Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 03 July 2025
DOI 10.3389/fenvs.2025.1588318

Research on the evolution and influencing factors of the spatial form of typical tourist towns: a case study of Wulingyuan district, China

Tengzhe Long[1], Bincheng Luo[1], Jinlin Wu[1,2], Jing Yang[1,2]* and Yunzhe Wang[1,2]

[1]School of Civil Engineering and Architecture, Jishou University, Zhangjiajie, Hunan, China, [2]Rural Planning and Development Research Center of Wuling Mountain Area, Zhangjiajie, Hunan, China

OPEN ACCESS

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

REVIEWED BY
You Peng,
National University of Singapore, Singapore
Zhi Cai,
Zhejiang Gongshang University, China

*CORRESPONDENCE
Jing Yang,
yangjing2010@jsu.edu.cn

RECEIVED 05 March 2025
ACCEPTED 09 June 2025
PUBLISHED 03 July 2025

CITATION
Long T, Luo B, Wu J, Yang J and Wang Y (2025) Research on the evolution and influencing factors of the spatial form of typical tourist towns: a case study of Wulingyuan district, China.
Front. Environ. Sci. 13:1588318.
doi: 10.3389/fenvs.2025.1588318

Introduction: Since its reform and opening up, China's new urbanization strategy, which provides institutional support for the optimization of the spatial form of tourism towns, has made remarkable progress and demonstrated great potential. In this study, the urban area of Wulingyuan District, China, a Natural World Heritage Site, is taken as the research object.

Methods: Based on Landsat remote sensing images at five time nodes between 2000 and 2022, the spatial and temporal characteristics and evolutionary patterns of urban expansion in Wulingyuan are quantitatively investigated and the driving factors are explored using fractal theory, the equal sector analysis method, partial least squares regression (PLSR), and the standard deviation ellipse.

Results: The results reveal the following. (1) From 2000 to 2022, urban expansion has undergone four clear stages, namely, medium-speed, low-intensity, low-speed, low-intensity, medium-speed, medium-intensity, and medium-speed, high-intensity. The period from 2015 to 2022 represents the peak of urban expansion. (2) The built-up land in the urban area has mainly expanded in the form of a belt. The overall direction of expansion tends to be in the southwest and northeast directions, while expansion in the other directions has occurred slowly due to terrain and heritage protection restrictions. (3) In terms of the evolution of spatial forms, the compactness index of the urban area has exhibited a "V"-shaped change, the fractal dimension has continued to decline, and the expansion pattern has undergone three stages: edge expansion dominance, parallel edge expansion and internal infilling, and internal infilling dominance. (4) The urban expansion of Wulingyuan has been driven by multiple factors such as urbanization, tourism, the economy, and policy. The intensity of the roles of these factors, from strongest to weakest, is as follows: urbanization > tourism > economy.

Discussion: Policy factors do not directly promote urban expansion, but rather enforce control over the direction, scale, and boundaries of urban expansion through the dual effects of positive guidance and negative constraints. Based on the results of this study, a conservation-oriented development (COD) path is proposed, aiming to provide a replicable model for other heritage cities or those characterized by ecologically sensitive tourism.

KEYWORDS

urban spatial form, urban expansion, world heritage site, influencing factors, fractal theory, tourist city, Wulingyuan

1 Introduction

Since its reform and opening up, China has made remarkable progress in urbanization, with the urbanization rate rising to 66.2% (according to data from the National Bureau of Statistics), placing it at the upper-middle level globally. The 2014 Central Urbanization Work Conference established a new urbanization strategy, further clarifying the development path of urbanization with Chinese characteristics. Tourism urbanization, a diversified urbanization mode, is a process of the spatial expansion of the population and industrial agglomeration, as well as urban land, with tourism as the core driving force (Wu et al., 2015). The evolution of the spatial form of tourism urbanization exhibits a dual pattern: it is constrained by macro-policy regulation and the broader urbanization process, while also being profoundly influenced by the endowment of tourism resources and the unique characteristics of the tourism industry. The 20th Party Congress proposed improving the institutional mechanism for new urbanization, stressing the integrated promotion of the coordinated development of large, medium-sized, and small cities and the optimization of the spatial layout of cities and towns. Furthermore, it proposed the provision of institutional guarantees for tourist cities and towns to achieve functional perfection, environmental upgrading, and the improvement of residents' quality of life. Studying the unique spatial form of tourist towns and exploring the laws of its evolution and influencing factors hold significant theoretical and practical value. This research is crucial for resolving the contradictions in the human-land relationship, balancing the goals of protection and development, and charting a path toward sustainable development.

The study of urban morphology began in the 19th century. With the rise of interdisciplinary research, especially the integration of architecture, geography, and urban studies, the concept of morphology has been incorporated into the framework of urban studies, prompting researchers to observe and analyze the city as an organic whole (Ding, 2015). Urban morphology examines the physical form and spatial layout of human settlements (e.g., buildings, plots, and streets) and how humans interact with and utilize these forms over time (Zhang et al., 2023a). In 1964, Boyce et al. first proposed the concept of urban spatial form from the perspective of the geography discipline (Boyce and Clark, 1964). Global research on urban spatial form can be categorized into two types, namely, research on the external form and internal structure of a city, respectively (Ding, 2015).

Research on external urban form focuses on the description and classification of the contours of urban built-up areas and their evolutionary history. Urban spatial forms can be classified into six main types: centralized, belt-shaped, radial, constellation-shaped, clustered, and scattered (Zhou and Feng, 2007). Moreover, there are three main types of urban expansion: infilling expansion, edge expansion, and leapfrog expansion (Ul Din and Mak, 2021) In large cities, expansion is dominated by edge and infilling expansion, with leapfrog expansion also present, influenced by the economy, topography, and traffic (Wang et al., 2019; Xi et al., 2018; Yue et al., 2013; Zhang et al., 2024). Conversely, small and medium-sized towns and tourist towns are dominated by leapfrog expansion (Xian et al., 2019; Xie et al., 2021; Yu and Ng, 2007); these towns develop around scenic spots or traffic corridors, and are significantly constrained by the tourism economy, policy, and ecology. Research on the internal structure of cities is relatively mature, and focuses on their functional layout and land-use structure (Maimaiti et al., 2021; Terfa et al., 2019; Zhang et al., 2020). In terms of research objects, scholars mainly focus on the dynamic process of the spatial expansion of individual cities (Doe et al., 2022; Xu et al., 2018), city clusters (Rahaman et al., 2019; Xiao et al., 2021), and multiple cities on a global scale (Maimaiti et al., 2021; Terfa et al., 2019; Van der Borght and Barbera, 2023). In terms of content, related research primarily focuses on the urban spatial form of characteristics (He et al., 2023; Shen et al., 2023), evolution (Zhang et al., 2020; Zhang H. et al., 2022; Zhang K. et al., 2022), driving mechanisms (Deng et al., 2020; Liu X. et al., 2024; Wu L. et al., 2019; Xu et al., 2020; Xu et al., 2018), and sustainabilityof urban spatial form (Wang, 2001; Zhang et al., 2023a). The research methodology has exhibited a trend toward diversification; for example, the use of night-time lighting data (Song et al., 2011; Zhang and Liu, 2022) and remote sensing technology (Liu Xiaobo et al., 2024; Xu et al., 2019; Yin et al., 2024) to extract built-up areas has enhanced the objectivity and accuracy of urban spatial research. In recent years, machine learning algorithms have been widely used in remote sensing image classification. Such algorithms can be classified into supervised and unsupervised techniques (Halder et al., 2011; Wu W. et al., 2019). Supervised classification techniques mainly include the random forest (RF) model, the spectral angle mapper (SAM), the Mahalanobis distance (MD), maximum likelihood classification (MLC), support vector machines (SVM) s, and the decision tree (DT) model, among others (Ma et al., 2019; Shih et al., 2019). Unsupervised classification techniques include the affinity propagation (AP) clustering algorithm, fuzzy c-means algorithms, the *k*-means algorithm, and ISODATA (iterative self-organizing data), among others (Camps-Valls et al., 2011; Maxwell et al., 2018). Accuracy assessment has become a fundamental component of thematic mapping research. A variety of methods have been discussed in the remote sensing literature (Aronoff, 1982; Chughtai et al., 2021; Wickham et al., 2021), with confusion matrices currently at the forefront (Foody, 2002).

As a special urban spatial form, tourism towns have unique spatial needs and development motivations, and their spatial form is closely related to the tourism industry, cultural protection, and the ecological environment. These characteristics have prompted scholars to shift their research perspective from traditional urban spatial form to tourism urban spatial form. Previous studies on the spatial form of

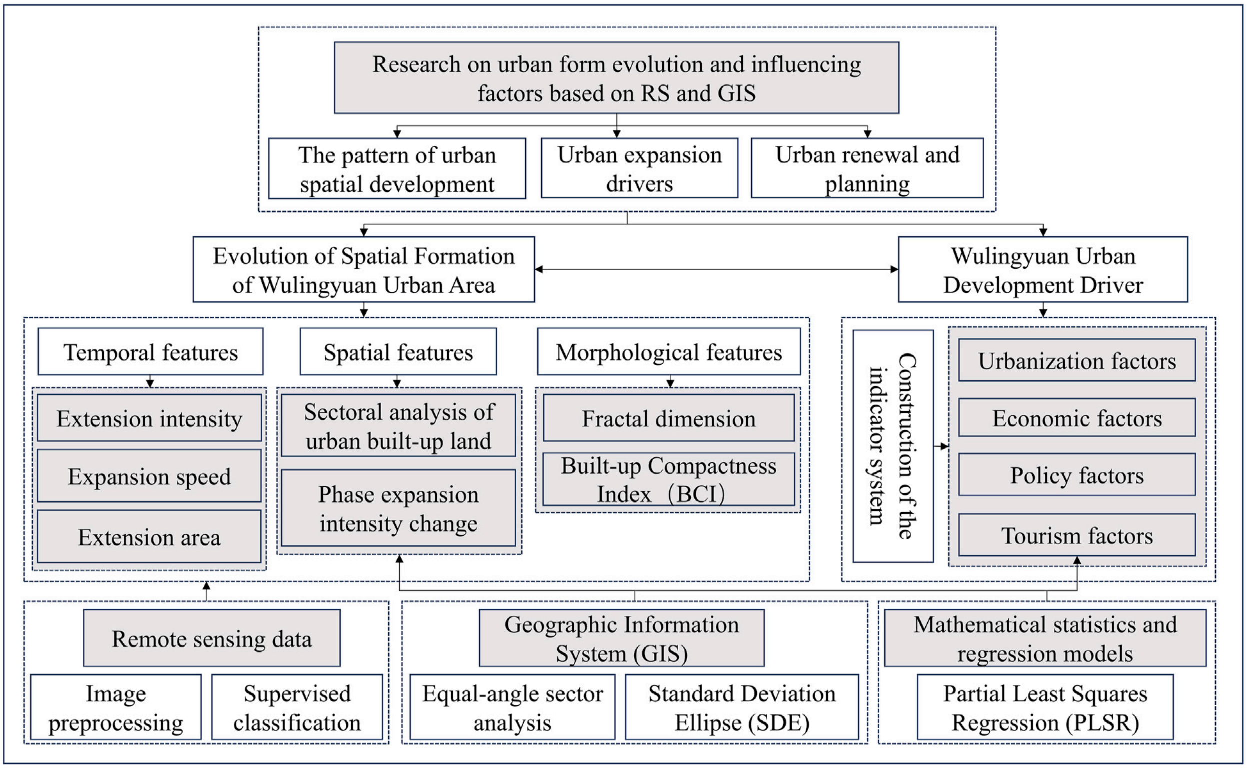

FIGURE 1
The research framework.

tourism towns have focused on two aspects: (1) the evolution of the spatial form of tourism towns and its driving factors (Gao et al., 2020; Ma et al., 2020; Tang et al., 2022; Hui et al., 2017; Wu et al., 2015), and (2) the relationship between the tourism industry and the spatial form of towns (Ma and Liu, 2019; Ma et al., 2019; Ma et al., 2022; Wang and Che, 2023). The former class of research is based on the use of multi-period remote sensing imagery or geographic information data to study the dynamic evolution characteristics of the urban boundary (Chen and Bao, 2012; Gao et al., 2020) or the spatial and temporal differences in urban land-use types (Hui et al., 2017; Wu et al., 2015). In addition, a few studies have innovatively combined the morphological evolution of the urban boundary with the conversion of land-use functions to comprehensively analyze the evolution pattern (Gao et al., 2020; Ma et al., 2020), and have used quantitative or qualitative methods to explore the driving factors. The second class of research, on the other hand, focuses on exploring spatial differentiation in tourism geography. Methods such as kernel density estimation (Ma and Liu, 2019; Ma et al., 2019; Ma et al., 2022) and Getis-Ord Gi* hotspot analysis (Wang and Che, 2023) are adopted to reveal the spatial distribution characteristics of various tourism industry elements. Furthermore, researchers combine these analyses with changes in the morphological contours of study areas to analyze spatial expansion trends, and using standard deviation ellipse (SDE) and other methods to characterize the relationship between the spatial layout of the tourism industry and the spatial form of towns and cities.

Regarding the extant research, while studies on the spatial form of towns are abundant, relatively few studies have focused specifically on the spatial form of tourist towns. Furthermore, the research objects of most studies are the evolution of spatial patterns in large cities or city clusters, while small towns, especially tourist-oriented small towns driven by natural heritage, have been relatively ignored. In view of the limitations of the extant research, Wulingyuan District, a Natural World Heritage Site with tourism as the leading industry, is selected as the research object of this study. This study used fractal theory and equal sector analysis to explore the speed, intensity, direction, and characteristics of Wulingyuan's spatial expansion, and combined partial least squares regression (PLSR) to quantitatively analyze the driving factors of Wulingyuan's spatial expansion. The goal is to reveal its evolution pattern and driving mechanism under the dual effects of urbanization development and conservation policies, and to provide a scientific basis for the sustainable development of Wulingyuan and similar areas. The detailed research framework is shown in Figure 1.

