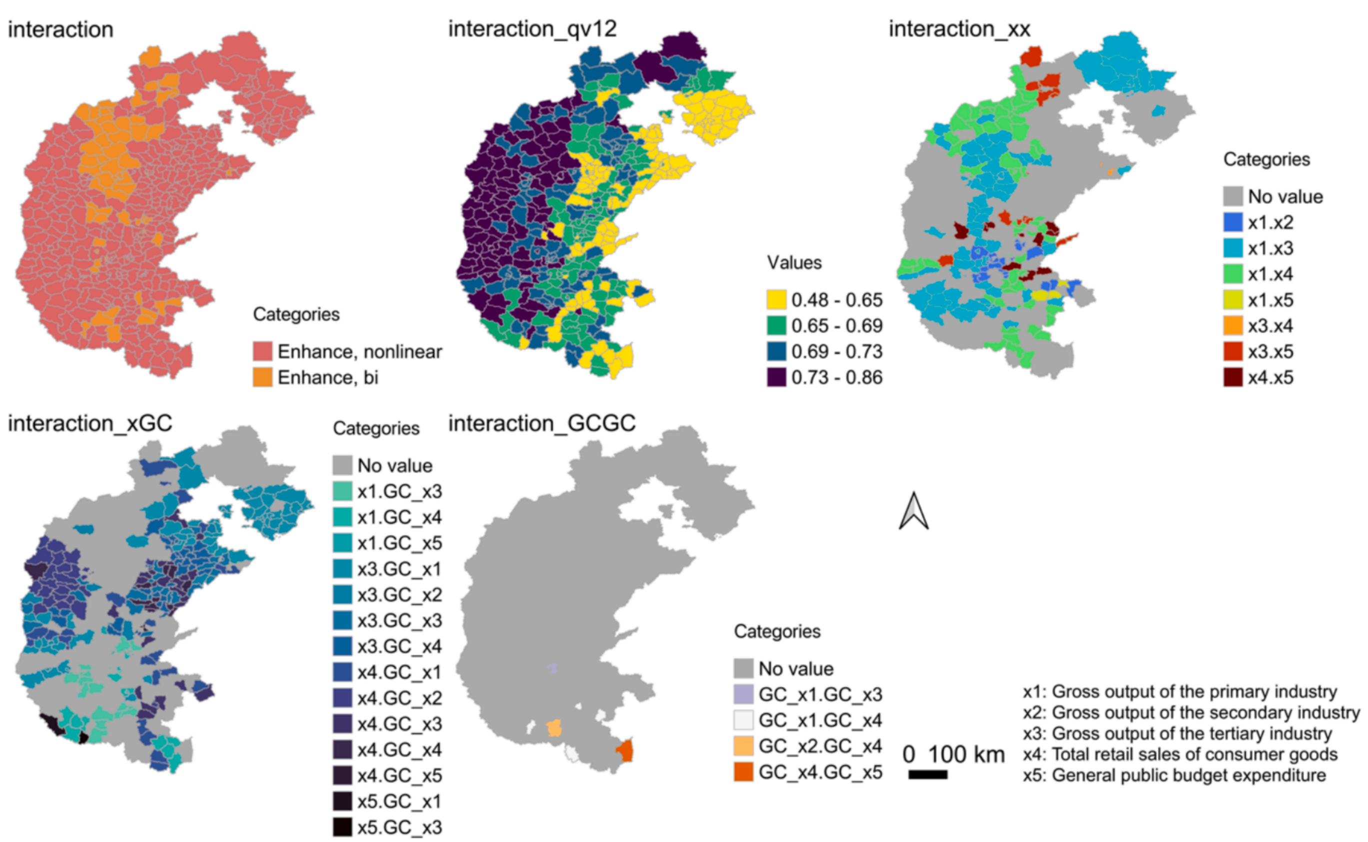

Fig. 9. Spatial distributions of the PD of pattern interactions. (interaction types; interaction strength; variables of interaction: interaction between variables, interaction between GC, interaction between variables and GC).

