Journal of Environmental Science and Engineering A 14 (2025) 79-98
doi:10.17265/2162-5298/2025.02.001

Evaluation and Optimization of Regional Ecological Corridor Network Patterns Based on MSPA: A Case Study of Huzhou, China

Guangyuan Feng, Jingxiang Zhang, Xiaopu Bi, Pengfei Zhou and Yihan Xu
School of Architecture and Urban Planning, Nanjing University, Nanjing 210093, China

Abstract: Global climate warming has placed immense pressure on the ecological environment worldwide, and the ecological issues affecting the quality of the living environment have garnered widespread attention. In this context, the question of "how to effectively optimize regional ecological network patterns" has become one of the critical issues that urban and rural planning and ecological geography need to address. This study takes Huzhou, Zhejiang Province, China, as the research area, and uses a combination of landscape type transition matrices and landscape pattern indices to analyze the evolution characteristics of green space landscape patterns from 2017 to 2022. Through geographical detectors and GBDT (Gradient Boosting Decision Tree) algorithms, the study explores the driving factors behind the changes in green space landscape patterns. Based on MSPA (Morphological Spatial Pattern Analysis), key ecological sources in Huzhou are extracted. Using a combination of resistance surfaces and gravity models, ecological corridors and networks are constructed. The study also provides suggestions for the evaluation and optimization of ecological network patterns. The aim is to summarize generalizable patterns of green space landscape evolution and methods for constructing and optimizing regional ecological corridor networks, offering insights and references for the improvement of the living environment and the construction of ecological civilization.

Key words: Green space landscape, MSPA, ecological corridor, network pattern, Huzhou.

1. Introduction

1.1 Research Background

In recent years, global climate warming has intensified, posing a serious threat to human living conditions and the quality of urban and rural living environments worldwide. Excessive greenhouse gas emissions have exacerbated the frequency of extreme climate events, with the melting of polar glaciers occurring at an unexpectedly fast pace. Rising sea levels have significantly increased the risks of flooding, storm surges, and other natural disasters, directly threatening coastal cities and villages. In response to these severe challenges, increasing attention has been paid to issues such as environmental protection and ecological conservation by the international community [1].

Land cover change is a key research topic in the field of environmental protection and sustainable development, significantly impacting urban ecological environments. Among these changes, green space landscapes play an essential role as a vital component of land cover. They are crucial within urban social, economic, and natural ecological network systems, as they not only mitigate the urban heat island effect [2] and optimize the atmospheric environment, but also play a pivotal role in the restoration and protection of urban ecosystem functions [3, 4]. Against this backdrop, both urban and rural planning and ecological geography urgently need to address the core question: "How to effectively optimize regional ecological network patterns?" On the other hand, with the widespread adoption of the concept of sustainable

Corresponding author: Jingxiang Zhang, Ph.D., professor and PhD supervisor, research fields: urban regional development strategy, urban and rural spatial governance.

Foundation: Major Program of National Fund of Philosophy and Social Science of China (24&ZD148).

development, strengthening ecological environment protection through comprehensive, all-region, and full-process approaches, along with green, circular, and low-carbon development, has become an inevitable trend. This is also a pressing administrative measure that governments around the world need to strengthen. Since the 1990s, the Chinese government has actively deployed related environmental protection actions and policies surrounding the "sustainable development strategy", continuously advancing the establishment of a resource-conserving and environmentally friendly society. China has made significant strides in the field of ecological civilization construction. Huzhou, a key regional center in the Yangtze River Delta, a national historical and cultural city, and a model for ecological civilization, has been actively exploring the path of ecological city development. In 2021, Huzhou's "14th Five-Year Plan and 2035 Vision" clearly emphasized the need to implement the "Lucid waters and lush mountains are invaluable assets" concept, prioritize green and ecological development, integrate environmental governance and protection, build ecological corridors, enhance ecological stability, and achieve the creation of a "waste-free city" throughout the urban area.

1.2 Research Objectives and Significance

This study focuses on land cover change in Huzhou, particularly on the evolution of green space landscapes, aiming to analyze its trends, explore the underlying principles and patterns, and gain a comprehensive understanding of the changes in green space landscapes in Huzhou. Furthermore, the research emphasizes the role and importance of key elements such as ecological corridors in the city's green space landscape, exploring their impact on ecological network patterns and proposing optimization suggestions. The goal is to provide scientific and reasonable guidance for the ecological civilization construction in Huzhou, promote its sustainable development, and enhance ecological environmental protection. Through an in-depth investigation of the driving forces behind green space landscape patterns, this research aims to better understand the intrinsic driving mechanisms of landscape pattern changes, providing crucial reference for the rational regulation and layout of landscape cover changes and the protection of ecological systems.

1.3 Literature Review

In the field of spatiotemporal landscape change research, since the concept of landscape ecology was proposed by German scholar Troll, research in areas such as ecological process coupling mechanisms and landscape pattern index analysis has become a core issue within the field [5-9]. In terms of analytical methods, the combination of ecology and 3S technology has fostered powerful tools for exploring the spatiotemporal evolution laws and causal relationships of these processes, such as moving window, dynamic degree, transition matrix, Markov chains, cellular automata, multiple regression analysis, and geographic detectors.

In the field of ecological corridor construction and network pattern research, the "patch-corridor-matrix", "source-sink", and "source-resistance surface-corridor" theoretical models in landscape ecology have provided feasible applications for simulating green habitat and improving ecological connectivity. Regarding ecological network construction methods, the primary theoretical approaches used in constructing ecological corridors include the index method, graph theory, landscape suitability, minimum cost theory, current theory, individual movement models, spatially explicit population models, and thermodynamic metabolic laws [10-12].

2. Study Area, Data Sources, and Research Methods

2.1 Study Area

This study focuses on the entire urban area of Huzhou, Zhejiang Province (including a 2 km buffer zone). Huzhou is located between longitudes 119°14′ E and 120°29′ E, latitudes 30°22′ N and 31°11′ N (Fig. 1).

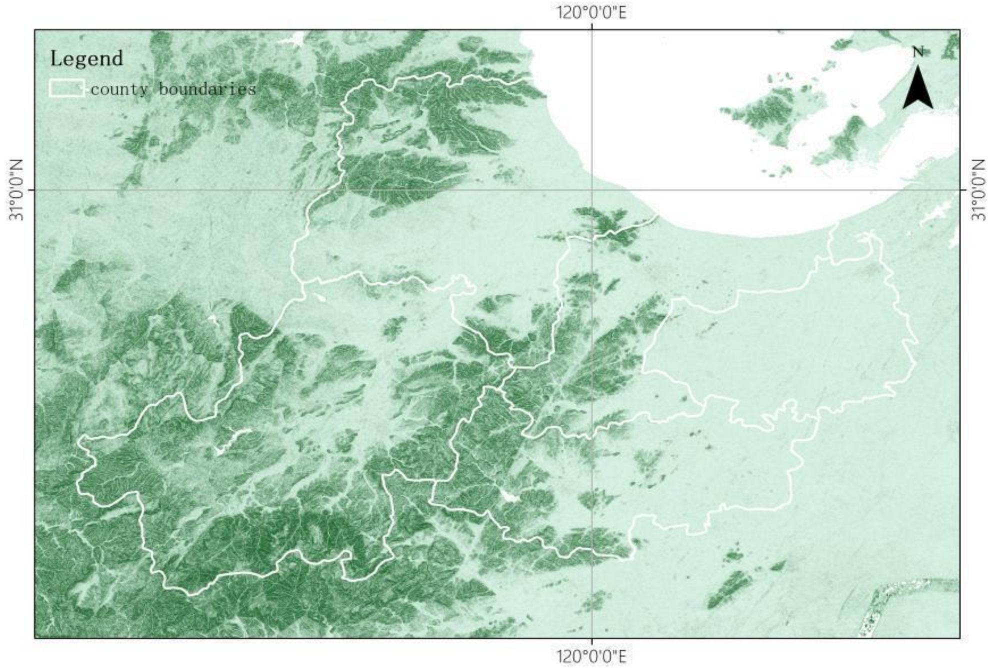

Fig. 1 Study area: Huzhou, China.

It has a longitudinal extent of 126 km and a latitudinal width of 90 km. Geographically, Huzhou is situated in the northern part of Zhejiang Province, bordered by Jiaxing to the east, Hangzhou to the south, Xuancheng to the west, Wuxi to the north, and Taihu Lake to the northeast. The eastern part of Huzhou consists of water-rich plains, while the western part is dominated by mountains and hills, earning the nickname "Five Mountains, One River, and Four Fields" with a total area of 5,820 km^2.

Huzhou is located in the northern subtropical monsoon climate zone. The climate is characterized by distinct seasons, significant monsoonal influences, abundant rainfall coinciding with the hot season, moderate temperatures, and relatively low sunlight. The city has a mild climate with high humidity, and the varied topography creates vertical climatic differences. Huzhou is in the upper reaches of the Taihu Lake Basin, and the city is divided into three major water systems (Tiao Creek, Grand Canal, and Changxing systems), providing ample water resources.