2 Research design

2.1 General situation of the research area

Wulingyuan District is located in the central part of Zhangjiajie City, upstream of the middle and upper reaches of the Zhangjiajie River. It is located in the Wuling Mountains, 32 km away from the Zhangjiajie downtown area, and is a county-level administrative district that was approved by the State Council in May 1988. It was included in UNESCO's list of Natural World Heritage Sites in 1992. The area under its administrative jurisdiction totals 397.58 km^2,

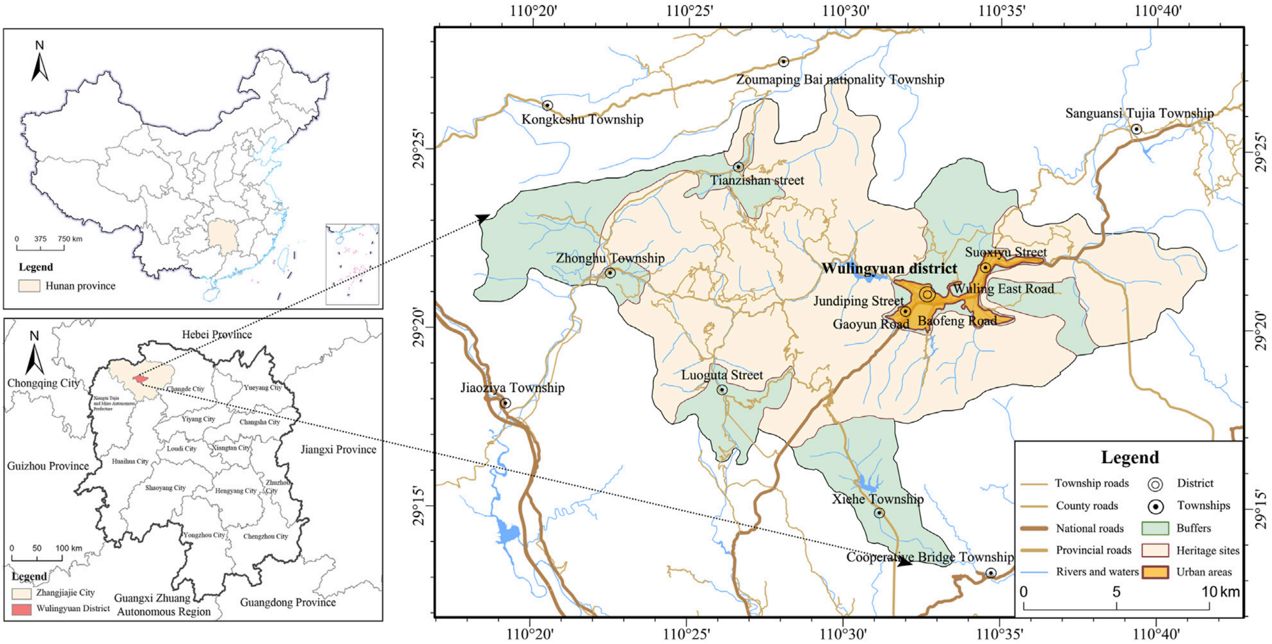

FIGURE 2
The scope of the research area.

TABLE 1 The development process of Wulingyuan.

Stage	Time	Spatial form features	Background
Preliminary stage with fragmented development	Before 1988	Scattered settlements, decentralized development, and isolated functional zones	Constrained by administrative boundaries; Zhangjiajie, Suoxiyu, and Tianzishan were developed independently, resulting in sluggish progress in both tourism-related development and urbanization processes
Accelerated development stage with scattered expansion	1988–1992	Sporadic and scattered expansion	The State Council approved the establishment of Wulingyuan; however, there was a lack of a planning system and inadequate management coordination
Disordered development stage with inadequate planning	1992–1998	Rapid expansion and unregulated sprawl	Following its inclusion on the Natural World Heritage List, tourism-driven growth led to significant urban expansion; however, the ineffective implementation of planning measures gave rise to conspicuous ecological issues
Sustainable development stage with centralized rectification	After 1998	Intensive layout and diversified functions	With the refinement of relevant regulations, the implementation of ecological resettlement, and the establishment of a monitoring system, the model has transitioned toward one that emphasizes scientific conservation and diversified development

which comprises the Natural World Heritage core area (264 km^2), a buffer zone (126.8 km^2), and a buildable area (6.3 km^2) designated to carry out tourism services and residential production functions. This study focuses on the urban expansion of urban built-up land within the buildable area (Figure 2), herein simply referred to as Wulingyuan, the historical evolution of which can be divided into four stages (Table 1).

2.2 Data sources and preprocessing

Considering the accessibility of remote sensing images and the policy-oriented characteristics of urban development, five time nodes (2000, 2005, 2010, 2015, and 2022) were selected to explore the evolution of the urban spatial form of Wulingyuan based on the Five-Year Plans. The study period ranges from the 9th to the 14th Five-Year Plans, with 2022 being the second year of the 14th Five-Year Plan. Remote sensing data were obtained from the Geospatial Data Cloud (https://www.gscloud.cn), and Landsat 5 TM, Landsat 7 ETM+, Landsat 8 OLI/TIRS, and Landsat 9 OLI/TIRS remote sensing images with a spatial resolution of 30 m and less than 5% cloudiness were selected (Table 2). Data on the economic, tourism, and urbanization indicators used for the impact factor analysis were sourced from the Hunan Provincial Statistical Yearbook and the Statistical Bulletin on the official website of the Wulingyuan District Government. Topographic maps, Google Earth high-resolution non-offset satellite images, and Wulingyuan planning maps were used to improve the spatial accuracy of urban built-up land classification.

TABLE 2 The satellite data parameters.

Year	Satellite and sensor	Date	Cloud cover
2000	Landsat 7 ETM+	May 14	0.03
2005	Landsat 5 TM	September 9	0.17
2010	Landsat 5 TM	May 2	0.38
2015	Landsat 8 OLI/TIRS	April 14	0.01
2022	Landsat 9 OLI/TIRS	October 10	0.1

Image pre-processing was carried out using ENVI 5.6 software, and a database of multispectral remote sensing images of the study area for the years 2000, 2005, 2010, 2015, and 2022 was formed through radiometric calibration, FLAASH atmospheric correction, band combination, and cropping. The geographic coordinate system used for all spatial data was WGS_1984, and the projected coordinate system was WGS_1984_UTM_ZONE_49N.

2.3 Research methods

2.3.1 Fractal theory

2.3.1.1 The expansion rate index M_{ue} and expansion intensity index I_{ue}.

These two indices are essential for characterizing urban expansion and reflect spatiotemporal disparities. The urban expansion rate index measures the average annual growth rate of urban built-up areas across defined time intervals and offers insights into the overall scale and trend of urban growth. It is calculated using (Equation 1). The urban expansion intensity index represents the proportion of area increase in a specific region over a given period relative to the region's total area. It is calculated using (Equation 2). By normalizing the average annual growth rate of built-up areas, I_{ue} facilitates comparisons and analyses across different periods. This index is frequently utilized to describe, analyze, and compare the trends and magnitudes of expansion across various periods and directions (Peng et al., 2015).

$$M_{ue} = \frac{\Delta U_{ij}}{\Delta t_j \times ULA_{ij}} \times 100\% \tag{1}$$

$$I_{ue} = \frac{\Delta U_{ij}}{\Delta t_j \times TLA_i} \times 100\% \tag{2}$$

where ΔU_{ij} expresses the expansion amount of the built-up area of research unit i in period j; Δt_j represents the time span of period j; ULA_{ij} denotes the total area of the built-up area of research unit i at the start of period j; and TLA_i depicts the total land area of unit i (Wang et al., 2023).

2.3.1.2 The compactness index *BCI*

This index describes the compactness of built-up land use and variations in the outer contour shape. It was initially proposed by Batty (1991), and it is calculated using (Equation 3); (Li et al., 2021):

$$BCI = 2\sqrt{\pi A}\big/P \tag{3}$$

where *BCI* represents the compactness index; *A* expresses the area of the urban built-up area; and *P* denotes the perimeter of the built-up area contour. *BCI* values range from 0 to 1, with higher values indicating a more compact shape, approaching that of a circle (the *BCI* of a circle is 1). Lower values signify a less compact shape (Zhong et al., 2020).

2.3.1.3 The fractal dimension

The fractal dimension characterizes a fractal pattern or set by quantifying its complexity as the ratio of detail variation to scale variation. There are three general methods applied to the study of urban spatial form fractals: the boundary dimension method, the grid dimension method, and the radius dimension method (Li et al., 2020). Boundary dimensions can effectively reflect the degree of irregularity and morphological stability of the land boundary. Thus, the boundary dimension method is an appropriate choice for studying the evolution of the external boundary morphology of a city. In the study of the external geometric features of urban spatial form, the general consideration is to calculate the fractal dimension of the external spatial form based on the perimeter-area relationship. Specifically, this is done by measuring the lg*P*-lg*A* scatter relationship diagram to determine whether the lg*P*-lg*A* scatter is on a straight line in a certain scale domain; if it is on the line, then the fractal dimension value *D* can be derived from the slope of the straight line. It is calculated using (Equation 4).

$$D = 2\ln(P/4)\big/\ln A \tag{4}$$

where *A* represents the area of the urban built-up area; *P* expresses the perimeter of the contour of the urban built-up area; and *D* denotes the boundary dimension. The value of *D* is between 1 and 2, with higher values corresponding to the greater complexity and irregularity of the figure. Typically, when $1 < D < 1.5$, the urban morphology is relatively simple; when $D = 1.5$, the city exhibits a random distribution and instability; when $1.5 < D < 2$, urban morphology becomes increasingly complex and is primarily represented by outward expansion (Liu et al., 2021).

2.3.2 Equal sector analysis

To explore the anisotropic features of urban expansion, the geometric center of the urban area (the Social Correction Center in Wulingyuan) was established as the central point in ArcGIS 10.8, and a reasonable radius was defined. The urban area was divided into 16 equal-sized, fan-shaped sectors with uniform angles. The construction land area in each sector was calculated for different years. By applying these calculated values, the intensity of urban expansion across the 16 directions in various periods was analyzed. A radar chart was then employed to visualize the urban expansion intensity of the central urban area across the analyzed years, and thus the dominant direction of urban expansion was identified for each year (Sun et al., 2020).

2.3.3 Partial least squares regression model

PLSR is a multivariate statistical method that can address the problem of covariance, simultaneously analyze multiple dependent variables *Y*, and deal with the effects of small samples. In principle, PLSR assembles three research methods, namely, multiple linear regression, typical correlation analysis, and principal component analysis. Multiple linear regression is used to study the influence relationship, typical correlation analysis is used to study the relationship between multiple *X's and multiple Y's*, and principal component analysis is used to condense the information of multiple X's or multiple Y's (Xu and Liu, 2021). The specific calculation steps are as follows.

Step I: The independent and dependent variable matrices are constructed. The p-dimensional independent variable is denoted as $X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}$, and the one-dimensional dependent variable is denoted as $Y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}$.

Step II: Standardization is carried out through (Equation 5). The independent variable X matrix is standardized as follows.

$$E_0 = \left[\frac{x_{ij} - \overline{x_j}}{s_j}\right]_{n\times p} \tag{5}$$

The dependent variable Y matrix is standardized through (Equation 6) as follows.

$$F_0 = \left[\frac{y_i - \bar{y}}{s_y}\right]_{n\times 1} \tag{6}$$

In these equations, $\overline{x_j}$ and $\bar{y}$ are the mean values of x_j and y, respectively, and s_j and s_y are the standard deviations of x_j and y, respectively.

Step III: The principal component extraction of the independent variables is carried out. The first component is extracted through (Equation 7) as:

$$t_1 = E_0 w_1 \tag{7}$$

where w_1 is the eigenvector corresponding to the largest eigenvalue of matrix $E_0'F_0F_0'E_0$, and $w_1 = \frac{E_0'F_0}{\|E_0'F_0\|}$.

The regression of E_0 on t_1 is calculated through (Equation 8) as:

$$E_1 = E_0 - t_1 p_1' \tag{8}$$

where $p_1 = \frac{E_0' t_1}{\|t_1\|^2}$.

The second component is extracted through (Equation 9) as:

$$t_2 = E_1 w_2 \tag{9}$$

where w_2 is the eigenvector corresponding to the largest eigenvalue of matrix $E_1'F_0F_0'E_1$, and $w_2 = \frac{E_1'F_0}{\|E_1'F_0\|}$.

The regression of E_1 on t_2 is calculated through (Equation 10) as:

$$E_2 = E_1 - t_2 p_2' \tag{10}$$

where $p_2 = \frac{E_1' t_2}{\|t_2\|^2}$.

This process continues until the mth principal component.

Step IV: Multiple linear regressions are conducted via (Equation 11):

$$F_0 = r_1 t_1 + r_2 t_2 + \ldots + r_m t_m \tag{11}$$

Because t_1, t_2, t_3, t_m are all linear combinations of E_0, (Equation 12) is derived:

$$F_0 = r_1 E_0 w_1^* + r_2 E_0 w_2^* + \ldots + r_m E_0 w_m^* \tag{12}$$

where $w_h^* = \prod_{j=1}^{h-1} (I - w_j p_j') w_h$, and I is the unit matrix. The following is then obtained calculate the regression coefficient using (Equation 13):

$$\hat{y}^* = a_1 x_1^* + a_2 x_2^* + \cdots + a_p x_p^* \tag{13}$$

where $a_j = \sum_{h=1}^{m} r_h w_{hj}^*$.