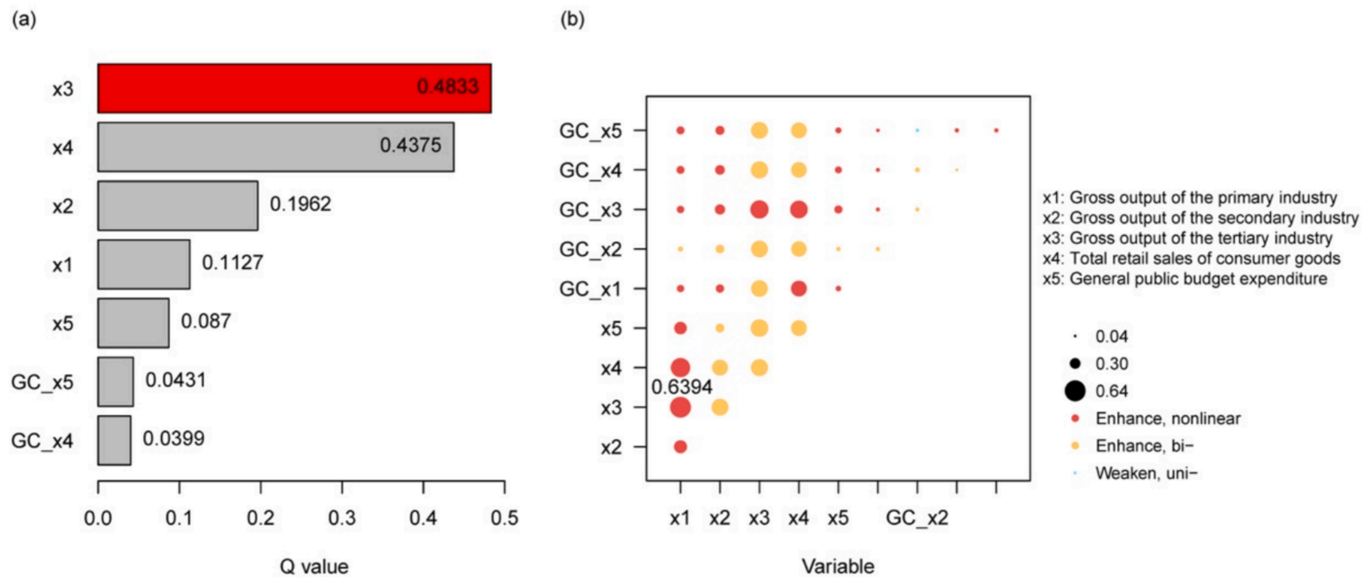

Fig. 10. Global PD values examined using OPGD model: (a) PD of individual variables, and (b) PD of variable interactions.

0.087, which are relatively lower compared to other explanatory variables. This suggests that these two variables have a limited overall driving effect on urbanization patterns, serving more as local influencing factors. Overall, the PD values of the geocomplexity of all explanatory variables are lower than those of their corresponding original variables, but the interaction between variables and geocomplexity can critically improve PD values.

This study evaluates the reliability and robustness of the LPI model in identifying the determinants of urbanization spatial patterns by comparing the local PD values of the variables of the LPI model with the global PD values derived using the OPGD model. The comparison results shown in Table 4 indicate that the LPI model has significant advantages over the OPGD model. The LPI model reflects the local explanatory power and influence of individual variables, whereas OPGD only provides global PD values confirming variable importance without revealing spatial variations in their effects. As shown in Table 4, the LPI model indicates that the gross output of the tertiary industry and total retail sales of consumer goods exert the strongest influence with the highest spatial consistency, exhibiting the highest average PD values of 0.454 and 0.434 respectively. These variables demonstrate significant spatial significance across all regions. The gross output of the secondary industry exhibits moderate influence, with an average PD value of 0.225, remaining significant in 95.92 % of regions. In contrast, the average PD values for the gross output of the primary industry and general public budget expenditure are relatively low at 0.152 and 0.113 respectively, although both remain significant in over half of the study areas. Compared to these detailed local variations, OPGD can only provide global PD values confirming variable importance without revealing spatial disparities.

LPI model can capture influencing factors driven by spatial patterns rather than individual data due to its advantage in revealing the drivers of spatial structure. OPGD model can only assess the impact of a variable's numerical magnitude on outcomes without capturing the influence of spatial structural complexity in certain variables on urbanization patterns. Among the geocomplexity variables, the geocomplexity of gross output of the tertiary industry and total retail sales of consumer goods exhibit strong spatial structural effects, with average PD values of 0.146 and 0.159, respectively. Their significance is not uniformly distributed across the entire study area, but is concentrated in specific local regions.