2.2 Data Sources

The primary data for this study are the land use data of Huzhou from 2017 to 2022 (Sentinel-2) sourced from the following website: https://livingatlas.arcgis.com/landcoverexplorer/. Other data include: administrative boundary data for Chinese provinces and cities, river/road/railway data, DEM (Digital Elevation Model) elevation data, GDP (Gross Domestic Product) and population data by region, and annual precipitation and average annual temperature raster data. Using tools such as ArcGIS 10.8, Geographic Detectors, Python, GuidosToolbox, and Conefor 2.6, the study aims to analyze the spatiotemporal changes in the green space landscape of Huzhou and the driving factors behind these changes. Based on this analysis, key ecological sources will be extracted, a comprehensive resistance surface will be constructed, and improvements to the ecological network (corridors and nodes) will be made.

2.3 Research Methods

The overall research approach is divided into three main parts: (1) Spatiotemporal analysis of green space landscapes; (2) Analysis of driving factors of landscape changes; (3) Ecological network pattern optimization. The specific research methods include:

2.3.1 Spatiotemporal Analysis Methods

(1) Landscape dynamic index

The landscape dynamic index is a metric used to measure the rate of change of a single landscape type over a period of time. It can be used to assess and compare the speed and extent of landscape changes across different periods, offering an intuitive analysis of the changes occurring within the study time frame for a specific landscape type. The formula for calculating the landscape dynamic index is:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \tag{1}$$

where: K is the landscape dynamic index, U_a and U_b are the area of a given landscape type at the initial and final time points, T is the time span of the study, measured in years.

(2) Landscape type transition matrix

The landscape type transition matrix is a quantitative description of changes in landscape structure, capturing the area changes of different landscape components and exploring the rules of landscape type transitions. The formula for the landscape type transition matrix is:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & S_{13} & \cdots & S_{1n} \\ S_{21} & S_{22} & S_{23} & \cdots & S_{2n} \\ S_{31} & S_{32} & S_{33} & \cdots & S_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & S_{n3} & \cdots & S_{nn} \end{bmatrix} \tag{2}$$

where: S is the area of the landscape type, n is the number of landscape types, i and j refer to the landscape types at the initial and final time periods, S_{ij} represents the area change corresponding to the transition of landscape type i to landscape type j from the start to the end of the study period.

2.3.2 Driving Factor Analysis Methods

Geographical Detector is a statistical method used to study spatial heterogeneity in data by comparing the variance differences within the entire study area and its stratified subregions. It measures the association between dependent and independent variables, including both linear and nonlinear statistical relationships, to reveal potential causal relationships. This method has been widely applied in various research fields, such as urbanization processes and ecology and environment studies.

The basic idea behind Geographical Detector is as follows: the study area is divided into regions or strata, and the relationship between the intra-variance within each layer and the total variance of the entire area is compared. If an independent variable has a significant influence on a dependent variable, the spatial distributions of the independent and dependent variables should exhibit statistical similarity. This method can employ various discrete forms of partitioning, such as time and attribute categorization, to measure the spatial heterogeneity of data, the spatial attribution of element changes, and explore spatial patterns. For this study, three modules from the four provided by Geographical Detector were selected: differentiation and factor detection, ecological detection, and interaction detection. These modules were used to investigate the impacts of various driving factors on the spatial distribution changes of green space landscapes from the perspectives of causality, interaction intensity, and differences in driving mechanisms.

2.3.3 GBDT (Gradient Boosting Decision Tree) Algorithm

GBDT is an iterative decision tree algorithm that constructs a series of weak learners (i.e., multiple decision trees) and combines the results of these trees to produce the final prediction output. The algorithm formula is as follows:

$$F_t(x) = F_{t-1}(x) + \sum\nolimits_{i=1}^{n} w_i h_i(x) \tag{3}$$

where $F_t(x)$ is the model output after the t-th iteration, $F_{t-1}(x)$ is the model output after the t-1-th iteration, w_i is the weight of the i-th sample in the t-th iteration, $h_i(x)$ is the output of the i-th weak classifier (decision tree) in the t-th iteration, and n is the number of samples.

In each iteration, GBDT adjusts the weight of each sample and the output of the weak classifiers, progressively optimizing the model's predictive performance. Through continuous iteration, GBDT can incrementally enhance the model's performance, making it highly effective in both classification and regression tasks.

2.3.4 Ecological Network Construction Methods

(1) Landscape Connectivity

Landscape connectivity is an index used to measure the spatial connection and continuity of corridors and matrices in regional ecological landscapes, which is critical for ecological processes. It describes the spatial structural features of landscapes and their ecological functions, including species conservation, material transfer, and energy exchange.

(2) Percolation Theory

Originally describing the movement of fluids in porous media, percolation theory is applied in landscape ecology to express the diffusion ecological processes of species based on the flow of energy and materials. In the percolation process, there is typically a percolation threshold. When the permeability of fluid in a porous medium exceeds this threshold (0.5928), effective percolation occurs.

(3) MCR (Minimum Cumulative Resistance) Model

The MCR model is a method used to describe and predict the movement of objects or individuals in space. This model is commonly applied in fields such as animal migration, urban planning, and traffic flow. In this model, a moving object (e.g., an animal or vehicle) is assumed to choose a path that minimizes the cumulative resistance encountered during its movement. Resistance refers to the difficulties or obstacles faced by the object when moving through different environments, which may include terrain, road conditions, and the distribution of other objects.

(4) Gravity Model

The Gravity Model is a mathematical formula used to quantitatively assess the degree of interaction between different elements in space. In the study of ecological networks, the Gravity Model is widely used to evaluate the importance of different ecological source areas by incorporating the cumulative resistance values and migration distances of habitat patches. The formula is as follows:

$$G_{ab} = \frac{N_a N_b}{D_{ab}^2} = \frac{L_{\max}^2 \ln(S_a)\ln(S_b)}{L_{ab}^2 P_a P_b} \tag{4}$$

where G_{ab} represents the interaction gravity between patches a and b, N_a and N_b are the quantized weight values, D_{ab} is the ecological corridor resistance value, $L_{\max}$ is the maximum cumulative resistance, S_a and S_b are the patch areas, L_{ab} is the cumulative resistance of the patch, and P_a and P_b are the individual resistance values of the patches.

3. Spatial-Temporal Analysis of Green Space Landscapes in Huzhou

Green space landscapes, as an essential component of land cover and a natural element of composite ecological networks [13], are crucial for optimizing air quality [14] and providing ecological services [15-16]. The temporal and spatial variations in these landscapes have a significant impact on urban ecological changes [17]. This section focuses on the spatial-temporal changes of green space landscapes in Huzhou from 2017 to 2022, analyzing the patterns within this period.

3.1 Spatial Structure Change Analysis

The area distribution of various land uses in Huzhou from 2017 to 2022 shows the following trends: (1) Water bodies, forests, farmland, and built-up areas are the main types of land use, together accounting for approximately 98% of the land use in the city; (2) Water bodies, forests, and grasslands, as the main landscape types, show minimal fluctuations, with almost no significant increase or decrease in their areas; (3) Farmland and built-up areas exhibit a reciprocal shift over the six years. The proportion of farmland decreased from 18.48% to 14.76%, while built-up areas increased from 21.67% to 26.10% (Fig. 2).

The analysis indicates that the expansion of urban areas mainly comes from the conversion of farmland into construction land.

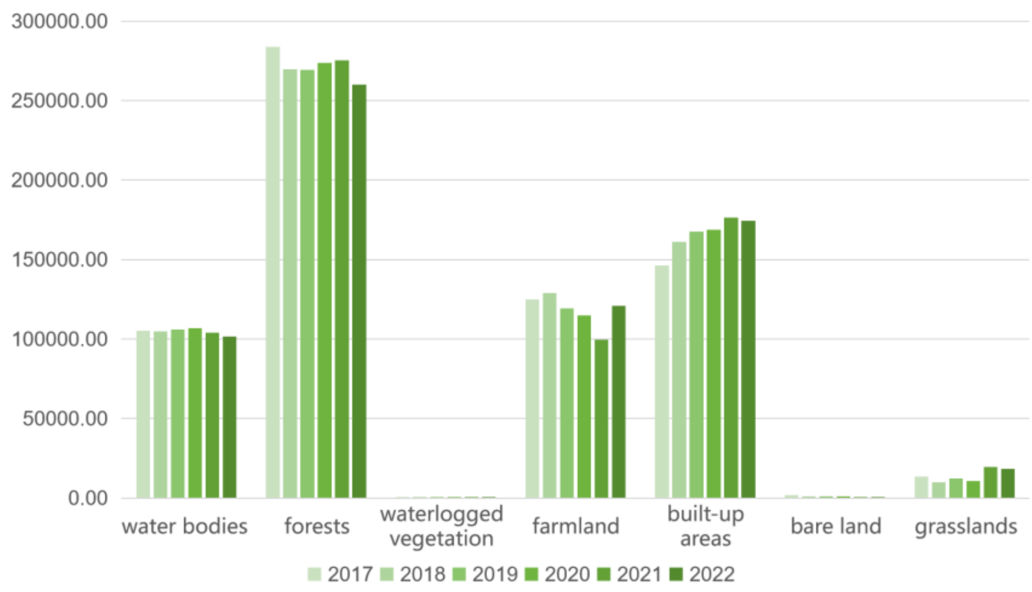

Fig. 2 Changes in land use types in Huzhou from 2017 to 2022.