Then, considering the principle of cross-validity, calculating the cross-validatory predictive power metric through (Equation 14).

$$Q_h^2 = 1 - \frac{PRESS_h}{ss_h} \tag{14}$$

where $PRESS_h = \sum_{i=1}^{n} (y_i - \hat{y}_{h(-i)})^2$ and $SS_h = \sum_{i=1}^{n} (y_i - \hat{y}_{h(i)})^2$. When $Q_h^2 \geq 0.0975$, the introduction of the new component enhances the explanatory power of the model; conversely, if Q_h^2 falls below this threshold, the new component does not improve the explanatory power of the model.

Finally, an interpretive test is required to show the level of significance of each variable, calculated through (Equation 15) as follows:

$$VIP_j = \sqrt{\frac{k}{Rd(y; t_1, t_2, \ldots, t_m)} \sum_{h=1}^{m} Rd(y; t_h) w_{hj}^2} \tag{15}$$

where $Rd(y; t_1, t_2, \ldots, t_m)$ and $Rd(y; t_h)$ respectively represent the cumulative explanatory power of t_1, t_2, t_m over y and th over y. Moreover, $\left.\begin{matrix} Rd(y; t_h) = r^2(y, t_h) \\ Rd(y; t_1, t_2, \cdots, t_m) = \sum_{h=1}^{m} Rd(y; t_h) \\ Rd(X) = \frac{1}{k}\sum_{h=1}^{m}\sum_{j=1}^{k} r^2 Rd(x_j, t_h) \end{matrix}\right\}$, and $r(y, th)$ and $r(xj, th)$ are respectively the correlation coefficients of the dependent and independent variables with the principal components. The larger the value of VIP, the greater the importance of the variable.

The choice of retaining one principal component in this study was justified based on the following comprehensive assessment. The cross-validity analysis showed that the first principal component had significant predictive power ($Q^2 = 0.647$), and the model had an explanatory power of 77.1%, indicating its ability to adequately capture the core variance of the dependent variable, namely, "Built-up area." The key variables contributed significantly to the principal components ($VIP > 1$), further validating the representativeness of the single component. In addition, the regression coefficients of all independent variables passed the significance test ($p < 0.05$, Table 5), supporting the robustness of the model results. Given the limited sample size (18) and the high covariance among variables, the choice of a single principal component can effectively balance the model's simplicity and explanatory power, and can also avoid the risk of overfitting in this small-sample context.

2.3.4 Standard deviation ellipse

The standard deviation ellipse analysis method was put forward by Lefever (Lefever, 1926) as a spatial analysis approach that describes the distribution range and directionality of a set of data points. It is frequently employed for the analysis of the spatial distribution patterns of geographical elements. The SDE of tourism-related industries and urban construction land can reveal the main direction of their spatial distribution and their degree of diffusion. The size of the ellipse area indicates the intensity of element agglomeration; the azimuth angle demonstrates the directional trend of the spatial distribution of the element; the center of the ellipse represents the centroid of the spatial distribution of the element; and the major and minor axes indicate the directions

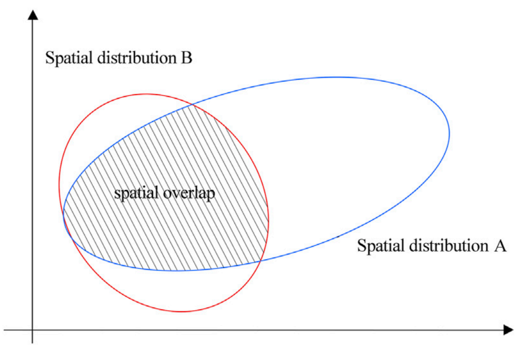

FIGURE 3
The graphic representation of the SDE.

with the strongest and weakest element diffusion capabilities, respectively. The calculation formulas are expressed as follows (Tao and Ye, 2022).

The centroid of the ellipse (centroid of the spatial distribution of elements) is calculated through (Equation 16) as:

$$\bar{X} = \frac{\sum_{i=1}^{n} X_i}{n}, \bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{16}$$

where X_i and Y_i are the coordinates of element i, and n is the total number of elements.

The azimuth angle of the ellipse is calculated through (Equation 17), with components A, B, and C determined through (Equation 18-20), respectively:

$$\tan\theta = \frac{A+B}{C} \tag{17}$$

$$A = \sum_{i=1}^{n} \tilde{X}^2 - \sum_{i=1}^{n} \tilde{y}^2 \tag{18}$$

$$B = \sqrt{\left(\sum_{i=1}^{n} \tilde{x}^2 - \sum_{i=1}^{n} \tilde{y}^2\right)^2 + 4\left(\sum_{i=1}^{n} \tilde{X}\tilde{Y}\right)^2} \tag{19}$$

$$C = 2\sum_{i=1}^{n} \tilde{X}_i \tilde{Y}_i \tag{20}$$

where $\tilde{X}$ and $\tilde{Y}$ respectively denote the deviations of the coordinates of each element from the average center.

The standard deviations of the x-axis and y-axis are calculated through (Equations 21, 22), respectively:

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n} (\tilde{x}_i \cos\theta - \tilde{y}_i \sin\theta)^2}{n}} \tag{21}$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^{n} (\tilde{x}_i \sin\theta - \tilde{y}_i \cos\theta)^2}{n}} \tag{22}$$

2.3.5 Spatial response factor

By comparing the basic parameters of standard deviation ellipses, such as size and orientation, for different periods in Wulingyuan and tourism-related industries, this study provides information on the differences and overlaps between different spatial distributions. It then defines the spatial response coefficient R to quantitatively characterize the degree of spatial response between different element distributions. For example, the quantitative mathematical expression for the spatial response factor $R_{A/B}$ of the spatial distribution A with respect to B is calculated through (Equation 23) as follows: (Ding, 2015). Figure 3 is used to display the overlapping area of the standard deviation ellipses between tourism-related industries and urban built-up area, with the overlapping area reflecting the spatial response between them.

$$R_{A/B} = \frac{Area\, of\, spatial\, overlap}{Area\, of\, spatial\, distribution\, A} \tag{23}$$

2.3.6 LULC change analysis

In this study, the supervised MLC method was employed to accurately identify urban land-use types and to map these land-use categories for the study period. The MLC method was chosen due to its optimal classification under Gaussian assumptions by considering the mean vector and covariance matrix for each category (Chughtai et al., 2021). With reference to the classification system of remote sensing monitoring of land-use dynamics in China (https://www.resdc.cn/data.aspx), five land categories, namely, built-up land, agricultural land, grassland, forests, and water bodies, were identified by integrating the spectral and remote sensing imagery features (Table 3). Emphasis was placed on analyzing the characteristics of the spatial and temporal changes of the built-up land.

To ensure high classification accuracy, sample selection should adhere to the principle of uniform distribution throughout the study area. First, based on *a priori* knowledge, the visual interpretation of satellite images, and existing reference data, training samples (regions of interest, ROIs) were created for each land category, and the separability of the training samples was evaluated using the Jeffries-Matusita (JM) distance. Moreover, the pair separation values of the training samples were calculated to be greater than 1.8, indicating good spectral differentiation and that the training samples are not confounded with one other. Second, the supervised classification of remote sensing images was carried out using the MLC method with manual editing, post-classification processing using auxiliary data (Google Earth images and Wulingyuan District planning maps), and majority/minority analysis, which improves the smoothness and reliability of the image classification results. Finally, the accuracy of the classification results was assessed by calculating the overall accuracy, producer accuracy, and user accuracy using a confusion matrix, and the classification reliability was assessed by the kappa coefficient.

2.3.7 Accuracy assessment

In order to verify the reliability of the classification results, this study uses a confusion matrix for accuracy assessment, i.e., by comparing the classification results with the ground truth or higher-resolution images to determine the accuracy and error rate of the classification. Ground truth data were primarily obtained through Google Earth imagery and field research. High-resolution Google Earth images, field research photographs, and land-use maps of Wulingyuan were used as reference data to assess the accuracy of the supervised classification results. Validation sample points, independent of the training samples, were manually and randomly selected to represent each feature type

TABLE 3 The LULC classification scheme.

LULC class	Description
Forests	Forestry land with trees, shrubs, bamboo, and coastal mangroves
Built-up land	Urban and rural settlements and surrounding land used for industry, mining, and transport
Agricultural land	Paddy fields, dry land, irrigated land
Water bodies	Natural terrestrial waters and water facility lands
Grassland	Predominantly herbaceous vegetation, including natural, artificial, and other grasslands

based on high-resolution remote sensing imagery and land-use maps. The classification accuracy was quantified by comparing the classified images with the reference data on an image-by-image basis and constructing a confusion matrix. The specific calculation metrics included overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and the kappa coefficient. The specific formulas can be found in a previous publication (Ul Din and Mak, 2021). These indicators enable a comprehensive assessment of the reliability of the classification results and their consistency with the reference data. The "Confusion Matrix Using Ground Truth ROIs" tool in ENVI 5.6 software was used for calculation. The final calculations yielded overall accuracies of 93.72% (kappa coefficient = 0. 76), 98.65% (kappa coefficient = 0. 88), 98.52% (kappa coefficient = 0. 92), 97.69% (kappa coefficient of 0. 90), and 98.15% (kappa coefficient = 0. 96) for the years 2000, 2005, 2010, 2015, and 2022, respectively. Across all types of satellite image classification, the overall accuracy exceeded 85%, and the accuracy for each LULC type was no less than 70%, which is widely accepted as an indicator of reliable data (Qin et al., 2022; Ranagalage et al., 2020).

2.3.8 Driver selection and indicator system construction

Based on the urban expansion characteristics of Wulingyuan and considering previous studies (Tang et al., 2022; Yin et al., 2024), 11 indicators were selected from three dimensions: tourism (number of tourists, number of tourist attractions, number of tourist hotels, total tourism income), the economy (GDP, total social consumer goods, total local financial income, fixed asset investment), and urbanization (urban population, level of urbanization, disposable income of urban residents). In the tourism dimension, the number of tourists is a visual indicator of the activity and attractiveness of the tourism industry; the number of tourist attractions reflects the degree of development and utilization of tourism resources; and the number of tourist hotels reflects the regional capacity to receive tourists. In the economic dimension, GDP is the core indicator of a region's overall economic output; total social consumer goods reflect the degree of activity of the regional consumer market; total local fiscal revenue reflects the financial strength of the government; and investment in fixed assets is the key force driving regional economic development and promoting urban expansion. In the urbanization dimension, population concentration and town construction are the intuitive material carriers of urban expansion; the urbanization rate measures the degree of population concentration in towns and cities, reflecting the speed and scale of urbanization; and the level of disposable income of urban residents reflects their demand for spatial quality, which is an important impetus to promote spatial optimization. The PLSR analysis of these indicators revealed that the *p*-value for the number of tourists was 0.645, which did not pass the significance test; thus, this indicator was excluded. (Because government data prior to 2005 were unavailable, raw data for all years from 2005 to 2022 were used for PLSR analysis. To further explore the influence of tourism factors on urban spatial form, four time nodes (2005, 2010, 2015, and 2022) were selected to analyze the spatial and temporal correlations between tourism-related industries and urban spatial form).

3 Results and analysis

3.1 Spatial and temporal features of urban expansion in Wulingyuan

3.1.1 Temporal features of urban expansion

Five time nodes (2000, 2005, 2010, 2015, and 2022) were selected to analyze the characteristics of Wulingyuan's urban expansion. During the study period, the urban area expanded from 0.976 km^2 to 4.955 km^2, representing an increase of 3.979 km^2, a nearly fivefold expansion. Figure 4 illustrates the changes of the urban expansion intensity index and expansion speed index of Wulingyuan from 2000 to 2022. Urban expansion was found to be volatile: the expansion intensity steadily increased, while the expansion speed index followed a "V"-shaped trend. Based on the comparative analysis of these two indices, the urban expansion process of Wulingyuan can be divided into four stages (Table 4).

Specifically, in the "medium-speed, low-intensity" development stage (2000–2005), the total expansion area of the urban area was 0.548 km^2, with an average annual expansion of 0.110 km^2. The expansion speed index was 0.112, indicating a medium-speed expansion, and the expansion intensity index was 0.017, which was the lowest among all the stages. The heritage preservation system was the core driving force in this stage. The pattern of urban expansion in this phase was similar to that of the Ha Long Bay region, where the government promoted the out-migration of residents during the early stages of development to protect the core landscape and to ensure the separation of the "landscape-city" functions, which led to moderate but limited urban expansion (Cobbinah et al., 2019).