The LPI model also reveals significant nonlinear enhancement effects between multiple interaction terms. The interaction between the gross output of the primary industry and the tertiary industry, as well as the interaction between the gross output of the primary industry and the total retail sales of consumer goods, show significant explanatory power with average PD values of 0.641 and 0.627. The interactions among multiple variables far exceed the individual effects of their constituent variables. The interaction between the gross output of the tertiary industry, total retail sales of consumer goods, and the geocomplexity of the tertiary industry also exhibits significant explanatory power, with

Table 4
A comparison of PD values between LPI model and OPGD model.

	Variable[a]	PD of LPI modelmean [min, max]	Percentage of $p < 0.05$	PD of OPGD model (Significance[b])
Individual variables	x1	0.152 [0.005, 0.431]	56.01 %	0.113 **
	x2	0.225 [0.085, 0.464]	95.92 %	0.196 **
	x3	0.454 [0.298, 0.627]	100.00 %	0.483 **
	x4	0.434 [0.275, 0.628]	100.00 %	0.438 **
	x5	0.113 [0.002, 0.258]	56.69 %	0.087 **
Geocomplexity of variables	GC_x1	0.076 [0.001, 0.310]	44.22 %	0.024 ($p =$ 0.543)
	GC_x2	0.144 [0.036, 0.446]	11.11 %	0.077 ($p =$ 0.920)
	GC_x3	0.146 [0.066, 0.458]	27.66 %	0.016 ($p =$ 0.134)
	GC_x4	0.159 [0.008, 0.464]	17.23 %	0.040 **
	GC_x5	0.086 [0.003, 0.251]	25.62 %	0.043 **
Interaction variables	x1 ∩ x3	0.641 [0.444, 0.821]	100.00 %	0.639 **
	x1 ∩ x4	0.627 [0.433, 0.822]	100.00 %	0.591 **
	x3 ∩ GC_x3	0.585 [0.377, 0.795]	100.00 %	0.554 **
	x4 ∩ GC_x3	0.610 [0.336, 0.783]	100.00 %	0.537 **

[a] Variables. x1: gross output of the primary industry; x2: gross output of the secondary industry; x3: gross output of the tertiary industry; x4: total retail sales of consumer goods; x5: general public budget expenditure.
[b] Significance level. **: $p < 0.01$; *: $p < 0.05$.

average PD values of 0.585 and 0.610, indicating a significant coupling relationship between economic activities and spatial structure in local areas. The global OPGD model fails to capture these locally enhanced interaction patterns.

5. Discussion

This study proposes and validates the LPI model. The model shows significant advantages in revealing the local heterogeneity and the complex interactions among variables in spatial data. The urbanization indices of the study areas in the application case exhibits a spatial pattern characterized by higher levels in the east and lower levels in the west. Provincial capital cities and major economic centers generally show higher levels of urbanization, reflecting their central roles in the urban development process. Regarding urbanization drivers, the gross output value of the tertiary industry and the total retail sales of consumer goods demonstrate the most significant influence on urbanization levels, whereas the impact of public fiscal expenditure is relatively limited. The result suggests that the proportion of consumption and services in the economic structure is a key driving force in the urbanization process. The research integrates multiple data sources, including statistical yearbooks from three provinces, LANDSAT imagery, and OpenStreetMap data. Through multi-scale integrated analysis, the study provides a more comprehensive depiction of urban spatial evolution characteristics.

Compared with traditional analytical methods, the innovation of the LPI (local pattern interaction) model lies in its integration of both local analysis and pattern interaction perspectives. Conventional global regression or spatial auto-correlation approaches typically provide only average effect estimates, making it difficult to capture internal differences and potentially masking local characteristics and edge effects within spatial processes. In contrast, the LPI model calculates local differences between local regions and their neighboring areas, allowing it to sensitively detect key phenomena such as spatial clustering, heterogeneity, and lag effects. Local analysis further reveals synergistic or suppressive interactions among variables in certain regions, which are relationships at the micro scale that are typically underrepresented or insufficiently captured in macro-level analyses. As such, the LPI model not only deepens the understanding of the nature of spatial heterogeneity but also provides a methodological pathway for identifying potential points of policy intervention.