3.2 Dynamics of Single Landscape Types

Considering the relative area proportions, the following changes can be observed: (1) Land types with smaller areas, such as waterlogged vegetation, bare land, and grasslands, show the largest relative fluctuations annually; (2) The areas of water bodies and forests fluctuate less, but both exhibit a declining trend to some extent; (3) Farmland area decreased continuously from 2018 to 2021, with an accelerated decline, but rebounded in 2022; (4) Built-up areas showed a generally steady increase, with a brief decline in 2022; (5) The overall trends in farmland and built-up area changes appear complementary (Table 1).

3.3 Landscape Type Transition Matrix Analysis

Taking the landscape type transition matrix from 2017 to 2018 as an example: (1) During this period, a large amount of farmland was converted into built-up areas, which is the primary cause of the increase in built-up area; (2) To compensate for the loss of farmland, large areas of forests and grasslands were converted into farmland, with significant conversions also occurring between farmland and water bodies; (3) This phenomenon indicates that the primary source of large-scale changes in landscape types is the expansion of built-up areas taking over farmland, while natural landscapes such as water bodies, forests, and grasslands were destroyed to make way for the restoration of farmland (Table 2).

However, from 2021 to 2022: (1) The land conversion trend shifted, with farmland expanding, and large areas of water bodies, forests, and grasslands were converted into farmland; (2) Compared to 2017-2018, the areas of water bodies, forests, and grasslands increased significantly, indicating effective ecological protection, with noticeable improvements and enhancements in the green space environment (Table 3).

3.4 Landscape Pattern Change Analysis

Landscape pattern indices are widely used to analyze ecological effects, reflecting the changes in different landscape elements within the ecological space. These indices reveal landscape heterogeneity and the orderliness of landscape patches, serving as important spatial analytical methods to assess landscape patterns and ecological processes. To more comprehensively evaluate the landscape ecology of Huzhou, five landscape pattern indices were selected to describe the changes in land cover in the city (Table 4).

Table 1 Dynamics of single landscape types.

Landscape types	Area (km^2)						2017-2018	2018-2019	2019-2020	2020-2021	2021-2022
	2017	2018	2018	2020	2021	2022					
Water bodies	105,244.5	104,884.6	106,149.5	106,810.5	103,820.6	101,404.5	-0.34%	1.21%	0.62%	-2.80%	-2.33%
Forests	283,733.0	269,611.6	269,135.6	273,636.1	275,238.5	260,046.1	-4.98%	-0.18%	1.67%	0.59%	-5.52%
Waterlogged vegetation	139.2	37.7	53.3	101.9	87.0	61.9	-72.89%	41.21%	91.25%	-14.66%	-28.87%
Farmland	124,874.4	129,019.2	119,272.5	114,681.3	99,713.0	120,967.5	3.32%	-7.55%	-3.85%	-13.05%	21.32%
Built-up areas	146,402.9	160,913.3	167,530.7	168,741.4	176,321.9	174,295.5	9.91%	4.11%	0.72%	4.49%	-1.15%
Bare land	1,653.3	1,172.9	1,083.0	828.9	708.3	651.5	-29.06%	-7.67%	-23.47%	-14.54%	-8.02%
Grasslands	13,537.3	9,945.0	12,360.4	10,783.5	19,694.0	18,157.2	-26.54%	24.29%	-12.76%	82.63%	-7.80%

Table 2 Landscape type transition matrix from 2017 to 2018.

2017	2018							
	Water bodies	Forests	Waterlogged vegetation	Farmland	Built-up areas	Bare land	Grasslands	Total (ha)
Water bodies	98,520.86	180.8	9.62	3,205.31	3,093.14	104.13	129.3	105,243.59
Forests	240.21	262,717.91	5.94	13,083.34	5,117.3	0.87	2,564.78	283,730.43
Waterlogged vegetation	20.65	4.42	6.27	34.12	66.2	0	7.54	139.2
Farmland	4,919.43	2,263.15	4.86	106,587.07	10,044.46	2.82	1,051.44	124,873.25
Built-up areas	897.64	1,025.09	2.97	3,271.41	140,601.59	118.87	483.93	146,401.57
Bare land	66.16	36.45	0.04	118.14	343.49	948.06	140.92	1,653.26
Grasslands	220.28	3,317.64	8.9	2,701.41	1,635.48	5.06	5,648.15	13,537.13
Total (ha)	104,885.23	269,545.52	38.6	129,000.81	160,901.85	1,179.81	10,026.32	675,578.95

Table 3 Landscape type transition matrix from 2021 to 2022.

2021	2022							
	Water bodies	Forests	Waterlogge d vegetation	Farmland	Built-up areas	Bare land	Grasslands	Total (ha)
Water bodies	95,557.26	131.77	15.37	6,029.95	1,834.09	43.37	212.88	103,824.69
Forests	278.27	251,697.56	9.42	11,072.79	4,063.31	0	8,128.01	275,249.38
Waterlogged vegetation	36.43	5.45	19.04	14.61	1.88	0	9.56	86.97
Farmland	3,243.03	799.13	4.13	91,188.21	3,509.55	0.07	972.84	99,716.98
Built-up areas	2,052.42	1,329.22	5.05	8,176.13	163,283.64	142.69	1,339.5	176,328.87
Bare land	41.25	1.71	0	27.25	125.31	465.35	47.48	708.35
Grasslands	199.87	6,091.46	8.85	4,463.3	1,483.56	0.04	7,447.68	19,694.76
Total (ha)	101,408.55	260,056.4	61.86	120,972.29	174,302.39	651.53	18,157.95	675,610.97

Table 4 Changes in landscape pattern indices in Huzhou from 2017 to 2022.

Landscape pattern indices	2017	2018	2019	2020	2021	2022
LPI (Largest Patch Index)	0.681607	0.693069	0.687401	0.679942	0.658887	0.439282
CPD (Patch Density) (per square kilometer)	5.952919	5.142777	5.419219	5.476597	5.132843	6.196476
CED (Edge Density)	0.00525	0.005058	0.005258	0.005288	0.005348	0.006066
MPI (Mean Proximity Index)	70.86217	68.78646	73.56654	70.23863	82.86266	96.46635
MPA (Mean Patch Area)	85,576.88	93,122.16	88,987.4	88,980.62	98,441.56	76,901.11

(1) LPI: This index indicates the proportion of the largest patch in the total landscape area. From 2017 to 2022, the LPI value significantly decreased, suggesting an increase in landscape fragmentation, especially in 2022, which may indicate a marked rise in fragmentation during that year.

(2) CPD: This index measures the number of patches per unit area. From 2017 to 2022, patch density fluctuated, reaching its highest value in 2022, which suggests an increase in the number of patches, potentially indicating higher landscape fragmentation.

(3) CED: This index measures the total length of landscape edges per unit area. From 2017 to 2022, this index steadily increased, indicating more landscape edges, which could also be a sign of increasing fragmentation.

(4) MPI: This index represents the average distance between a patch and its nearest neighbor. From 2017 to 2022, the MPI value generally increased, suggesting that the average distance between patches grew, indicating greater isolation between patches.

(5) MPA: This index indicates the average size of each patch. The data showed fluctuations from 2017 to 2022, with a significant decrease in 2022, which could be associated with the appearance of much smaller patches.

The analysis of these indices indicates that from 2017 to 2022, the landscape structure of Huzhou became more fragmented and dispersed. The number of patches increased, patch isolation grew, the size of the largest patch decreased, and the overall continuity and integrity of the landscape may have diminished. This trend could be related to human activities such as urbanization and agricultural expansion, potentially having adverse effects on wildlife habitats and ecological processes.

3.5 Summary

From 2017 to 2022, urban built-up areas in Huzhou expanded continuously, occupying a significant amount of former farmland. Meanwhile, natural landscapes (water bodies, forests, and grasslands) remained relatively stable, reflecting a trend of farmland being replaced by urbanization. However, this trend changed significantly in 2022, with a large amount of other land types being converted into farmland. The changes in the transition matrix over the six years suggest a possible shift in agricultural recovery or land management policies, potentially influenced by the relevant requirements of the "Three Zones and Three Lines" planning. According to multiple landscape pattern indices, the increasing fragmentation of the landscape suggests that large continuous natural areas are becoming more fragmented, which may reflect the rise of small-scale land development.

Overall, Huzhou's land use and landscape patterns experienced significant changes between 2017 and 2022, particularly the expansion of urban areas and the reduction of farmland, which may have implications for the ecological environment. At the same time, this also indicates the intervention of natural resource management and urban development planning in transforming land landscape types.

4. Analysis of the Driving Forces of Green Space Landscape Changes

Research on the driving factors of green space landscape changes, including the identification of driving factors, the ecological environment evolution process, and their mechanisms, can effectively predict the driving effects and spatial distribution of future green space landscapes. This research provides scientific evidence for urban ecological civilization construction decisions and planning [18-21].