In the "low-speed, low-intensity" development stage (2005–2010), the urban expansion speed index decreased significantly, from 0.112 to 0.074, as compared with the previous stage. However, the intensity of expansion increased. This change

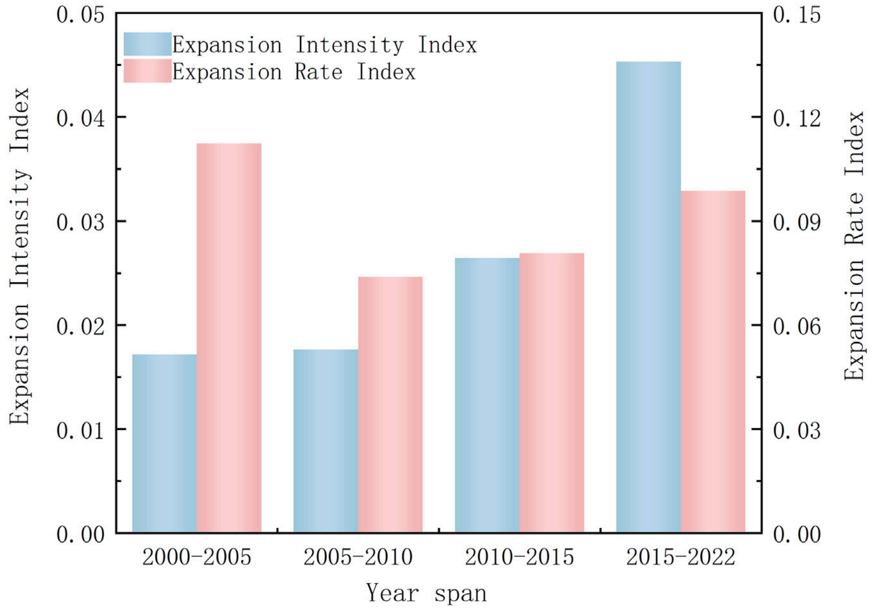

FIGURE 4
The expansion intensity index and expansion speed index of Wulingyuan throughout the study period.

TABLE 4 The expansion intensity and speed of Wulingyuan from 2000 to 2022.

Period	Total expansion area (km^2)	Average annual increase area (km^2)	Expansion speed index	Expansion intensity index	Expansion type
2000–2005	0.548	0.110	0.112	0.017	Medium-speed and low-intensity
2005–2010	0.563	0.113	0.074	0.018	Low-speed and low-intensity
2010–2015	0.843	0.169	0.081	0.026	Medium-speed and medium-intensity
2015–2022	2.024	0.289	0.099	0.045	Medium-speed and high-intensity

was closely related to the adjustment of tourism development policies and the improvement of the planning system. This is consistent with Phuket Island's approach of regulating land use through improved planning and environmental controls, relying on large-scale investments in airports, roads, and sewage treatment facilities to drive a significant increase in the intensity of land use within the city (Moukomla and Marome, 2025).

In the "medium-speed, medium-intensity" development stage (2010–2015), with the gradual improvement of infrastructure and the substantial increase in tourism reception capacity, which triggered spatial reconstruction, the speed and intensity indices of urban expansion respectively increased to 0.081 and 0.026. The urban area increased from 2.087 km^2 to 2.930 km^2, representing a total expansion area of 0.843 km^2. The urbanization process of attracting tourism industry agglomeration through increased investment in tourism infrastructure, which in turn promotes urban expansion and functionality, is similar to the tourism urbanization process in the Florianópolis region of Brazil (Jaramillo-Benavides and Patricio-Karnopp, 2019).

In the "medium-speed, high-intensity" development stage (2015–2022), the urban area of Wulingyuan continued to grow, with an average annual increase of 0.289 km^2. Moreover, the speed and strength indices of expansion were respectively 0.099 and 0.045, and urban expansion increased significantly. Supported by national and local policies, the consolidation of tourism elements and the improvement of the planning systems in Wulingyuan have jointly promoted the upgrading of the tourism industry and the synergistic optimization of urban space development.

3.1.2 Spatial features of urban expansion

To analyze the characteristics of the urban expansion direction of Wulingyuan, equal sector analysis was introduced to calculate the expansion intensity in different directions, and radar maps were used to visualize the dominant direction of expansion in each period (Figure 5). The urban expansion of Wulingyuan in the study period was found to be stronger in the northwest (NW), southwest (SW), and northeast (NE) directions, while north-south (N-S) expansion was relatively weak. An overall spatial pattern of "belt dominance

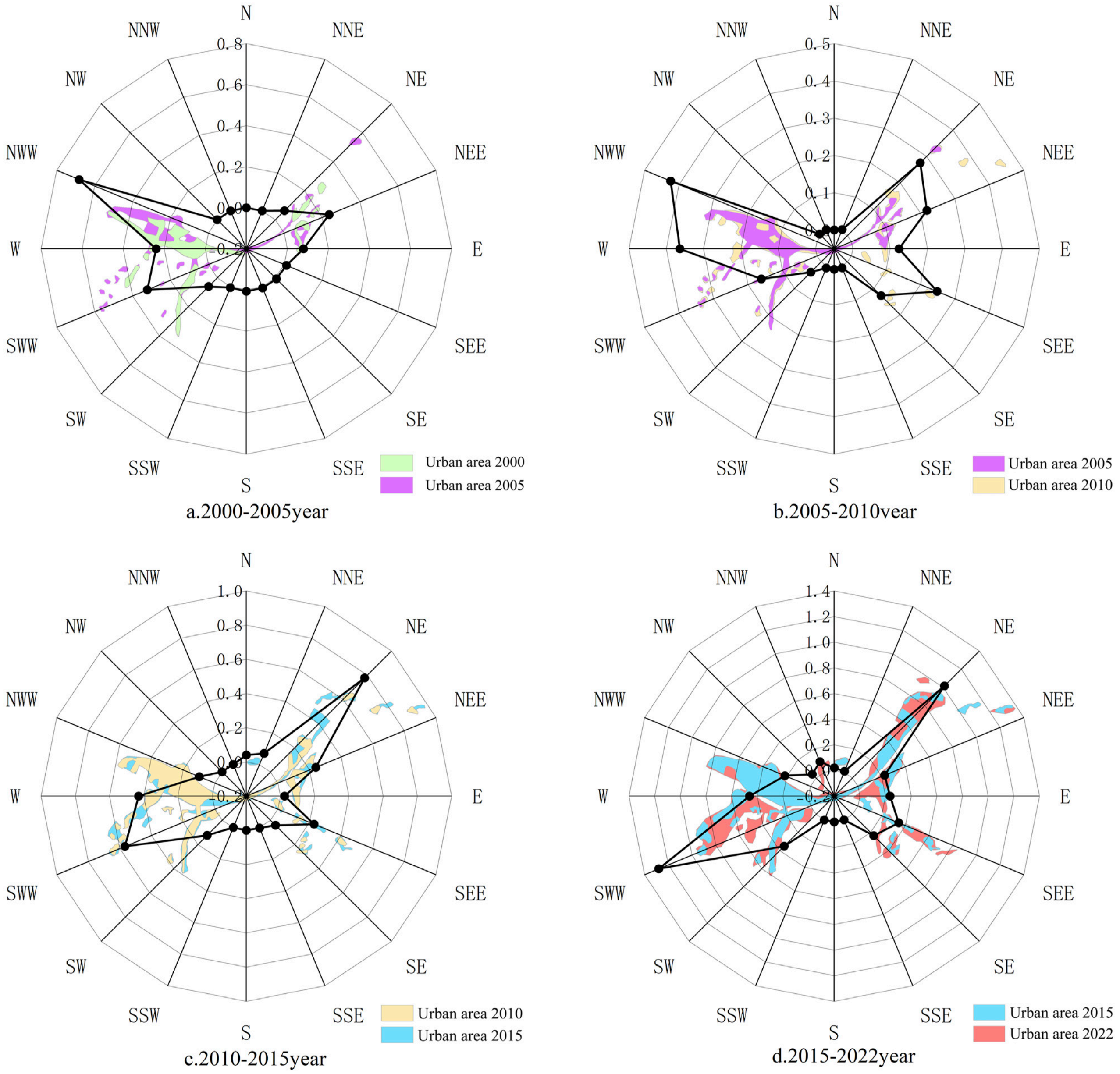

FIGURE 5
The radar charts of the urban expansion intensity of Wulingyuan in different directions. **(a)** 2000–2005 year. **(b)** 2005–2010 year. **(c)** 2010–2015 year. **(d)** 2015–2022 year.

and two-side extension" was identified, indicating that the urban expansion of Wulingyuan is restricted by strict topographic conditions. This urban expansion characteristic is similar to that of Dunhuang City, i.e., the optimization of traffic conditions has an obvious pulling effect on urban land expansion (He and Chen, 2017). The topography of Wulingyuan is generally high in the northwest and low in the southeast, and the urban area is mainly located in the river valley downstream of Suoxi Lake. Because the south and north are mostly home to mountains and hills with steep terrain, which limit the N-S expansion of the urban area, urban expansion has primarily occurred along the river valley, basin, and other relatively flat terrain.

Figure 5 presents Wulingyuan's expansion intensity in different directions in different periods. From 2000 to 2005, the expansion intensity indices in the northwest-west (NWW), northeast-east (NEE), west (W), and southwest-west (SWW) directions were 0.68%, 0.24%, 0.24%, and 0.32%, respectively, which were significantly higher than in other directions. This resulted in two main expansion zones: the NWW-W-SWW west wing and the NEE northeast wing. Among these, the new area of 0.22 km^2 in the NWW direction presented the most significant growth, followed by the SWW direction. In contrast, the urban area in the N-S direction experienced almost no expansion, with a low expansion intensity index of each wing. This indicates the slow expansion of the two

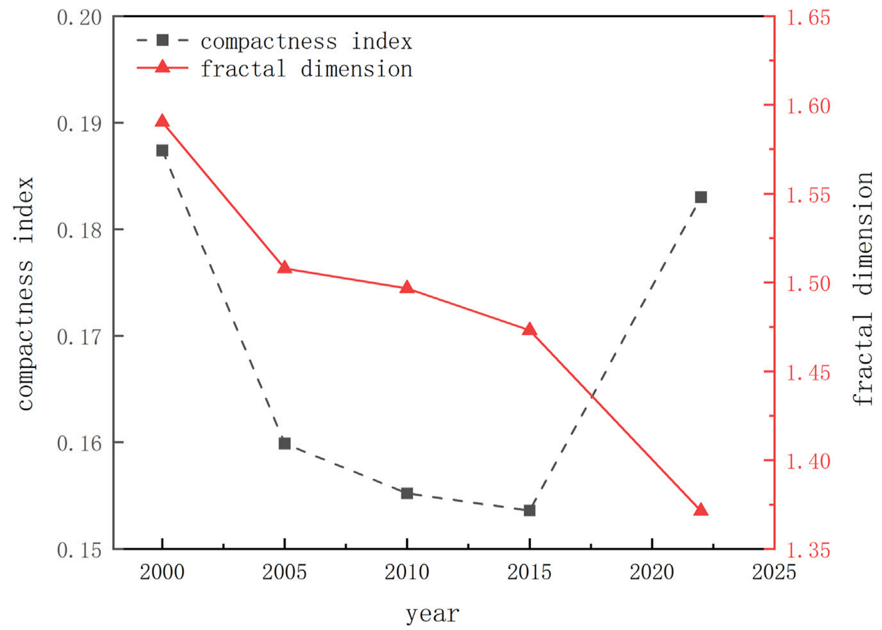

FIGURE 6
The compactness index and fractal dimension of Wulingyuan throughout the study period.

wings, marking the initial formation of a belt-shaped urban spatial pattern.

From 2005 to 2010, Wulingyuan mainly expanded along the NWW-W-SWW, NE-NEE, and southeast-east (SEE) directions, which had respective expansion intensity indices of 0.38%, 0.33%, 0.14%, 0.25%, 0.19%, and 0.22%. These values are similar to those in the previous period. The expansion intensity remained at an overall low level, and urban expansion presented a dendritic and slow trend.

From 2010 to 2015, compared with the previous period, the speed of expansion increased. Moreover, the belt-shaped pattern became more obvious, mainly along the SW and NE directions. The NE direction exhibited the highest expansion intensity index of 0.78%, and an increase of 0.25 km^2 in the urban area. This was followed by the SWW direction, which had an expansion intensity index of 0.57% and an increase of 0.18 km^2 in the urban area. These directions represent those with the most rapid expansion in this period.

From 2015 to 2022, the direction of expansion continued to be dominated by the SW and NE, but the discrete nature of the direction increased and the rate of expansion rose further, ushering in another high point of rapid urban expansion.

3.2 Evolutionary features of the urban spatial form of Wulingyuan

Overall, from 2000 to 2022, the compactness index of Wulingyuan exhibited a "V"-shaped evolutionary trend, and the highest value was 0.187. This indicates a relatively low efficiency of urban space utilization, and the characteristics of a belt-shaped layout are obvious. Moreover, the fractal dimension ranged from 1.371 to 1.590. Except for the period from 2000 to 2005, when the fractal dimension was close to 1.5 and the boundary form was unstable, the fractal dimension in other periods remained between 1 and 1.5. This suggests the tendency of the urban spatial form to be simple and regular, with urban expansion is dominated by internal infilling and edge expansion (Figures 6, 7). Regarding expansion stages, three main expansion patterns were observed: "edge expansion dominance" from 2000 to 2005, "parallel edge expansion and infilling from 2005 to 2015, and "infilling dominance" from 2015 to 2022. Wulingyuan's urban expansion pattern differs from that of other cities, where edge expansion is generally a stable contributor, and the importance of infilling and leapfrog expansion alternate. However, the expansion of Wulingyuan was found to be dominated by edge expansion in the early stage and infilling in the later stage, with minimal leapfrog expansion (Li et al., 2022; Liao et al., 2022; Lu et al., 2023; Terfa et al., 2019).