To further clarify the functional distinctions among different metrics used in spatial determinant analysis, Table 5 compares the capabilities of the LPI-based PD, OPGD-based PD, and the aspatial correlation coefficient (R). As shown in the table, both LPI and OPGD models capture variable associations and spatial associations, whereas the correlation coefficient only reflects general variable relationships without spatial context. More importantly, the LPI model uniquely identifies locally varied effects, spatial pattern determinants, and interactions among spatial patterns.

Future research should focus on the interaction effects of spatial data interactions and explore the integrated application of various interaction modalities. Attention should also be given to cross-scale spatial data analysis, aiming to integrate data across different spatial scales and uncover cross-scale phenomena and patterns.

6. Conclusions

This study develops an LPI model to address a key gap in capturing interactions among spatial patterns, a critical challenge in existing spatial analyses of spatial association and spatial interaction. While previous approaches have primarily focused on individual variables or global spatial associations, the LPI model integrates local complexity patterns, variable deviation, and interaction effects to uncover the localized mechanisms of synergy and suppression among urbanization drivers. This study contributes a significant intellectual advancement to Geographic Information Science by proposing a spatial analytical paradigm that combines local structural heterogeneity with pattern-based interaction modeling. The LPI model provides a more detailed representation of spatial association by capturing how variables and their complexity patterns interact. LPI improves both methodological and practical understanding of spatial pattern interactions and spatial driver analysis. Future studies are recommended from the following aspects. First, the LPI model relies on predefined spatial neighborhood structures, and future work could incorporate adaptive spatial weighting schemes or machine learning–based optimization to enhance robustness. In addition, the use of cross-sectional data limits the ability to capture temporal dynamics in urbanization. Extending the LPI model to a spatiotemporal setting and integrating time-series data would substantially strengthen its capacity to model urban evolution.

Table 5
Comparison of functions among PD values derived by LPI and OPGD, and aspatial correlation coefficient for spatial determinant analysis.

Characteristics	LPI-based PD	OPGD-based PD	Correlation coefficient (R)
Association between variables	✓	✓	✓
Spatial association between variables	✓	✓	×
Identifying interaction of variables	✓	✓	×
Identifying locally varied effects of variables	✓	×	×
Identifying spatial pattern determinants	✓	×	×
Identifying interaction of spatial pattern determinants	✓	×	×

CRediT authorship contribution statement

Yanfang Sun: Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Guosheng Wu:** Writing – original draft, Formal analysis, Data curation. **Yongze Song:** Supervision, Methodology, Formal analysis, Conceptualization. **Haiyang Liu:** Visualization, Formal analysis. **Lin Wang:** Resources, Funding acquisition. **Zehua Zhang:** Writing – review & editing. **Jiao Hu:** Writing – review & editing.

Declaration of competing interest

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

Acknowledgement

This work was supported by the China Scholarship Council under Grant 202306930039; Key Laboratory of Highway Construction & Maintenance Technology in Loess Region, Ministry of Transport, PRC under Grant KLTLR-Y23-14; and Fujian Provincial Department of Science and Technology's Guided Program under Grant 2021H0018.

Data availability

Data will be made available on request.

References

Anselin, L., 1988. *Spatial econometrics: Methods and models*. Springer.
Anselin, L., 1995. Local indicators of spatial association—LISA. Geogr. Anal. 27 (2), 93–115.
Anselin, L., 2019. A local indicator of multivariate spatial association: Extending Geary's C. Geogr. Anal. 51 (2), 133–150.