4.1 Driving Factors and Minimum Unit Scale

4.1.1 Selection of Driving Factors

Numerous studies have shown that the driving factors of regional green space landscape changes primarily come from natural and socio-economic aspects [22]. Natural environmental factors, such as elevation, slope, and precipitation, significantly impact long-term green space spatial changes. Conditions like sunlight and temperature largely determine plant species and growth within cities. In such long-term ecological processes, the cumulative effect of natural factors determines the spatial pattern of urban green spaces. Social factors, including economic and policy planning factors, are primarily derived from statistical yearbooks, consisting of a series of basic economic indicators.

This study involves the changes in the urban landscape of Huzhou over a 6-year period, where both natural and socio-economic factors have significant impacts on green space. After considering all aspects, the green space landscape changes from 2017 to 2022 were selected as the dependent variable (*Y*), and 11 representative driving factors were selected as independent variables (*X*).

4.1.2 Selection of Minimum Unit Scale

Considering the size of the study area, the scale starts at 3,000 m, with each step increasing by 1,000 m. A total of 5 experiments were conducted, with experimental scales of 3,000 m, 4,000 m, 5,000 m, 6,000 m, and 7,000 m. The data for each scale were processed into grids and analyzed using geographical detectors, yielding *q*-values for each driving factor corresponding to the five experiments. The results show that as the scale increases, the *q*-values of driving factors increase significantly between 3,000 m and 5,000 m, indicating that the explanatory power of driving factors on green space changes strengthens with the increasing scale, with the effect becoming more pronounced as the scale increases. At the 6,000 m scale, a turning point appears for some driving factors, after which the explanatory power of several factors decreases, which hinders the display of overall spatial relationships in the data (Fig. 3).

In summary, the 6,000 m scale provides the best explanatory effect for the analysis of driving forces on green space, with stable spatial stratification, making it the optimal scale for driving force analysis.

4.2 Spatial Grid Processing of Data

For vector data (dependent variable *Y*): First, a 6,000 m fishnet and corresponding fishnet points were established using ArcGIS software. Operations such as patch fusion, fishnet clipping, and spatial linking were performed on the extracted green space vector data to obtain the green space distribution maps for 2017 and 2022 at the 6,000 m grid scale (Fig. 4). The total area of all green space patches in each grid cell was calculated for the corresponding data of each period, and the area changes between 2017 and 2022 were

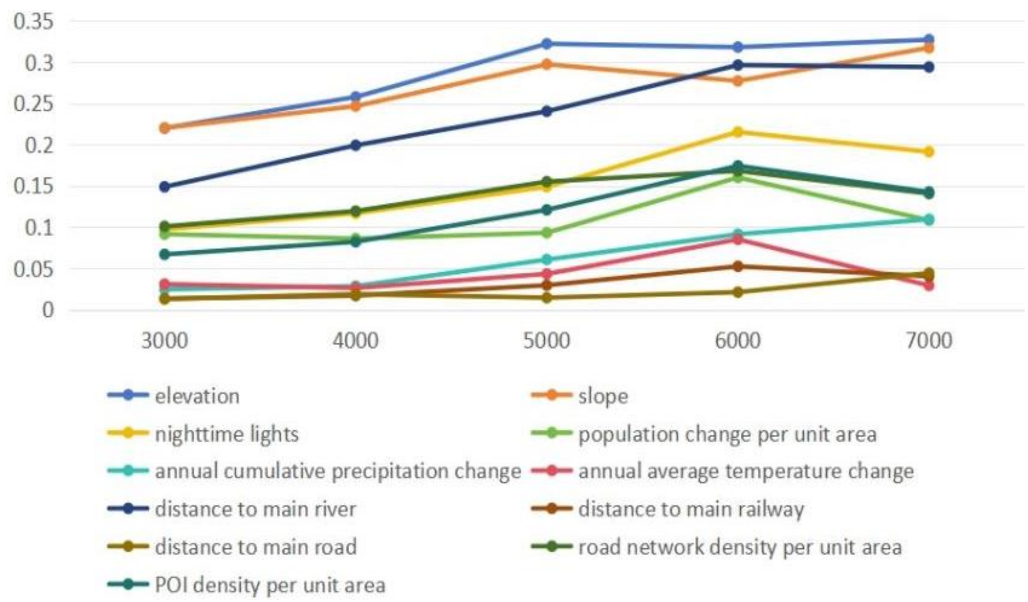

Fig. 3 Explanation power of each factor with scale variation.

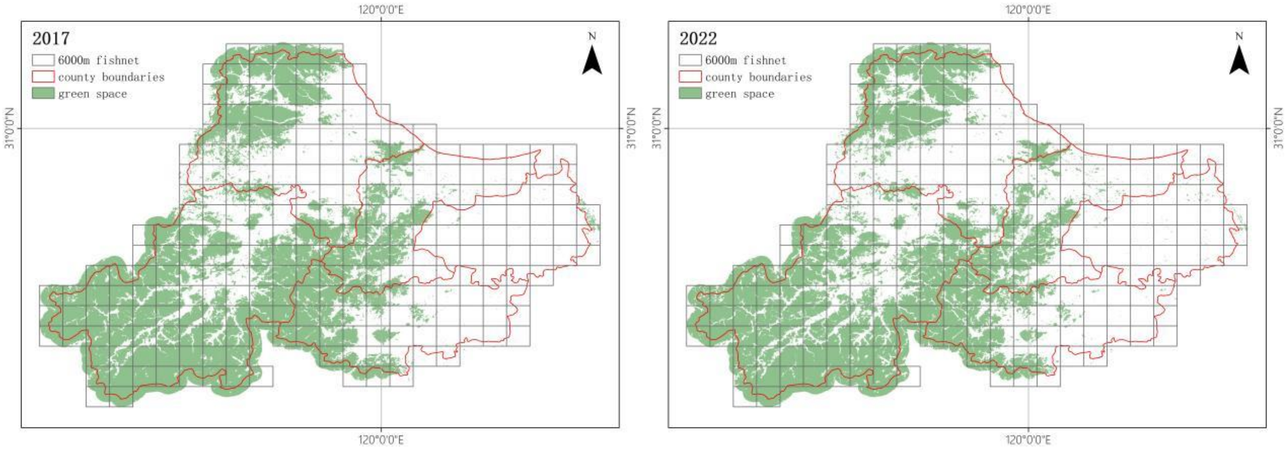

Fig. 4 Vector data spatial grid processing.

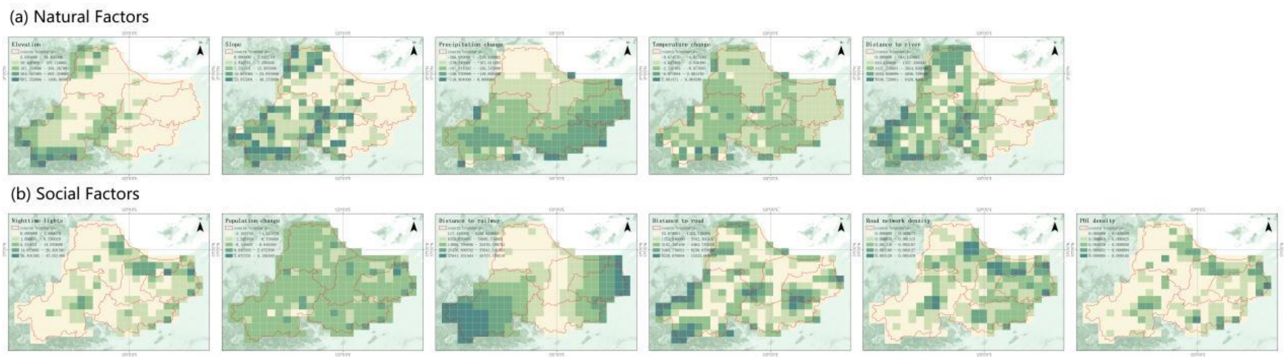

Fig. 5 Raster data spatial grid processing.

computed as the dependent variable for the green space driving force analysis. These values were assigned to the fishnet point attribute table to construct the driving force analysis database for the *Y* field.

For raster data (independent variable *X*), spatial grid processing was also conducted (Fig. 5).

4.3 Geographical Detector Analysis

4.3.1 Factor Detection

Spatial distribution raster maps of each driving factor (*X*) were created, and values were extracted to the point tool and assigned to the fishnet point attribute table. The natural breaks method was used to discretize the data into five categories, matching the fields of driving factor *X* in the driving force analysis database. Geographical detectors were used for analysis [23]. The factor detection results show: (1) The explanatory power of each factor (*X*) on the green space change (*Y*) decreases in the following order: elevation > distance to main river > slope > nighttime lights > POI (Point of Interest) density per unit area > road network density per unit area > population change per unit area > annual cumulative precipitation change > annual average temperature change > distance to main railway > distance to main road. (2) Both natural and social factors affect green space landscape changes, with natural factors having a greater influence (Table 5).

4.3.2 Interaction Detection

The interaction detection results (Table 6) show that the explanatory power of each factor on green space change is statistically significant. Significant double-factor enhancement effects exist between natural factors (elevation, slope, distance to main river) and socio-economic factors (nighttime lights, POI density, road network density), indicating that both natural and socio-economic factors significantly influence the green space landscape pattern in the study area, and both are indispensable. Furthermore, the interaction

Table 5 Factor detection results for driving factors at optimal scale.