Figure 6 presents the changes in the compactness index and fractal dimension of the built-up urban area of Wulingyuan in different periods from 2000 to 2022. Figure 7 presents the changes in the LULC in the urban area of Wulingyuan and its surrounding areas in different periods from 2000 to 2022. Specifically, Figure 6 reveals that the compactness index and fractal dimension declined rapidly from 2000 to 2005. In this period, the compactness index dropped to 0.160 and urban expansion exhibited a trend of decentralization. Furthermore, the fractal dimension decreased to 1.508, approaching 1.5, indicating the reduced stability and complexity of urban spatial form. From 2005 to 2010, the compactness index and fractal dimension continued to decline. However, the rate of decline slowed, and the pattern of urban expansion gradually shifted from being dominated by edge expansion to one in which edge expansion and infilling were equally important. As the tourism industry entered a period of steady development, the spatial layout of Wulingyuan was slated for optimization, and the city formulated and implemented the Wulingyuan Scenic Spot Master Plan (2005–2020). This plan

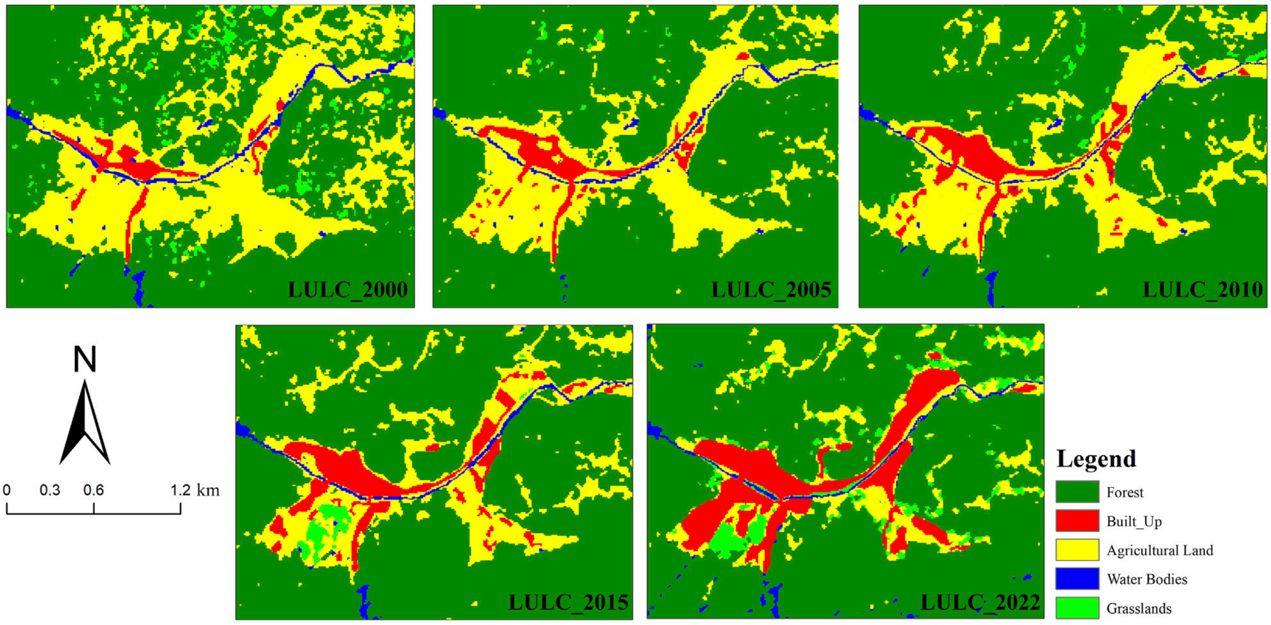

FIGURE 7
The LULC maps of Wulingyuan in 2000, 2005, 2010, 2015, and 2022.

aimed to promote the intensive and standardized development of tourism service facilities around the core scenic spots. By 2015, the compactness index reached its lowest value of 0.154, with the most dispersed urban construction land, and the fractal dimension decreased from 1.497 to 1.473, indicating the regularity and simplicity of the urban spatial form. Moreover, expansion was dominated by infilling. From 2015 to 2022, the compactness index rebounded to 0.183, a significant increase from 0.154. This indicates the enhancement of the compactness of urban land use, the significant improvement of the land-use efficiency and carrying capacity of tourism, and the effective intensification of development. Moreover, the fractal dimension decreased to 1.371, the lowest value in the entire study period, reflecting the greater regularity of the urban spatial form and the tendency of the belt-shaped pattern to stabilize.

4 Analysis of factors influencing changes in the urban spatial form of Wulingyuan

The PLSR analysis yielded an R^2 value of 0.771, reflecting a good model fit, and all indicators were significantly correlated with the area of Wulingyuan at the 0.01% or 0.05% level. The independent variables with *VIP* values greater than 1 were found to be the following: the number of tourist attractions (*VIP* = 1.032), the number of tourist hotels (*VIP* = 1.156), the urban population (*VIP* = 1.242), the level of urbanization (*VIP* = 1.196), and the *per capita* disposable income of urban residents (*VIP* = 1.210); these variables have largely influenced the expansion of Wulingyuan. Variables with *VIP* values between 0.8 and 1 included GDP (*VIP* = 0.942) and total consumer goods (*VIP* = 0.934); these also have some explanatory power for the expansion of Wulingyuan. Tourism revenue (*VIP* = 0.567), total local revenue (*VIP* = 0.743), and fixed asset investment (*VIP* = 0.728) were identified as potential influencing factors.

4.1 Tourism factors

Table 5 shows that the *VIP* values of the tourism-related indicators are ranked as follows: the number of tourist hotels > the number of tourist attractions > total tourism revenue. The regression coefficients of the three variables were calculated as 0.085, 0.092, and 0.049, respectively. The numbers of tourist attractions and hotels were therefore identified as primary drivers of urban expansion, while total tourism revenue was identified as the potential driver. Figure 8 shows the degree of agglomeration and the spatial distribution of tourism-related industries (tourist attractions and hotels) over time from 2000 to 2022. From 2005 to 2022, the overall distribution of tourist attractions and hotels followed a "point-axis diffusion pattern." This pattern is characterized by the gradual expansion of tourist attractions and hotels, with development extending along the city's main roads. The core areas of agglomeration varied in different periods.

Specifically, in 2005, tourism-related industries were mainly concentrated in the Wujiayu community, Painted Scroll Road community, and Baofeng Lake community. There was a tendency for these industries to extend from the Wujiayu community to the Yujiazui community. During this period, the number of tourist attractions and hotels was relatively small, resulting in the formation of a relatively high-density central area in the Painted Scroll Road community (along Gao Yun Road). From this central area, two main sub-centers were formed to the east and north: the Wujiayu community (along Wuling Road) and the Baofenghu community (along Baofeng Road).

TABLE 5 The analysis of factors influencing expansion from 2005 to 2022.

Dimension	Index	Regression coefficient	Standard error	*t*	*p*	*VIP*
Tourism factors	X1: Total tourism revenue (100 million yuan)	0.049	0.021	2.294	0.035	0.567
	X2: Number of tourist attractions	0.092	0.022	4.141	0.001	1.032
	X3: Number of tourist hotels	0.085	0.016	5.378	0.000	1.156
Economic factors	X4: GDP (100 million yuan)	0.056	0.014	4.069	0.001	0.942
	X5: Total local fiscal revenue (100 million yuan)	0.066	0.018	3.623	0.002	0.743
Urbanization factors	X6: Fixed-asset investment (100 million yuan)	0.062	0.017	3.560	0.002	0.728
	X7: Total retail sales of consumer goods (100 million yuan)	0.068	0.016	4.160	0.001	0.934
	X8: Urban population (10,000 people)	0.102	0.017	6.142	0.000	1.242
	X9: Urbanization level (%)	0.111	0.014	8.031	0.000	1.196
	X10: Per capita disposable income of urban residents (yuan)	0.095	0.014	6.774	0.000	1.210

Note: ** and * indicate significant correlations at the 0.01 and 0.05 levels (two-tailed), respectively; independent variables with $VIP > 1$ are considered core drivers, those with $0.8 < VIP < 1$ are secondary drivers, and those with $VIP < 0.8$ are non-significant drivers.

By 2010, the number of tourist attractions and hotels had increased, and the main catchment area remained located in the Painted Scroll Road community. However, the Baofeng Lake community became more clustered. In 2015, due to the strict restrictions on construction activities within the core scenic area, many tourism facilities were relocated to the urban area, resulting in a spike in tourist attractions and hotels. The spatial distribution of tourist attractions and hotels during this period was concentrated in the Baofeng Lake community, in the area surrounding the Wulingyuan government offices, and in the Wujiayu community. The main agglomeration area relocated from the Painted Scroll Road community to the Baofeng Lake community, while the area surrounding the Wulingyuan government offices evolved into a sub-center.

While the number of tourist attractions and hotels further increased in 2022, the growth rate slowed. The main catchment area was relocated to the Wujiayu community, and the Baofenghu community was relegated to the sub-center area.

Figure 9 and Table 6 demonstrate the spatial distribution of tourism-related industries in relation to urban built-up land and the degree of response in different periods from 2000 to 2022. From 2005 to 2010, the SDE of the urban area exhibited a SW-NE trend, with the area increasing from 4.919 km^2 to 6.612 km^2, and the city further expanded outward. The SDE of tourism-related industries presented a NW-SE trend, and the agglomeration increased relative to that in the previous period. Moreover, the spatial overlap between the urban area and tourism-related industries decreased from 2.318 km^2 to 2.303 km^2, and the spatial responsiveness index decreased from 0.471 to 0.348.

From 2010 to 2015, the direction of the urban area SDE remained the same as that in the previous period. The area increased from 6.612 km^2 to 8.049 km^2 and the compactness decreased. The SDE of tourism-related industries gradually shifted to the NE-SW direction, with the area increasing from 2.606 km^2 to 3.2 km^2. These industries expanded to the Yujiazui community, presenting weakened agglomeration. At this stage, the area of spatial overlap between the urban area and tourism-related industries increased from 2.303 km^2 to 3.162 km^2, and the spatial response of the urban area to tourism-related industries became larger.

From 2015 to 2022, the SDEs of both the urban area and tourism-related industries aligned in the NW-SE direction. During this period, the SDE of the urban area increased from 8.049 km^2 to 9 km^2, at which time the expansion of the urban area shifted from edge expansion to internal infilling. The SDE of tourism-related industries increased from 3.2 km^2 to 5.769 km^2, and the degree of agglomeration was weakened. The spatial response coefficient of urban construction land to tourism-related industries increased from 0.393 to 0.563, indicating a stronger spatial correlation between the two.

Overall, the direction of urban area expansion influenced the direction of the expansion of tourism-related industries, which remained consistent with the direction of urban area expansion after 2015. In terms of spatial layout, the comprehensive analysis of the spatial response coefficient, compactness index, and fractal dimension indicates that the increasing number of tourist attractions and hotels has played a role in gradually optimizing the spatial layout of the urban area. However, this sharp increase also presents new challenges for urban planning. On the one hand, the upper-level plan designates most of the northeastern part of the urban area as residential land, which somewhat restricts the outward expansion of tourism-related industries. Consequently, the development of tourist attractions and hotels must focus on the deeper exploration and more efficient use of existing land resources to enhance the efficiency of spatial utilization. This shift became particularly evident after 2015, when the pattern of urban expansion gradually shifted from marginal expansion to predominantly infill development. On the other hand, the spatial response of urban built-

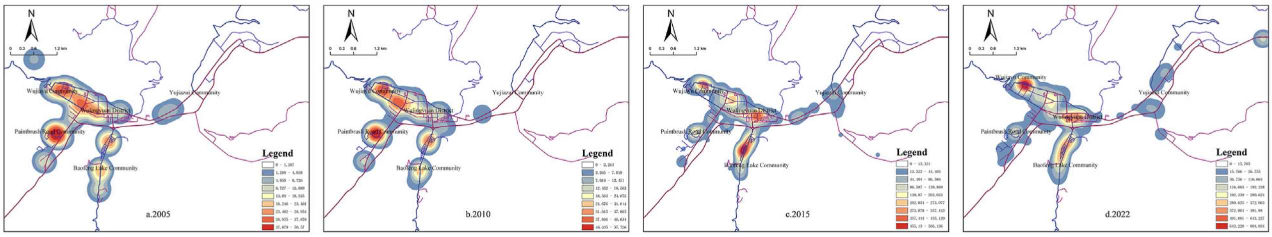

FIGURE 8
The kernel density maps of tourism-related industries in Wulingyuan in 2000, **(a)** 2005, **(b)** 2010, **(c)** 2015, and **(d)** 2022.

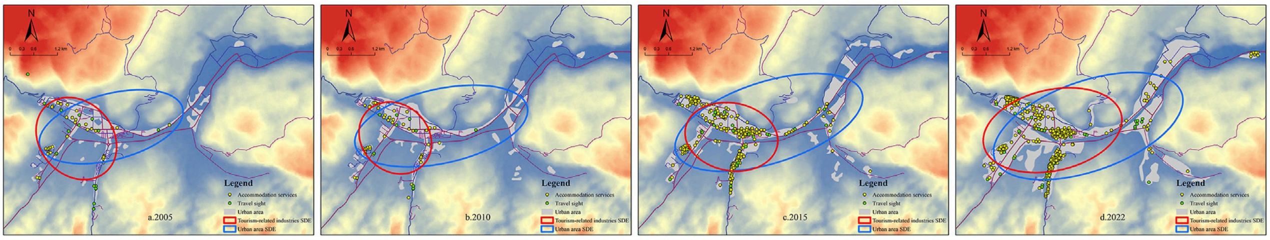

FIGURE 9
The standard deviation ellipses of tourism-related industries and the urban area of Wulingyuan in 2000, **(a)** 2005, **(b)** 2010, **(c)** 2015, and **(d)** 2022.

TABLE 6 The response coefficients of urban construction land to tourism-related industries in 2005, 2010, 2015, and 2022.