Ben-Moshe, S., Itzkovitz, S., 2019. Spatial heterogeneity in the mammalian liver. Nat. Rev. Gastroenterol. Hepatol. 16 (7), 395–410.
Chen, W., Wang, G., Zeng, J., 2022. Impact of urbanization on ecosystem health in chinese urban agglomerations. Environ. Impact Assess. Rev. 98, 1–14.
Elhorst, J.P., 2010. Applied spatial econometrics: raising the bar. Spat. Econ. Anal. 5 (1), 9–28.
Hao, H., Jiang, Z., He, C., 2024. Efficiency improvement of urban spatial economic interaction and regional economic development in the context of industrial circulation. Applied Mathematics and Nonlinear Sciences 9 (1).
Ge, Y., Hu, S., Song, Y., Zheng, H., Liu, Y., Ye, X., Zhou, C., 2023. Sustainable poverty reduction models for the coordinated development of the social economy and environment in China. Science Bulletin 68 (19), 2236–2246.
Harvey, E.P., O'Neale, D.R.J., 2024. The importance of spatial heterogeneity in disease transmission. Nat. Phys. 20 (7), 1053–1054.
Hu, J., Song, Y., Zhang, T., 2025. A local indicator of stratified power. Int. J. Geogr. Inf. Sci.
Liu, Y., Liu, X., Gao, S., Gong, L., Shi, L., 2015. Social sensing: a new approach to understanding our socioeconomic environments. Ann. Am. Assoc. Geogr. 105 (3), 1–19.
Luo, P., Wang, X., Zhang, H., Li, Q., Chen, Y., Liu, J., Smith, A.B., 2022. Identifying determinants of spatio-temporal disparities in soil moisture of the Northern Hemisphere using a geographically optimal zones-based heterogeneity model. ISPRS J. Photogramm. Remote Sens. 185, 111–128.
Mahato, R.K., Htike, K.M., Sornlorm, K., Koro, A.B., Kafle, A., Sharma, V., 2024. A spatial autocorrelation analysis of road traffic accidents by severity using moran's i spatial statistics: a study from nepal 2019–2022. BMC Public Health 24 (1), 14.
Olea, R.A., 2006. A six-step practical approach to semivariogram modeling. Stoch. Env. Res. Risk A. 20 (5), 307–318.
Qian, H., Qian, S., Zhang, J., Kessler, M., 2024. Effects of climate and environmental heterogeneity on the phylogenetic structure of regional angiosperm floras worldwide. Nat. Commun. 15 (1), 13.
Ren, K., Song, Y., Yu, Q., 2025. Second-dimension outliers for spatial prediction. Int. J. Geogr. Inf. Sci. 1–28.
Rey, S.J., Kang, W., Wolf, L., 2022. Spatial dynamics and regional systems: advances in spatial econometrics. Spat. Econ. Anal. 17 (2), 143–167.
Song, Y., Wang, J., Ge, Y., Xu, C., 2020. An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data. Giscience & Remote Sensing 57 (5), 593–610.
Song, Y., Wu, P., 2021. An interactive detector for spatial associations. *International Journal of Geographical*. Information Science(530), 1–26.
Tobler, W.R., 1970. A computer movie simulating urban growth in the detroit region. Econ. Geogr 46 (2), 234–240.
Vicca, K., Yudi, W., Fadhlullah, R., Jaka, S., Irmadi, N., 2023. Exploring driving factors of soil erosion using a multiscale GWR model: a case study at Central Citarum Watershed, West Java, Indonesia. IOP Conf. Ser.: Earth Environ. Sci 1266 (1), 012012.
Liu, W., Yue, X., Wang, X., Lin, Z., Yao, X., Xu, Z., 2025. Spatial distribution and driving factors of carbon emission in a furnace city using Luojia1–01 nighttime data and optimal parameters-based geodetector. Urban Clim. 61, 102462.
Luo, P., Li, Y., Song, Y., Li, Z., Meng, L., 2025. Measuring univariate effects in the interaction of geographical patterns. Int. J. Geogr. Inf. Sci. 1–32.
Luo., P., Song, Y., Zhu, D., Cheng, J., & Meng, L., 2023. A generalized heterogeneity model for spatial interpolation. Int. J. Geogr. Inf. Sci. 37 (3), 634–659.
Wang, L., Zhou, Y., Li, Q., Zuo, Q., Gao, H., Liu, J., Tian, Y., 2021. Forest land quality evaluation and protection zoning of subtropical humid evergreen broadleaf forest region based on the PSO-TOPSIS model and the local indicator of spatial association: a case study of Hefeng County, Hubei Province. China. Forests 12 (3), 325.
Wang, J.F., Li, X.H., Christakos, G., Liao, Y.L., Zhang, T., Gu, X., Zheng, X.Y., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. Int. J. Geogr. Inf. Sci. 24 (1), 107–127.
Yang, X., Song, Y., Yoo, C., Ren, K., Wu, P., 2025. Irregular anisotropy in surface urban heat island footprint. Sustain. Cities Soc. 106779.
Zhang, Z., Song, Y.S., Luo, P., Wu, P., 2023. Geocomplexity explains spatial errors. Int. J. Geogr. Inf. Sci. 37, 1449–1469.
Zhang, Z., Song, Y., Karunaratne, L., Wu, P., 2024. Robust interaction detector: a case of road life expectancy analysis. Spatial Statistics, 100814.