Factor types	Driving factors	*q* statistical values	*p* values
Natural factors	elevation	0.312840	0.000
	slope	0.277183	0.000
	annual cumulative precipitation change	0.091222	0.003506
	annual average temperature change	0.085020	0.005514
	distance to main river	0.296338	0.000
Social factors	nighttime lights	0.215236	0.000
	population change per unit area	0.160063	0.000
	distance to main railway	0.052276	0.058529
	distance to main road	0.020994	0.444631
	road network density per unit area	0.168085	0.000
	POI density per unit area	0.174195	0.000

Table 6 Interaction detection results for driving factors at optimal scale.

	Elevation	slope	Nighttime lights	Population change per unit area	Annual cumulative precipitation change	Annual average temperature change	Distance to main river	Distance to main railway	Distance to main road	Road network density per unit area	POI density per unit area
Elevation	0.32										
slope	*0.45	0.28									
Nighttime lights	*0.46	*0.43	0.22								
Population change per unit area	*0.45	*0.43	*0.34	0.16							
Annual cumulative precipitation change	0.47	0.41	0.40	0.36	0.09						
Annual average temperature change	0.45	0.39	0.31	0.29	0.27	0.09					
Distance to main river	*0.43	*0.47	*0.39	0.48	0.42	0.41	0.30				
Distance to main railway	0.40	0.39	0.33	0.29	0.19	0.27	0.41	0.05			
Distance to main road	0.42	0.41	0.31	0.25	0.28	0.20	0.39	0.17	0.02		
Road network density per unit area	*0.40	*0.40	*0.34	*0.32	0.38	0.33	*0.38	0.28	0.24	0.17	
POI density per unit area	*0.41	*0.44	*0.32	*0.32	0.37	0.27	*0.40	0.28	0.23	0.37	0.17

* for dual factor enhancement, no * for non-linear enhancement (better enhancement effect).

between natural and socio-economic factors has a coupling effect, allowing a better explanation of the driving mechanism behind green space landscape changes.

4.3.3 Ecological Detection

The ecological detection results reveal that: (1) Among the three natural factors and three socio-economic factors with significant interactions, elevation and slope show significant spatial distribution differences with the three socio-economic factors. (2) There is no significant spatial distribution difference between the distance to the main river cluster and the three socio-economic factors, indicating that areas with high economic vitality and construction density are mostly located in regions with low elevation and slope, and near main rivers (Table 7).

4.4 GBDT Algorithm Analysis

4.4.1 Relationship between Major Influencing Factors and Green Space Change

The GBDT algorithm was used to further explore the direction of influence of various factors and the non-linear relationship between major influencing factors and green space landscape changes [24].

The relationships between various influencing factors and green space changes are shown in Fig. 6. The X-axis represents green space change, with the color of the points reflecting the size of the influencing factors, with red indicating high values and blue indicating low values. From the figure, it can be seen that elevation, nighttime lights, and POI density show a positive correlation with green space change, while the distance to water systems shows a negative correlation with green space change.

4.4.2 Non-linear Relationship between Natural Factors and Green Space Change

According to the geographical detector analysis, elevation and distance to water systems are the most closely related natural factors to green space landscape changes (Fig. 7):

(1) Elevation changes have a significant threshold effect on green space change. When elevation values range from 20 to 280, elevation changes show a significant positive correlation with green space increase or decrease. However, when elevation exceeds 280, the impact of elevation changes on green space increase or decrease becomes insignificant.

Table 7 Ecological detection significance results for driving factors at optimal scale.

	Elevation	slope	Nighttime lights	Population change per unit area	Annual cumulative precipitation change	Annual average temperature change	Distance to main river	Distance to main railway	Distance to main road	Road network density per unit area	POI density per unit area
Elevation											
slope	N										
Nighttime lights	N	N									
Population change per unit area	Y	N	N								
Annual cumulative precipitation change	Y	Y	N	N							
Annual average temperature change	Y	Y	N	N	N						
Distance to main river	N	N	N	N	Y	Y					
Distance to main railway	Y	Y	N	N	N	N	Y				
Distance to main road	Y	Y	Y	N	N	N	Y	N			
Road network density per unit area	Y	N	N	N	N	N	N	N	N		
POI density per unit area	Y	N	N	N	N	N	N	N	N	N	

Y represents a significant difference in the spatial distribution of the dependent variable between the two factors, while N represents no significant difference.

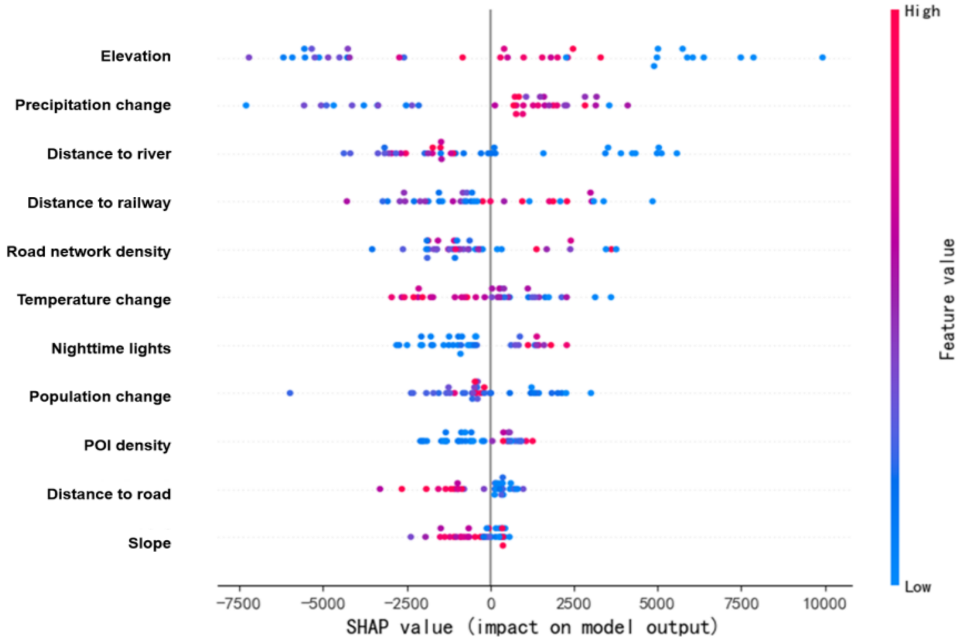

Fig. 6 Relationship between major influencing factors and green space change.

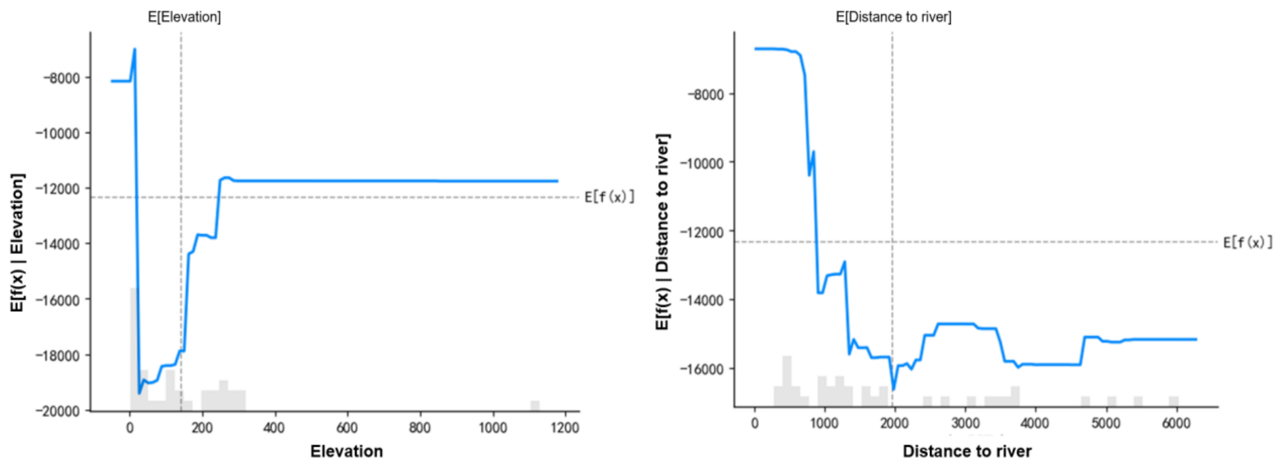

Fig. 7 Non-linear relationship between natural factors and green space change.

(2) The distance to river has a significant negative impact on green space change. When the distance to river is between 0 and 2,000 m, the farther the distance, the more significant the reduction in green space. When the distance is between 2,000 and 6,000 m, the green space change fluctuates within a certain range and gradually becomes more stable.

4.4.3 Non-linear Relationship between Socio-Economic Factors and Green Space Change

According to the geographical detector analysis, nighttime lights and POI density are the socio-economic factors most closely related to green space landscape changes (Fig. 8):

(1) Nighttime lights have a positive effect on green space change, with a significant threshold effect. When nighttime light values are between 0 and 7, green space increases significantly as nighttime light increases. When light values exceed 7, the change in light value no longer has a significant effect on green space.