Year	Urban area SDE			Tourism-related industries SDE			Overlapping area	Response coefficient
	Coordinates	Area	Azimuth	Coordinates	Area	Azimuth		
2005	110.549°, 29.349°	4.919	75.272	110.540°, 29.346°	3.283	137.725	2.318	0.471
2010	110.552°, 29.349°	6.612	77.579	110.540°, 29.346°	2.606	133.736	2.303	0.348
2015	110.555°, 29.350°	8.049	72.245	110.545°, 29.347°	3.200	100.303	3.162	0.393
2022	110.555°, 29.349°	9.000	70.608	110.546°, 29.348°	5.769	77.295	5.063	0.563

up land to tourism-related industries has gradually increased, reaching its highest level. This indicates that between 2015 and 2022, tourist attractions and hotels not only improved the compactness of urban areas but also reduced the complexity of boundaries through rational planning and layout adjustments, achieving more intensive land use and an optimized spatial layout. This series of changes marks the entry of Wulingyuan into a stage of high-quality spatial development characterized by "shaping the city with tourism," i.e., optimizing urban space through tourism development and promoting the high-quality and sustainable development of the city.

4.2 Economic factors

Table 5 shows that the *VIP* values of the economic-related indicators are ranked as follows: GDP > total social consumer goods > total tourism revenue > total local revenue > fixed asset investment. The regression coefficients of these four variables are 0.056, 0.068, 0.066, and 0.062, respectively. Among them, GDP and total social consumer goods are the secondary drivers of the expansion of the urban area, while total local revenue and fixed asset investment are non-significant drivers.

From 2005 to 2010, the increased funds from GDP growth and total social consumption goods primarily flowed into the land finance sector. The government obtained funds through extensive land concessions, driving the growth rates of GDP and total social consumption goods to 19.6% and 19%, respectively–the fastest growth rates in this period. Under this development model, the expansion of Wulingyuan mainly relied on land concessions and was dominated by outward growth, resulting in a decline in the compactness index of the urban area.

From 2010 to 2015, with the strengthening of control measures, Wulingyuan ceased large-scale land concessions, and instead significantly invested in the development of tourist attractions and hotels, emphasizing inward infilling. However, the rapid increase in the number of tourist attractions and hotels in this period caused the compactness index of the urban area to decrease to its lowest value. Moreover, the development of the urban area of Wulingyuan was extremely unstable from 2005 to 2015 with complex boundary shapes and a fractal dimension close to 1.5.

Between 2015 and 2022, Wulingyuan continued to invest in tourist attractions and hotels, but the rate of investment slowed with a new focus on improving spatial quality. The urban expansion of Wulingyuan during this period was dominated by internal infilling. The compactness index increased, the fractal dimension decreased sharply, and the urban morphology became more regular. Local fiscal revenue and fixed asset investments continued to provide institutional and financial protection for GDP growth and consumption upgrading through targeted investments, which supported the development of the urban area to a certain extent.

4.3 Urbanization factors

Table 5 shows that the *VIP* values of the urbanization-related indicators are ranked as follows: urban population size > disposable income *per capita* of urban residents > urbanization level. Their regression coefficients are respectively 0.102, 0.095, and 0.111, and all three variables were identified as core driving factors.

From 2005 to 2015, the urban population of Wulingyuan increased from 25,400 to 35,300, and the urbanization level rose from 53.59% to 55.21%. The large increase in residential land significantly pushed the expansion of Wulingyuan's urban area to the northeast. Additionally, rising disposable incomes among urban residents increased demand for public services (e.g., education and healthcare), prompting the government to invest in the construction of schools, community hospitals, and other facilities. These new facilities required additional land, and the separate allocation of land for these facilities contributed to a decrease in land intensification and the compactness index.

From 2015 to 2022, the urban population of Wulingyuan increased from 35,300 to 42,200, and the urbanization level rose from 55.21% to 70.1%. During this period, Wulingyuan focused more on sustainable development. Developers met the demand by building new residential areas and public supporting facilities, as well as renovating existing land. New land expansion was concentrated along the SW-NE transport corridor, forming a belt-shaped layout that reduced disorderly multi-directional sprawl, leading to a decrease in the fractal dimension. The increase in the disposable income of urban residents promoted consumption upgrading and environmental awareness, which supported the government's "green renewal" project. The optimization of existing land replaced outward expansion, exemplified by the construction of an ecological complex (commercial + green space) following the demolition of inefficient buildings in the Yujiazui community. This project enhanced multifunctional, intensive land use and contributed to an increase in the compactness index.

4.4 Policy factors

As a typical heritage-based tourist city, the evolution of the urban spatial form of Wulingyuan District shows significant policy response characteristics. Research shows that the policy system deeply intervenes in the process of urban spatial expansion through a dual mechanism of positive guidance and negative constraints. To facilitate analysis, this paper divides the relevant policies of Wulingyuan into two dimensions and three types: the positive guidance dimension includes tourism development policies and urban planning and spatial governance policies, while the negative constraint dimension mainly includes ecological protection policies.

In terms of positive guidance, the core role of tourism development policies is to guide the concentration of tourism functions, enhance the momentum of urban expansion, and promote the optimization of urban spatial structure and functional layout by regulating the development path and spatial layout of tourism-related industries. In 2006, the national special support policy for the construction of tourist cities included Wulingyuan in the first batch of pilot cities, providing special financial support for the construction of tourism infrastructure. Driven by this policy, major tourist routes such as Gaoyun Road, Huanglong Cave Avenue, and Wulingyuan East Road were upgraded and renovated, significantly improving the accessibility of the urban area and core scenic spots, and leading to the formation of a main axis of urban spatial expansion from southwest to northeast. In 2015, Wulingyuan was designated as a pilot city for the "all-round tourism" demonstration zone, promoting the deep integration of scenic area resources, tourism functions, and urban space. This policy guides the orderly relocation of facilities originally scattered across ecologically sensitive areas into designated urban zones such as the Wujiaoyu Community, Baofeng Road Community, and areas surrounding the district government. Tourist commercial streets, tourist distribution centers, cultural performance venues, and other facilities gradually gathered in the core area of the city, forming a comprehensive cluster centered on tourism services in the southwestern part of Wulingyuan. This process has promoted the transformation of the city's tourism functions from a dependent type to a composite development type, further promoting the shift from extensive expansion to infilling of urban space. The urban functional layout has also become more compact and composite, effectively promoting the optimization of the urban spatial structure. Another type of positive guidance policy is urban planning and spatial governance policy, which intervenes in the direction, scope, and form of urban spatial expansion through means such as planning guidance, functional zoning, and land use control. The 2001″Zhangjiajie City Master Plan (2000–2020) " positioned Wulingyuan District as a dual-function city combining tourism services and ecological living, proposing the Suoxiyu community as the main direction for development. In 2014, the "Wulingyuan District Urban and Rural Master Plan (2013–2030)" first explicitly proposed a "compact city" spatial strategy. This strategy promoted the formation of a functional zoning structure within the city space, with tourism services at its core and administrative offices and residential facilities as supporting functions, effectively improving spatial concentration and land use efficiency. In 2022, the "Wulingyuan Urban Expansion Plan (2021–2035) " was completed, establishing rigid boundaries for urban expansion by delineating "three zones and three lines. " New urban projects are required to be strictly controlled within the planned boundaries, promoting urban infill in existing built-up areas. Under the strict restrictions of the newly delineated urban development boundary, Wulingyuan's future urban expansion will focus on internal land readjustment rather than external expansion. In this context, tourism will become the dominant force driving urban space filling, guiding the reuse of existing land, and restructuring functions. Tourism-related industries will penetrate residential areas, promoting the deep integration of urban living functions and tourism functions. The changing trends in the standard deviation ellipses of tourism-related industries and urban built-up areas in Figure 8 support this judgment.

In the negative constraint dimension, the core role of ecological protection policies is to fundamentally curb the disorderly expansion of urban space by demarcating ecological red lines, implementing zoning protection, and prohibiting construction. Such policies do not directly promote urban growth, but rather force cities to optimize their internal development by establishing strict ecological boundaries. In 2001, the "Wulingyuan World Natural Heritage Protection Regulations" mandated the removal of tourist facilities from the core scenic area, guiding the migration of tourism services to urban built-up area. The 2005 revision of the "Wulingyuan Scenic Area Master Plan (2005–2020)" divided the Wulingyuan area into different protection levels, demarcating core protection areas, construction control areas, and constructable areas, limiting urban expansion to constructable areas and reducing the scope of urban development. After the 2010 "Hunan Province Main Functional Zone Plan" was introduced, Wulingyuan District was designated as a "key ecological functional zone." Urban construction must comply with ecological bottom line controls, and strict requirements have been imposed on compact urban development. By 2015, urban expansion will shift to a focus on infilling. Overall, positive guidance policies promote the spatial restructuring of Wulingyuan urban areas through functional aggregation and structural optimization, while negative constraint policies strengthen boundary control through spatial restrictions. The interaction between them has led to a shift in the urban expansion model from extensive expansion to intensive, efficient, compact, and orderly development.

5 Discussion

5.1 Comparative analyses

The evolution of traditional urban spatial form mostly presents centralized or clustered characteristics (Xu et al., 2019; Yin et al., 2024), with development patterns often presenting dynamic evolution characteristics alongside urbanization. However, the urban expansion of Wulingyuan has been different from that of typical cities and ordinary tourist cities. Surrounded by mountains on three sides and constrained by World Heritage protection policies, Wulingyuan's urban growth is limited to eastern expansion, resulting in a persistent belt-shaped structure. Unlike Huangshan City, where the main urban area has transformed from a belt to a cluster (Ding et al., 2014), Wulingyuan's special geographical conditions and policy restrictions prevent multi-center expansion. As a typical tourism-driven town, Wulingyuan relies on tourism for more than 70% of its economy. This single-industry reliance has resulted in poor resistance to external shocks. For example, the 2019 COVID-19 public health emergency caused Wulingyuan's GDP to plummet from 5.973 billion yuan in 2018 to 4.326 billion yuan in 2020, a 27.5% decrease, far exceeding the national average decline of 9.6% in cities and towns. Although it has somewhat recovered, the GDP has yet to return to pre-pandemic levels. This dual challenge of spatial form rigidity and industrial homogenization highlights a fundamental contradiction in the sustainable development of tourism towns located in Natural World Heritage Sites.

5.2 Conservation-development tensions and conservation-oriented development pathways

As a Natural World Heritage Site, Wulingyuan has consistently faced the dual pressures of ecological protection and urban development during its urban expansion. On the one hand, strict ecological protection policies prohibit all construction activities within the core scenic area and the ecological red line due to its protected status. On the other hand, the rapid development of tourism and the increased level of urbanization have enhanced the need for urban land expansion and functional reconfiguration. The results of this study show that this tension has been particularly pronounced in the different stages of urban expansion. Since Wulingyuan's designation as a Natural World Heritage Site in 1992, the rapid increase in tourist facilities in the core scenic area has compromised the authenticity of the landscape. In 1998, UNESCO issued a serious warning, marking the culmination of the conflict between conservation and development. To this end, the 2001″Wulingyuan World Natural Heritage Protection Regulations" called for the relocation of tourism facilities from within the core scenic area to the urban area to alleviate ecological pressure while stimulating urban expansion. This led to three phases of urban expansion: from 2000 to 2005, conservation dominated and development was suppressed, resulting in low-intensity and limited urban expansion; from 2005 to 2015, conservation and development began to harmonize, characterized by parallel edge expansion and infilling; and from 2015 to 2022, conservation and development entered a synergistic and co-promotional stage, urban compactness increased, the fractal dimension decreased, and the urban spatial form tended to be regular and stable.

On this basis, the development path of the conservation-oriented development (COD) model is proposed and verified. COD is a spatial development strategy that prioritizes the authenticity and integrity of the World Heritage Site, aiming to achieve a synergistic outcome between ecological protection and urban development. This is realized through compact development, functional integration, and policy regulation. The model is tailored specifically to Wulingyuan and is characterized by the following: (1) the protection of ecological integrity by limiting urban expansion to designated development zones; (2) the integration of tourism and residential functions in a unified spatial structure to improve land-use efficiency; (3) the promotion of internal infilling and functional densification, thus avoiding fragmentation or leapfrogging; and (4) the use of planning tools (e.g., "three zones and three lines") to draw strict boundaries and encourage redevelopment within existing built-up areas. The validity of this development path was empirically verified by a number of indicators and multivariate methods, such as the expansion intensity index, expansion speed index, compactness index, fractal dimension, SDE, and PLSR model. Overall, Wulingyuan provides a replicable model for other heritage cities or ecologically sensitive tourist cities, demonstrating how urban development can take place within certain limits to support economic growth and environmental sustainability.

5.3 Policy implications

Based on the findings and the general background of new urbanization, and taking into account Wulingyuan's designation as a Natural World Heritage Site, the following targeted recommendations are put forward from the four aspects of tourism, the economy, urbanization, and policy. (1) In the tourism dimension, tourism facilities should be relocated to areas where agglomeration effects have already been formed, such as Jundiping Street. Moreover, the infilling of the urban area should be promoted with expansion in the SW-NE directions, with a focus on integrating the tourism service and urban living functions. (2) In the economic dimension, the diversification of industries should be promoted, as should the introduction of new industries such as cultural creativity, healthcare, green agriculture, etc. The aim is to reduce Wulingyuan's over-dependence on the traditional tourism industry. (3) In the urbanization dimension, the renewal of old cities and urban micro-renovation are encouraged. Activating the inner space of cities via squatter reforms and consolidating unused assets are important considerations. Moreover, urban expansion into edge areas such as mountains and forests should be strictly controlled to safeguard spatial compactness and ecological security. (4) In terms of policy, it is recommended that "conservation-oriented development (COD)" be adopted as the core concept, and that a unified urban spatial management information platform and ecological compensation mechanism be established to coordinate urban development and ecological protection.