(2) When POI density is low, an increase in the number of POIs has a significant positive effect on green space change. As POI density further increases, the impact on green space change becomes negative and eventually stabilizes.

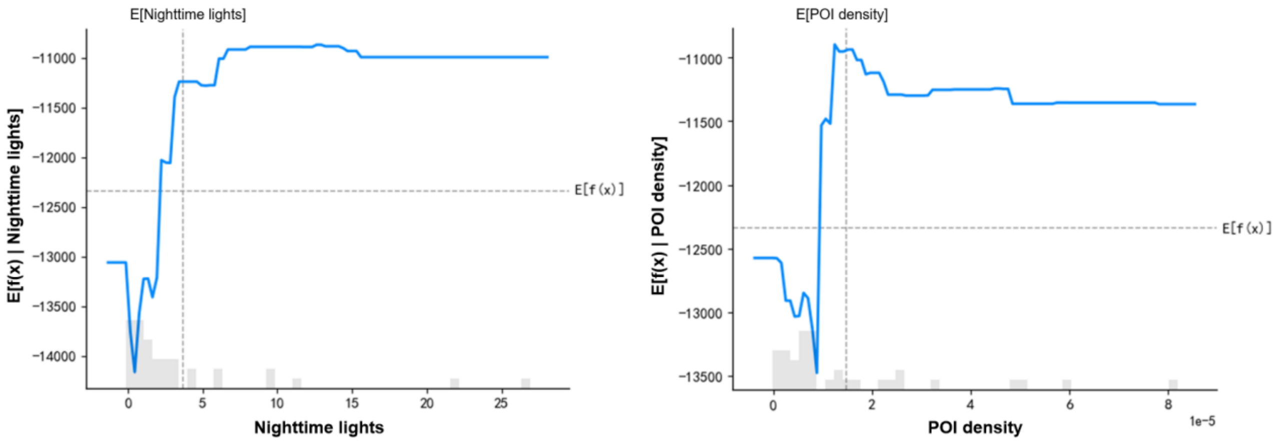

Fig. 8 Non-linear relationship between socio-economic factors and green space change.

This result may stem from the indirect reflection of tourism development's role in promoting ecological protection through changes in nighttime lighting and POI density. In areas with better economic vitality and infrastructure, eco-tourism development has improved ecological protection. However, as economic activities increase, their negative impact on ecological protection becomes more apparent, leading to a non-linear relationship between economic development and green space change.

5. Ecological Network Pattern Optimization in Huzhou

5.1 Selection of Ecological Source Areas

5.1.1 Extraction of Core Green Areas

The green ecological network is formed by connecting fragmented patches using linear green corridors, based on the "patch-corridor-matrix" theory, creating a high-connectivity organic network. This network emphasizes a comprehensive consideration of landscape structure and function, ecological processes, and the impacts on living and production spaces. Ecological patches are core elements within the green ecological network that require focused protection. Ecological source areas are crucial nodes for the migration of species and energy transfer, linking various ecological patches and providing migration corridors for species. They enhance connectivity between different landscapes, facilitating ecological processes such as animal reproduction, migration, and plant habitation and diffusion, and maintaining the environmental balance of biological habitats within the landscape [25-26].

Based on MSPA (Morphological Spatial Pattern Analysis) [27], core areas within green patches with minimal disturbance were identified using the Guidos Tool Box software.

As shown in Table 8, the results are as follows: (1) The total size of the green landscape in Huzhou is relatively large, accounting for 41.07% of the total study area. (2) The core type occupies the largest proportion in the green landscape at 88.87%, accounting for 36.5% of Huzhou's entire landscape. The second-largest area is the edge type, accounting for 6.58%, serving as a transition zone between the core habitat patches and other non-green patches. (3) The proportions of islet, perforation, loop, bridge and branch types are relatively small.

5.1.2 Extraction of Ecological Source Areas

(1) Delimiting the Taihu Buffer Zone

Considering the ecological and natural value of the Taihu water system, this study proposes to delimit a buffer zone for the Taihu ecological source area, aligning with the green development philosophy guiding the Taihu Basin's ecological protection and high-quality development strategy [28]. A 4,000 m buffer zone is drawn around the main shoreline of Taihu (Fig. 9), to select significant ecological patches within the Taihu ecological landscape as source areas.

Table 8 MSPA landscape type area and proportion statistics.

Landscape type	Core	Islet	Perforation	Edge	Loop	Bridge	Branch
Area (ha)	246,612.99	1,664.51	6,179.39	18,265.4	1,230.47	935.986	2,595.43
Proportion of green landscape	88.87%	0.60%	2.23%	6.58%	0.44%	0.34%	0.94%
Proportion of the entire landscape	36.50%	0.25%	0.91%	2.70%	0.18%	0.14%	0.38%

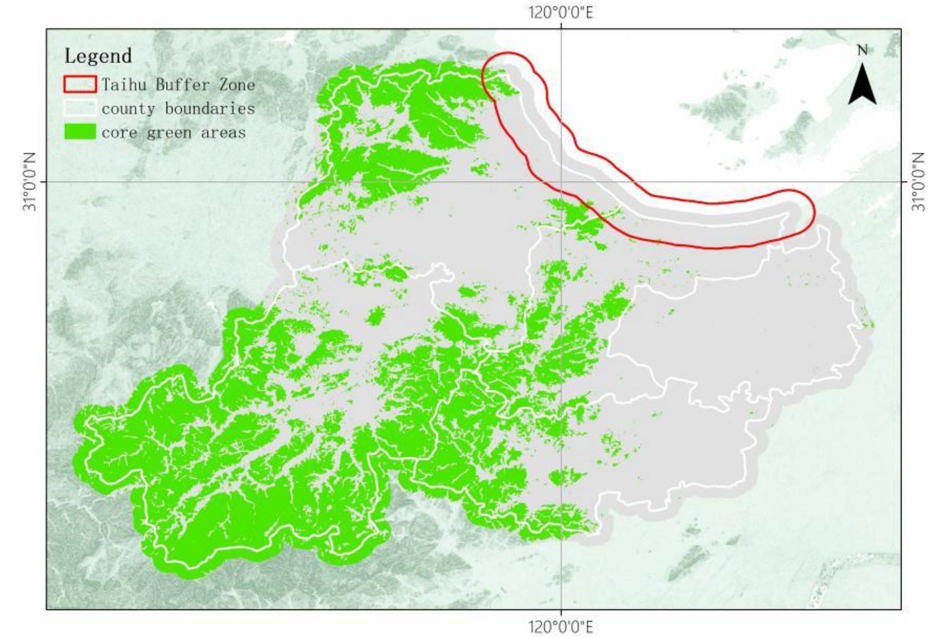

Fig. 9 Taihu ecological source area buffer zone map.

(2) Extracting Ecological Source Areas

Using landscape connectivity and species permeability theory, the permeability threshold (0.5928) was chosen as a key parameter in calculating the connectivity index. The Conefor 2.6 software was employed to calculate the connectivity index for each core area patch. Based on species dispersal ability, probability, and response capacity, 45 core area patches with a PC value greater than 0.1 were selected as ecological source areas. Considering patch area, connectivity, and the influence of the Taihu buffer zone, 10 core patches were identified as important ecological source areas, while the others were categorized as general ecological source areas (Fig. 10).

5.2 Construction of Resistance Surface

Based on the geographic detector analysis and relevant studies on ecological network research [29], resistance factors and their corresponding resistance values were comprehensively considered. Six factors—landscape type, elevation, slope, human activity intensity, railway, and highway—were selected to construct a composite resistance surface. Landscape type was assigned a weight of 0.4, while the remaining 0.6 weight was distributed among the other factors based on their geographic detector's *q*-values in an inverse proportional manner. The specific weight distribution is shown in Table 9, and the assignment rules for each resistance factor are detailed in Table 10.

Using ArcGIS 10.6 software, resistance surfaces for six factors were calculated, including landscape type resistance, elevation resistance, slope resistance, human activity intensity resistance, major highway resistance, and major railway resistance. By applying the weight distribution table in the raster calculator, the composite resistance surface for the green ecological network in Huzhou was constructed (Fig. 11).