5.4 Limitations and future goals

This study uses remote sensing image data and social data to systematically analyzed the characteristics of the evolution of the urban spatial form of Wulingyuan District, China, a Natural World Heritage Site, with a focus on changes in the city's external form. It offers valuable insights into the spatial development process. However, the spatial resolution of the Landsat remote sensing images used by this study is 30 m. Although the overall accuracy exceeds 85% based on accuracy assessments, there are certain limitations in identifying built-up area boundaries and small-scale land use changes. Additionally, this study is also insufficient in terms of subdividing built-up land types and analyzing the internal spatial structure of the city. This study have focused on the evolution of the boundary morphology of the built-up area, emphasizing external indicators such as compactness, the fractal dimension, and the expansion speed. However, there is currently a lack of quantitative analysis regarding the land-use organization within cities, the degree of functional mixing, and the efficiency of vertical spatial utilization. This gap limits a deeper understanding of the efficiency of spatial organization and functional coordination within cities. Future research could address this by integrating multiple data sources, such as high-resolution remote sensing imagery, land-use maps, POI data, and street network data (Li, 2021; Qian et al., 2021; Zhang et al., 2023b). Additionally, combining methods like spatial syntax, landscape pattern indices, and information entropy (Ortiz-Báez et al., 2021; Xia et al., 2021; Xing and Guo, 2022) would enable the quantification of functional mixing, accessibility, and spatial equilibrium within the city. Furthermore, incorporating network-based spatial structure analysis (Das and Ram, 2024; Fang et al., 2021) could help assess the connectivity between tourism facilities and residents' living spaces, thus revealing how tourism development refigures the internal morphology of the city at the micro level. In addition, a multi-case comparative study would help validate the utility of the COD model and provide broader policy recommendations for heritage or ecologically sensitive cities.

6 Conclusion

Based on Landsat remote sensing image data from 2000 to 2022, the urban area of Wulingyuan, China, a Natural World Heritage Site, was extracted and analyzed. Quantitative assessments were conducted on the scale, speed, intensity, direction, and type of urban expansion. Additionally, the driving factors affecting the evolution of the urban spatial form of Wulingyuan were explored. The key findings of this research are as follows. (1) From 2000 to 2022, the urban area of Wulingyuan expanded from 0.976 km^2 to 4.955 km^2, a nearly fivefold increase. The overall urban expansion can be divided into four stages: "medium-speed, low-intensity," "low-speed, low-intensity," "medium-speed, medium-intensity," and "medium-speed, high-intensity." The period from 2015 to 2022 marks the peak time of urban expansion. The relocation of tourism facilities has brought strong momentum to urban expansion, and the area of construction land has increased significantly compared with other periods. (2) The urban expansion of Wulingyuan has mainly occurred along the SW-NE directions, forming a belt-shaped layout constrained by topography and ecological controls that have limited N-S expansion. This spatial pattern, characterized by expansion mainly at the two edges of the belt, is closely linked to the guiding role of the tourism traffic corridor. (3) In terms of spatial form, the compactness index of Wulingyuan has exhibited a "V"-shaped trend, reaching its lowest value in 2015 before gradually rising to 0.183 in 2022. This reflects a shift from crude outward expansion to intensive internal infilling. Concurrently, the fractal dimension decreased overall, indicating the regularization of urban boundaries and the gradual stabilization of urban spatial forms. The urban expansion of Wulingyuan has experienced three phases: edge expansion dominance, parallel edge expansion and internal infilling, and internal infilling dominance. (4) Quantitative analysis using the PLSR model indicated that the intensity of the three types of drivers of urban expansion in Wulingyuan, from highest to lowest, is as follows: urbanization factors > tourism factors > economic factors. Urbanization is a direct driver, primarily by increasing the demand for land to drive urban expansion. Tourism influences the optimization of the urban land-use structure mainly through the adjustment of site layouts, which in turn promotes functional reorganization and structural optimization within the city. Finally, economic factors play a more indirect role, primarily providing financial support that facilitates tourism and urbanization. In addition, policy factors mainly control the direction, scale, and boundaries of urban expansion through the dual functions of positive guidance and negative constraints.

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: Writing – original draft, Conceptualization, Methodology, Visualization, Writing – review and editing. BL: Data curation, Investigation, Software, Writing – review and editing. JW: Formal Analysis, Funding acquisition, Supervision, Validation, Writing – review and editing. JY: Conceptualization, Resources, Validation, Writing – review and editing. YW: Project administration, Validation, Writing – original draft.

Funding

The author(s) declare that financial support was received for the research and/or publication of this article. This research was funded by the National Natural Science Foundation (Grant Number: 42061036) and the Hunan College Students Innovation and Entrepreneurship Training Program (Grant Number: S202410531037).

Acknowledgments

The authors would like to thank the editors and instructors for their insightful and constructive comments, and are also grateful to all the panelists for their hard work.

Conflict of interest

The authors declare 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.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2025.1588318/full#supplementary-material

References

Aronoff, S. (1982). Classification accuracy: a user approach. *Photogrammetric Eng. Remote Sens.* 48 (8), 1299–1307.

Batty, M. (1991). "Cities as fractals: simulating growth and form," in *Fractals and chaos* (New York, NY: Springer New York), 43–69.

Boyce, R. R., and Clark, W. A. (1964). The concept of shape in geography. *Geogr. Rev.* 54 (4), 561–572. doi:10.2307/212982

Camps-Valls, G., Benediktsson, J. A., Bruzzone, L., and Chanussot, J. (2011). Introduction to the issue on advances in remote sensing image processing. *IEEE J. Sel. Top. Signal Process.* 5 (3), 365–369. doi:10.1109/jstsp.2011.2142490

Chen, Z., and Bao, J. (2012). Spatial morphological evolution and influencing mechanism of recreation and commercial areas in typical tourist cities: a case study of Yangshuo County, Guangxi. *Geogr. Res.* 31 (7), 1339–1351.

Chughtai, A. H., Abbasi, H., and Karas, I. R. (2021). A review on change detection method and accuracy assessment for land use land cover. *Remote Sens. Appl. Soc. Environ.* 22, 100482. doi:10.1016/j.rsase.2021.100482

Cobbinah, P. B., Asibey, M. O., Opoku-Gyamfi, M., and Peprah, C. (2019). Urban planning and climate change in Ghana. *J. Urban Manag.* 8 (2), 261–271. doi:10.1016/j.jum.2019.02.002

Das, J., and Ram, S. (2024). Exploring the relationship of transport network and land use patterns: an approach through weighted centrality assessment. *Urban, Plan. Transp. Res.* 12 (1), 2323946. doi:10.1080/21650020.2024.2323946

Deng, T., Wang, D., Hu, Y., and Liu, S. (2020). Did high-speed railway cause urban space expansion? empirical evidence from China's prefecture-level cities. *Res. Transp. Econ.* 80, 100840. doi:10.1016/j.retrec.2020.100840

Ding, J., Jiao, H., and Junfeng, L. (2014). The mechanism of industrial evolution on the evolution of spatial form of tourism city: a case study of huangshan city. *Geogr. Res.* (10), 1966–1976. doi:10.11821/dlyj201410016

Ding, J. (2015). *Research on the evolution process and mechanism of urban spatial morphology in the main urban area of Huangshan City driven by tourism industry.* Doctoral dissertation, Wuhu: Anhui Normal University. Aavailable online at: https://kns.cnki.net/kcms2/article/abstract?v=C4JADW50D8srI7gqE8r8AfmJKnPKyJDKduV4q3lEjMaqhplZwH7SGbw1DnNC07hkqFtxZmUTyxS0hLOgqNbXzy1vwFZAIEL6e2F9tJBdnKYdMSirr7xdOaWZj6zwJOFsMZ7EtkSNTEbQkr0MoeCL31jmLBRQzs8J0RQreGAusIDl7vbG_P5RzIz0hKZRlSgYNlZoQ8OH98Q=&uniplatform=NZKPT&language=CHS

Doe, B., Amoako, C., and Adamtey, R. (2022). Spatial expansion and patterns of land use/land cover changes around Accra, Ghana–Emerging insights from Awutu Senya East Municipal Area. *Land Use Policy* 112, 105796. doi:10.1016/j.landusepol.2021.105796

Fang, C., He, S., and Wang, L. (2021). Spatial characterization of urban vitality and the association with various street network metrics from the multi-scalar perspective. *Front. Public Health* 9, 677910. doi:10.3389/fpubh.2021.677910

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sens. Environ.* 80 (1), 185–201. doi:10.1016/s0034-4257(01)00295-4

Gao, P., Xi, J., and Liu, S. (2020). Research on the spatial process and dynamic mechanism of tourism urbanization: a case study of huangshui town, chongqing. *Hum. Geogr.* 35 (1), 104–113. doi:10.13959/j.issn.1003-2398.2020.01.012

Halder, A., Ghosh, A., and Ghosh, S. (2011). Supervised and unsupervised landuse map generation from remotely sensed images using ant based systems. *Appl. Soft Comput.* 11 (8), 5770–5781. doi:10.1016/j.asoc.2011.02.030

He, J., Zhang, S., Liu, L., Guan, Z., and Zhou, Z. (2023). Information extraction and feature analysis of urban spatial morphology in Shijiazhuang. *Remote Sens. Technol. Appl.* 38 (6), 1373–1380. doi:10.11873/j.issn.1004-0323.2023.6.1373

He, Z., and Chen, X. (2017). Research on the spatial expansion characteristics of different types of small and medium-sized cities: based on the analysis of Dunhuang, jinchang and zhangye. *Mod. Urban Stud.* (1), 111–118. doi:10.3969/j.issn.1009-6000.2017.01.016

Hui, T., Liu, J., Hu, Y., and Zhu, H. (2017). Spatial reconstruction model of tourism urbanization area: a case study of Mayangxi eco-tourism area. *Geogr. Res.* 36 (6), 1123–1137. doi:10.11821/dlyj201706010

Jaramillo-Benavides, A. S., and Patricio-Karnopp, Z. M. (2019). Durabilidad de los materiales naturales de construcción: Percepciones de proyectistas, constructores y usuarios en Florianópolis-Brasil. *Rev. Arquit.* 21. doi:10.14718/RevArq.2019.21.2.1825

Lefever, D. W. (1926). Measuring geographic concentration by means of the standard deviational ellipse. *Am. J. Sociol.* 32 (1), 88–94. doi:10.1086/214027

Li, S., Sun, Z., Wang, Y., and Wang, Y. (2021). Understanding urban growth in Beijing-Tianjin-Hebei region over the past 100 years using old maps and landsat data. *Remote Sens.* 13 (16), 3264. doi:10.3390/rs13163264

Li, W. (2021). Mapping urban land use by combining multi-source social sensing data and remote sensing images. *Earth Sci. Inf.* 14, 1537–1545. doi:10.1007/s12145-021-00624-3

Li, Y, Zhang, L, Ye, S, and Qi, X (2020). Improvement and application of two-dimensional fractal model of urban growth and morphology. *Journal of Geo-information Science*, 22 (11), 2140–2151. doi:10.12082/dqxxkx.2020.190640

Li, Z., Gurgel, H., Li, M., Dessay, N., and Gong, P. (2022). Urban land expansion from scratch to urban agglomeration in the federal district of Brazil in the past 60 years. *Int. J. Environ. Res. Public Health* 19 (3), 1032. doi:10.3390/ijerph19031032

Liao, K., Huang, W., Wang, C., Wu, R., and Hu, Y. (2022). Spatio-temporal evolution features and impact factors of urban expansion in underdeveloped cities: a case study of nanchang, China. *Land* 11 (10), 1799. doi:10.3390/land11101799

Liu, X., Wang, H., Liu, Y., and Yibin, L. (2024b). Characteristics and driving mechanism of urban spatial expansion in the center of Chengdu-Chongqing urban agglomeration. *J. Chongqing Normal Univ. Nat. Sci. Ed.* 41 (03), 121–132. doi:10.3390/su15032188

Liu, X., Xu, H., and Zhang, M. (2024a). The effects of urban expansion on carbon emissions: based on the spatial interaction and transmission mechanism. *J. Clean. Prod.* 434, 140019. doi:10.1016/j.jclepro.2023.140019

Liu, Y., Zuo, R., and Dong, Y. (2021). Analysis of temporal and spatial characteristics of urban expansion in Xiaonan District from 1990 to 2020 using time series Landsat imagery. *Remote Sens.* 13 (21), 4299. doi:10.3390/rs13214299

Lu, H., Wang, R., Ye, R., and Fan, J. (2023). Monitoring long-term spatiotemporal dynamics of urban expansion using multisource remote sensing images and historical maps: a case study of hangzhou, China. *Land* 12 (1), 144. doi:10.3390/land12010144

Ma, H., Xi, J., Wang, Q., Liu, J., and Gong, Z. (2020). Spatial complex morphological evolution and influencing factors for mountain and seaside resort tourism destinations. *Complexity* 2020 (1), 1–11. doi:10.1155/2020/4137145

Ma, L., Liu, Y., Zhang, X., Ye, Y., Yin, G., and Johnson, B. A. (2019). Deep learning in remote sensing applications: a meta-analysis and review. *ISPRS J. photogrammetry remote Sens.* 152, 166–177. doi:10.1016/j.isprsjprs.2019.04.015

Ma, X., and Liu, Y. (2019). The relationship between the growth of tourism industry and the evolution of urban spatial form. *Econ. Geogr.* 39 (5). doi:10.15957/j.cnki.jjdl.2019.05.026