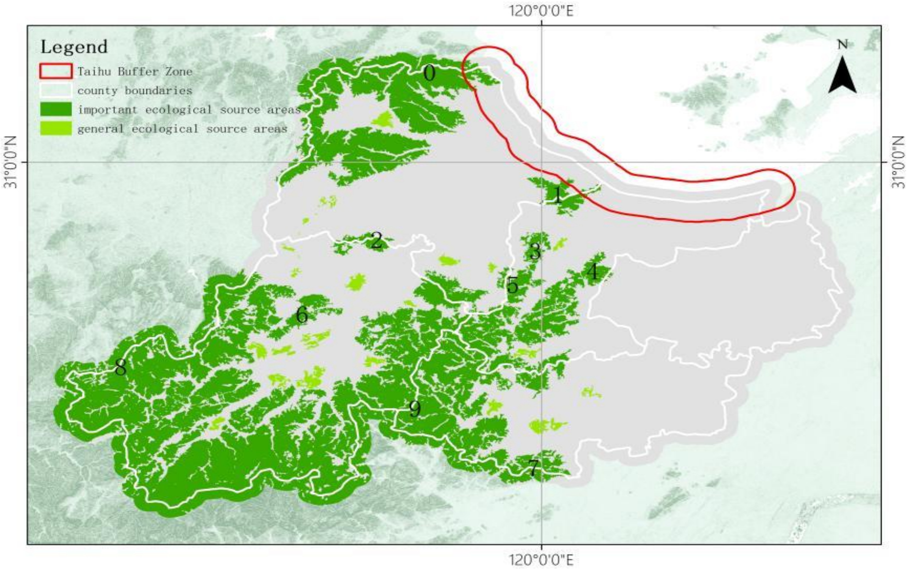

Fig. 10 **Distribution map of Huzhou's green ecological source areas.**

Table 9 **Resistance factor weight distribution table.**

	Landscape type	Elevation	Slope	Human activity intensity	Railway	Highway
q value		0.318123865	0.277182673	0.160063059	0.052275833	0.020994293
Weight	0.4	0.024	0.024	0.048	0.144	0.36

Table 10 **Resistance factor value assignment rules table.**

Landscape types	Resistance values	Transportation land types	Resistance values	Slope types	Range	Resistance values
Forests	1	Highway	80	Flat slope	<5°	1
Grasslands	20	Railway	90	Gentle slope	5°-15°	10
Farmland	40			Inclined slope	15°-25°	30
Water bodies	60			Steep slope	25°-35°	80
Unutilized land	90			Sheer slope	>35°	100
Built-up areas	100					

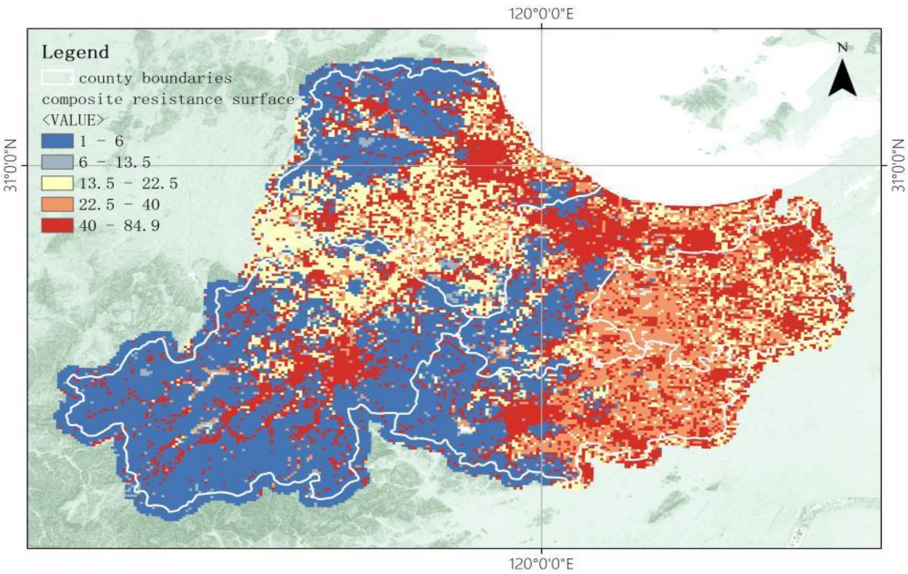

Fig. 11 **Spatial distribution of the composite resistance value of Huzhou's green ecological network.**

5.3 Ecological Network Construction

The study, using ecological source area vector data and composite resistance surface raster data, applied the cost connectivity tool in ArcGIS 10.6 software to simulate the cumulative resistance that species would have to overcome during migration and diffusion between ecological sources. The minimum-cost path representing ecological corridors was identified, enhancing species interaction and ecological connectivity between source areas [30].

The minimum cumulative cost model established 45 potential ecological corridors between 10 source area patches, forming a circular layout connecting the ecological source areas. Using the minimum cost values of these corridors, the gravity model was applied to calculate the interaction between corridors (Table 11).

Potential corridors with a gravity interaction (Gab) greater than 10 were classified as first-level ecological corridors, those with values between 1 and 10 as second-level corridors, and those less than 1 as third-level corridors. Ecological nodes were extracted from the corridors to form three levels of ecological nodes. The final network includes 203 segments of ecological greenways and 113 ecological nodes, thus establishing the green ecological network of Huzhou (Fig. 12).

Table 11 Interaction degree of ecological corridors between patches.

	0	1	2	3	4	5	6	7	8	9
0										
1	0.018692									
2	0.530581	0.631948								
3	0.048665	2.270430	4.164584							
4	0.052079	1.540656	4.316389	104.3599						
5	0.045554	1.735382	4.087357	97084.39	185.8955					
6	0.068317	0.488878	7.666889	5.404402	5.316031	5.755351				
7	0.023895	0.543770	1.875433	11.98777	11.93191	14.93153	2.604147			
8	0.003601	0.022927	0.411783	0.240773	0.241693	0.254050	2,625.347	0.223121		
9	0.001048	0.028233	0.111571	12.66876	4,957.981	798.4205	0.572823	1,724.905	112.8724	

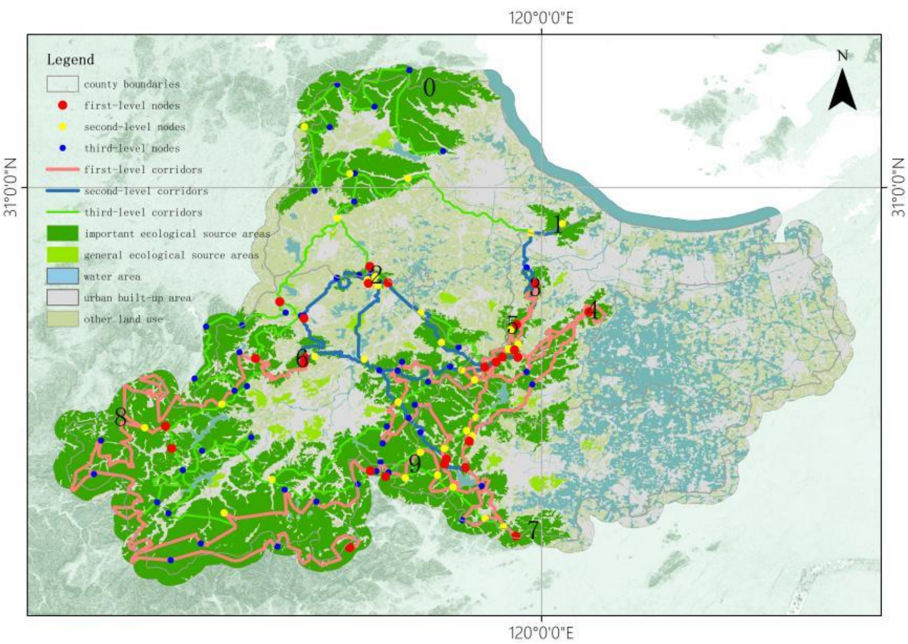

Fig. 12 Distribution map of Huzhou's green ecological network.

Table 12 Ecological network structure evaluation index statistics.

Index types	Calculation results	Range of values for similar research results
α	0.411764706	0.2-0.5
β	1.796460177	1.4-1.9
γ	0.60960961	0.3-0.8

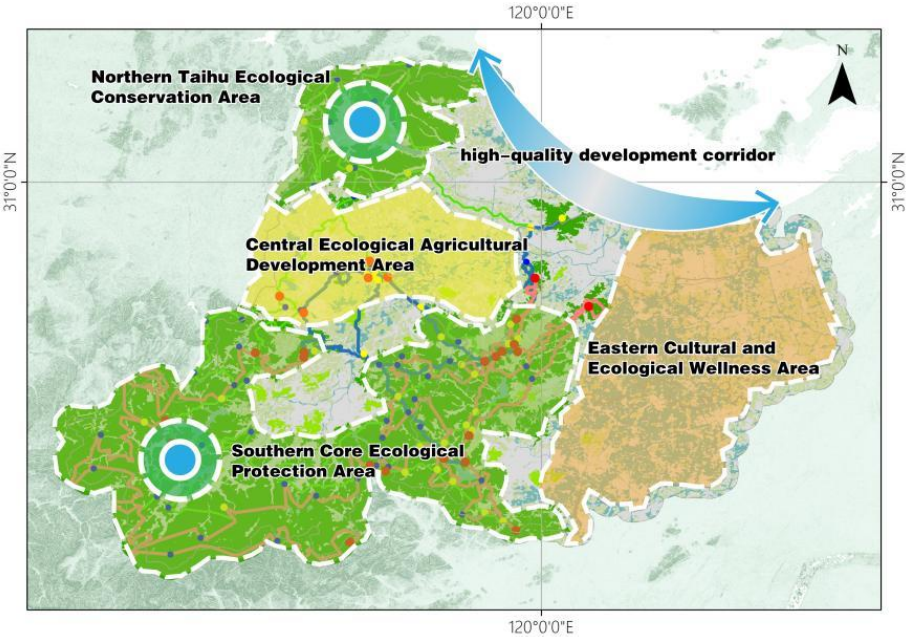

Fig. 13 Ecological pattern optimization suggestions.