Ma, X., Tan, J., and Zhang, J. (2022). Spatial–temporal correlation between the tourist hotel industry and town spatial morphology: the case of Phoenix ancient town, China. *Sustainability* 14 (17), 10577. doi:10.3390/su141710577

Ma, X., Yang, X., and Zhilong, L. (2019). The impact of spatial growth of tourism enterprises on urban spatial morphology in Zhangjiajie. *Geogr. Res.* 38 (8), 1965–1978. doi:10.11821/dlyj020180436

Maimaiti, B., Chen, S., Kasimu, A., Simayi, Z., and Aierken, N. (2021). Urban spatial expansion and its impacts on ecosystem service value of typical oasis cities around Tarim Basin, northwestChina. *Int. J. Appl. Earth Observation Geoinformation* 104, 102554. doi:10.1016/j.jag.2021.102554

Maxwell, A. E., Warner, T. A., and Fang, F. (2018). Implementation of machine-learning classification in remote sensing: an applied review. *Int. J. remote Sens.* 39 (9), 2784–2817. doi:10.1080/01431161.2018.1433343

Moukomla, S., and Marome, W. (2025). Tourism-induced urbanization in Phuket Island, Thailand (1987–2024): a spatiotemporal analysis. *Urban Sci.* 9 (3), 55. doi:10.3390/urbansci9030055

Ortiz-Báez, P., Cabrera-Barona, P., and Bogaert, J. (2021). Characterizing landscape patterns in urban-rural interfaces. *J. Urban Manag.* 10 (1), 46–56. doi:10.1016/j.jum.2021.01.001

Peng, W., Wang, G., Zhou, J., Zhao, J., and Yang, C. (2015). Studies on the temporal and spatial variations of urban expansion in Chengdu, western China, from 1978 to 2010. *Sustain. Cities Soc.* 17, 141–150. doi:10.1016/j.scs.2015.03.004

Qian, J., Liu, Z., Du, Y., Liang, F., Yi, J., Ma, T., et al. (2021). Quantify city-level dynamic functions across China using social media and POIs data. *Environ. Urban Syst.* 85, 101552. doi:10.1016/j.compenvurbsys.2020.101552

Qin, F., Fukamachi, K., and Shibata, S. (2022). Land-use/landscape pattern changes and related environmental driving forces in a Dong Ethnic Minority Village in Southwestern China. *Land* 11 (3), 349. doi:10.3390/land11030349

Rahaman, M., Dutta, S., Sahana, M., and Das, D. N. (2019). Analysing urban sprawl and spatial expansion of Kolkata urban agglomeration using geospatial approach. *Appl. challenges geospatial Technol. potential future trends*, 205–221. doi:10.1007/978-3-319-99882-4_12

Ranagalage, M., Gunarathna, M. H. J. P., Surasinghe, T. D., Dissanayake, D., Simwanda, M., Murayama, Y., et al. (2020). Multi-decadal forest-cover dynamics in the tropical realm: past trends and policy insights for forest conservation in dry zone of Sri Lanka. *Forests* 11 (8), 836. doi:10.3390/f11080836

Shen, Z., Ning, J., and Liu, J. (2023). Thermal environmental effects of urban spatial form from the perspective of local climate zones: a case study of Quanzhou City. *Build. Sci.* 39 (04), 104–112. doi:10.13614/j.cnki.11-1962/tu.2023.04.14

Shih, H. C., Stow, D. A., and Tsai, Y. H. (2019). Guidance on and comparison of machine learning classifiers for Landsat-based land cover and land use mapping. *Int. J. Remote Sens.* 40 (4), 1248–1274. doi:10.1080/01431161.2018.1524179

Song, S., Bai-Lang, Y. U., Jian-Ping, W. U., and Hong-xing, L. I. U. (2011). Methods for deriving urban built-up area using night-light data: assessment and application. *Remote Sens. Technol. Appl.* 26 (2), 169–176.

Sun, W., Shan, J., Wang, Z., Wang, L., Lu, D., Jin, Z., et al. (2020). Geospatial analysis of urban expansion using remote sensing methods and data: a case study of Yangtze River Delta, China. *Complexity* 2020 (1), 3239471–12. doi:10.1155/2020/3239471

Tang, J., Zhu, Y., Liu, Y., and He, Q. (2022). Evolution and influencing factors of spatial form of typical tourism cities: a case study of Zhangjiajie. *Econ. Geogr.* 42 (1), 221–229. doi:10.15957/j.cnki.jjdl.2022.01.026

Tao, Y., and Ye, R. (2022). Analysis of the spatio-temporal characteristics of Nanjing's urban expansion and its driving mechanisms. *ISPRS Int. J. Geo-Information* 11 (7), 406. doi:10.3390/ijgi11070406

Terfa, B. K., Chen, N., Liu, D., Zhang, X., and Niyogi, D. (2019). Urban expansion in Ethiopia from 1987 to 2017: characteristics, spatial patterns, and driving forces. *Sustainability* 11 (10), 2973. doi:10.3390/su11102973

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

Van der Borght, R., and Barbera, M. P. (2023). How urban spatial expansion influences CO2 emissions in Latin American countries. *Cities* 139, 104389. doi:10.1016/j.cities.2023.104389

Wang, G., Peng, W., Zhang, L., Xiang, J., Shi, J., and Wang, L. (2023). Quantifying urban expansion and its driving forces in Chengdu, western China. *Egypt. J. Remote Sens. Space Sci.* 26 (4), 1057–1070. doi:10.1016/j.ejrs.2023.11.010

Wang, L., and Che, Z. (2023). Research on the evolution of spatial morphology of small cities in the context of tourism development: a case study of the main urban area of chuxiong city. *South Architecture/Nanfang Jianzhu* (7).

Wang, S., Luo, X., Gu, Z., Tang, M., and Zhang, P. (2019). Evolution characteristics and driving mechanism of urban spatial expansion in Shanghai under the background of smart growth. *Econ. Geogr.* 39 (6), 58–65. doi:10.3969/j.issn.1000-0232.2023.07.001

Wang, Z. (2001). A discussion on sustainable urban forms: an introduction to designing cities – towards a more sustainable urban form. *Urban Plan. Abroad* (2), 41–45. doi:10.15957/j.cnki.jjdl.2019.06.007

Wickham, J., Stehman, S. V., Sorenson, D. G., Gass, L., and Dewitz, J. A. (2021). Thematic accuracy assessment of the NLCD 2016 land cover for the conterminous United States. *Remote Sens. Environ.* 257, 112357. doi:10.1016/j.rse.2021.112357

Wu, L., Huang, Z., Cao, F., and Zhou, W. (2015). The evolution of land use pattern and its driving mechanism in ancient towns under the background of tourism urbanization: a case study of zhouzhuang. *Geogr. Res.* 34 (3), 587–598. doi:10.11821/dlyj201503016

Wu, L., Zhu, X., Lawes, R., Dunkerley, D., and Zhang, H. (2019b). Comparison of machine learning algorithms for classification of LiDAR points for characterization of canola canopy structure. *Int. J. Remote Sens.* 40 (15), 5973–5991. doi:10.1080/01431161.2019.1584929

Wu, W., Zhao, S., and Henebry, G. M. (2019a). Drivers of urban expansion over the past three decades: a comparative study of Beijing, Tianjin, and Shijiazhuang. *Environ. Monit. Assess.* 191, 34–15. doi:10.1007/s10661-018-7151-z

Xi, Y., Qiang, L., Yixiong, X., and Jin, C. (2018). Urban sprawl patterns in China based on GlobeLand30 and their impact on ecological land use. *Geogr. Geo-Information Sci.* 34 (3), 5–12. doi:10.3969/j.issn.1672-0504.2018.03.002

Xia, X., Lin, K., Ding, Y., Dong, X., Sun, H., and Hu, B. (2021). Research on the coupling coordination relationships between urban function mixing degree and urbanization development level based on information entropy. *Int. J. Environ. Res. public health* 18 (1), 242. doi:10.3390/ijerph18010242

Xian, S., Li, L., and Qi, Z. (2019). Toward a sustainable urban expansion: a case study of Zhuhai, China. *J. Clean. Prod.* 230, 276–285. doi:10.1016/j.jclepro.2019.05.087

Xiao, R., Yu, X., Xiang, T., Zhang, Z., Wang, X., and Wu, J. (2021). Exploring the coordination between physical space expansion and social space growth of China's urban agglomerations based on hierarchical analysis. *Land Use Policy* 109, 105700. doi:10.1016/j.landusepol.2021.105700

Xie, X., Zhang, L., Sun, H., Chen, F., and Zhou, C. (2021). Spatiotemporal difference characteristics and influencing factors of tourism urbanization in China's major tourist cities. *Int. J. Environ. Res. Public Health* 18 (19), 10414. doi:10.3390/ijerph181910414

Xing, Z., and Guo, W. (2022). A new urban space analysis method based on space syntax and geographic information system using multisource data. *ISPRS Int. J. Geo-Information* 11 (5), 297. doi:10.3390/ijgi11050297

Xu, J., Zhao, J., Zhang, H., and Guo, X. (2020). Evolution of the process of urban spatial and temporal patterns and its influencing factors in Northeast China. *J. Urban Plan. Dev.* 146 (4), 05020017. doi:10.1061/(asce)up.1943-5444.0000606

Xu, Q., Zheng, X., and Zhang, C. (2018). Quantitative analysis of the determinants influencing urban expansion: a case study in Beijing, China. *Sustainability* 10 (5), 1630. doi:10.3390/su10051630

Xu, X., and Liu, J. (2021). Analysis of the dynamics and influencing factors of business environment construction based on entropy value-PLS. *J. Bus. Res.* 63 (4), 10. doi:10.13902/j.cnki.syyj.2021.04.002

Xu, Y, Wang, D, and Sha, M (2019). Evolution and influencing mechanism of urban spatial morphology in Suzhou from a two-dimensional perspective. *Economic Geography*, 39 (4), 75–84. doi:10.15957/j.cnki.jjdl.2019.04.010

Yatong, L., Zhang, L., Shilin, Y., and Qi, X. (2020). Improvement and application of two-dimensional fractal model of urban growth and morphology. *J. Geo-information Sci.* 22 (11), 2140–2151. doi:10.12082/dqxxkx.2020.190640

Yin, B., Wang, L., and Song, Y. (2024). Morphological evolution and driving development: a study on urban spatial expansion and influencing factors in tianjin. *Mod. Urban Stud.* 2, 1–8. doi:10.3969/j.issn.1009-6000.2024.02.001

Yinfeng, X., Wang, D., and Sha, M. (2019). Evolution and influencing mechanism of urban spatial morphology in Suzhou from a two-dimensional perspective. *Econ. Geogr.* 39 (4), 75–84. doi:10.3969/j.issn.1009-6000.2024.02.001

Yu, X. J., and Ng, C. N. (2007). Spatial and temporal dynamics of urban sprawl along two urban–rural transects: a case study of Guangzhou, China. *Landsc. urban Plan.* 79 (1), 96–109. doi:10.1016/j.landurbplan.2006.03.008

Yue, W., Wang, R., and Fan, B. (2013). Spatial pattern of urban expansion: a case study of Hangzhou. *J. ZheJiang Univ. Sci.* 40 (05), 596–605. doi:10.3785/j.issn.1008-9497.2013.05.023

Zhang, H., Liang, C., and Pan, Y. (2022a). Spatial expansion of built-up areas in the beijing–tianjin–hebei urban agglomeration based on nighttime light data: 1992–2020. *Int. J. Environ. Res. Public Health* 19 (7), 3760. doi:10.3390/ijerph19073760

Zhang, K., Meng, H., Ba, M., and Sun, Y. (2022b). Characteristics analysis of urban space expansion in luoyang, China. *J. Geoscience Environ. Prot.* 10 (1), 123–139. doi:10.4236/gep.2022.101009

Zhang, P., Ghosh, D., and Park, S. (2023a). Spatial measures and methods in sustainable urban morphology: a systematic review. *Landsc. Urban Plan.* 237, 104776. doi:10.1016/j.landurbplan.2023.104776

Zhang, Y., Liu, P., and Biljecki, F. (2023b). Knowledge and topology: a two layer spatially dependent graph neural networks to identify urban functions with time-series street view image. *ISPRS J. Photogrammetry Remote Sens.* 198, 153–168. doi:10.1016/j.isprsjprs.2023.03.008

Zhang, Y., Wang, H., Xie, P., Rao, Y., and He, Q. (2020). Revisiting spatiotemporal changes in globalurban expansion during 1995 to 2015. *Complexity* 2020 (1), 1–11. doi:10.1155/2020/6139158

Zhang, Z., and Liu, Y. (2022). Spatial expansion and correlation of urban agglomeration in the yellow river basin based on multi-source nighttime light data. *Sustainability* 14 (15), 9359. doi:10.3390/su14159359

Zhang, Z., Liu, Y., Sheng, S., Liu, X., and Xue, Q. (2024). Evolving urban expansion patterns and multi-scenario simulation analysis from a composite perspective of "social–economic–ecological": a case study of the hilly and gully regions of northern loess plateau in shaanxi Province. *Sustainability* 16 (7), 2753. doi:10.3390/su16072753

Zhong, Y., Lin, A., He, L., Zhou, Z., and Yuan, M. (2020). Spatiotemporal dynamics and driving forces of urban land-use expansion: a case study of the Yangtze River economic belt, China. *Remote Sens.* 12 (2), 287. doi:10.3390/rs12020287

Zhou, R., and Feng, X. (2007). Research progress on urban spatial morphology. *J. Sun Yat-sen Univ.* 27 (12), 295–298.