5.4 Ecological Evaluation and Optimization Suggestions

5.4.1 Ecological Network Structure Evaluation

This study objectively evaluated the structure and composition of Huzhou's green ecological network. The network structural index was used to describe the network's loop structure from three dimensions: network closure, line-point ratio, and network connectivity.

Compared to most research results (Table 12), the following conclusions can be drawn: (1) The α index value is 0.412, indicating that the more closed loops are formed in the network, the more migration routes are available for species, allowing them to avoid predators and disturbances, thus reducing migration distance and time. (2) The β index value is 1.796, suggesting that the established network is complex and complete in a mesh structure. (3) The γ index value is 0.610, demonstrating good network connectivity, which is conducive to the migration, foraging, and reproduction activities of various species.

5.4.2 Ecological Network Optimization Suggestions

The study identifies urbanization, agricultural development, and the fragmentation of landscape patterns as the primary challenges to ecological protection in Huzhou. Additionally, it was found that appropriate economic development can have a positive impact on ecological protection. Future ecological protection work may consider combining with eco-tourism development.

In terms of spatial pattern optimization, the study proposes a "Four Areas and One Corridor" ecological pattern (Fig. 13). The "Southern Core Ecological Protection Area" should focus on creating a circular ecological protection core area centered around Tianmu Mountain; the Northern Taihu Ecological Conservation Area should protect the ecological environment of Taihu Lake; the Central Ecological Agricultural Development Area should develop ecological agriculture while reserving ecological corridors connecting the southern and northern ecological sources; the Eastern

Cultural and Ecological Wellness Area could serve as a reserve space for Huzhou's future development and a demonstration area for ecological civilization construction. "One Corridor" refers to the high-quality development corridor around Taihu, where economic vitality is strong and a balance between economic development and ecological protection should be emphasized.

6. Conclusion

This study is centered on Huzhou, a city in Zhejiang Province, China, as the study area. It adopts an integrated approach of landscape type transition matrices and landscape pattern indices to conduct a comprehensive analysis of the evolution characteristics of the green space landscape patterns from 2017 to 2022. By virtue of the geographical detector and the Gradient Boosting Decision Tree (GBDT) algorithms, the study delves into the driving factors underlying the changes in the green space landscape patterns. Based on the Morphological Spatial Pattern Analysis (MSPA), the key ecological sources in Huzhou are precisely extracted. Employing a combination of resistance surfaces and gravity models, ecological corridors and networks are systematically constructed. Additionally, this study proffers well-founded suggestions for the evaluation and optimization of the ecological network patterns.

The conclusions and empirical inspirations obtained from this study mainly include the following points:

(1) The expansion of urban areas mainly comes from the conversion of farmland into construction land. Therefore, such an urban expansion process will inevitably threaten the food supply security and ecological environment quality of the region.

(2) Massive human activities, such as urbanization and agricultural expansion, potentially have adverse effects on wildlife habitats and ecological processes. As a result, the landscape structure may become more fragmented and dispersed.

(3) Faced with the severe situation of ecological environment protection, natural resource management and urban development planning should actively intervene in the transformation process of regional landscape types, scientifically and reasonably construct green space ecological network systems, and plan regional ecological patterns according to local conditions.

References

[1] Zhang, C. E., and Yue, T. M. 2024. "Historical Exhibition of Ecological Issues and Innovation in China's Ecological Civilization Construction." *Ningxia Social Sciences* 43 (2): 21-8.

[2] Wang, L., Zhang, S. W., and Yao, Y. L. 2014. "The Impacts of Green Landscape on Urban Thermal Environment: A Case Study in Changchun City." *Geographical Research* 33 (11): 2095-104.

[3] Zhang, X. R., Liu, L. P., Fang, S., Jiang, W. C., and Wang, J. C. 2014. "Research Advances on the Relationship between Land Use/Cover Change and Environmental Change." *Ecology and Environmental Sciences* 23 (12): 2013-21.

[4] Huang, X. J. 2017. "A Review of Effects of Urban and Rural Land Market Integration on Land Use and Land Cover Change." *Scientia Geographica Sinica* 37 (2): 200-8.

[5] Ersoy, E. 2019. "Landscape Pattern and Urban Cooling Island." *Fresenius Environmental Bulletin* 28 (3): 1943-51.

[6] Kim, M., Song, K., and Chon, J. 2021. "Key Coastal Landscape Patterns for Reducing Flood Vulnerability." *Science of the Total Environment* 759: 143454.

[7] Uuemaa, E., Roosaare, J., and Mander, U. 2007. "Landscape Metrics as Indicators of River Water Quality at Catchment Scale." *Nordic Hydrology* 38 (2): 125-38.

[8] Yang, W. R. 2015. "Spatiotemporal Change and Driving Forces of Urban Landscape Pattern in Beijing." *Acta Ecologica Sinica* 35 (13): 4357-66.

[9] Pan, J. H., and Liu, X. 2015. "Assessment of Landscape Ecological Security and Optimization of Landscape Pattern Based on Spatial Principal Component Analysis and Resistance Model in Arid Inland Area: A Case Study of Ganzhou District, Zhangye City, Northwest China." *Chinese Journal of Applied Ecology* 26 (10): 3126-36.

[10] Hofman, M. P. G., Hayward, M. W., Kelly, M. J., and Balkenhol, N. 2018. "Enhancing Conservation Network Design with Graph-Theory and a Measure of Protected Area Effectiveness: Refining Wildlife Corridors in Belize, Central America." *Landscape and Urban Planning* 178: 51-9.

[11] Roy, A., Devi, B. S. S., Debnath, B., and Murthy, M. S. R. 2010. "Geospatial Modelling for Identification of Potential

Ecological Corridors in Orissa." *Journal of the Indian Society of Remote Sensing* 38 (3): 387-99.

[12] Pierik, M. E., Dell'Acqua, M., Confalonieri, R., Bocchi, S., and Gomarasca, S. 2016. "Designing Ecological Corridors in a Fragmented Landscape: A Fuzzy Approach to Circuit Connectivity Analysis." *Ecological Indicators* 67: 807-20.

[13] Zhou, Y., Shi, T. M., Hu, Y. M., and Liu, M. 2014. "Study on Green Space Landscape Pattern Optimization Based on Urban Climatic Environment Features." *City Planning Review* 38 (5): 83-9.

[14] Han, Y., and Zhou, Z. X. 2015. "Evaluation on Ecosystem Services in Haze Absorption by Urban Green Land and Its Spatial Pattern Analysis in Xi'an." *Geographical Research* 34 (7): 1247-58.

[15] Xiong, C. N., Wei, H., and Lan, M. J. 2008. "Analysis of Connectivity on Greenland Landscape in Metropolitan Region of Chongqing City." *Acta Ecologica Sinica* 28 (5): 2237-44.

[16] Wurihan, Wen, X. R., Zhao, H. X., and She, G. H. 2010. "Dynamic Analysis and Prediction of Green Space Landscape Based on the RS and GIS in Shenzhen Special Economic Zone." *Journal of Beijing Forestry University* 32 (6): 42-7.

[17] Maghah, J. A., and Fokeng, R. M. 2021. "The Degradation of the Bafut-Ngemba Forest Reserve Revisited: A Spatio-Temporal Analysis of Forest Cover Change Dynamics." *American Journal of Remote Sensing* 9 (1): 33-41.

[18] Liu, J., Yin, H. W., Kong, F. H., and Li, M. H. 2018. "Structure Optimization of Circuit Theory-Based Green Infrastructure in Nanjing, China." *Acta Ecologica Sinica* 38 (12): 4363-72.

[19] Zhang, H. B., Liu, H. Y., and Hao, J. F. 2012. "Landscape Spatial and Temporal Evolutions of Yancheng Coastal Wetlands in Jiangsu Province." *Bulletin of Soil and Water Conservation* 32 (6): 226-9.

[20] Peng, J., Zhao, H. J., Liu, Y. X., and Wu, J. S. 2017. "Research Progress and Prospect on Regional Ecological Security Pattern Construction." *Geographical Research* 36 (3): 407-19.

[21] Li, K., Hou, Y., Skov-Petersen, H., and Andersen, P. S. 2021. "Research Progress of Green Infrastructure Oriented by Landscape Planning: From the Perspective of 'Pattern-Process-Services-Sustainability' Research Paradigm." *Journal of Natural Resources* 36 (2): 435-48.

[22] Guo, H. 2021. "Spatiotemporal Analysis and Ecological Network Construction and Evaluation of Green Landscape in Ji'nan Based on Remote Sensing Information." M.Sc. thesis, Shandong Jianzhu University.

[23] Wang, J. F., and Xu, C. D. 2017. "Geodetector: Principle and Prospective." *Acta Geographica Sinica* 72 (1): 116-34.

[24] Hancock, J. T., and Khoshgoftaar, T. M. 2020. "CatBoost for Big Data: An Interdisciplinary Review." *Journal of Big Data* 7 (1): 94.

[25] Liu R. C., Shen, C. Z., Jia, Z. Y., Wang, J. X., Lu, C. X., and Zhou, S. L. 2019. "Construction and Optimization of Ecological Network under the Stress of Road Landscape in Coastal Beach Area: A Case Study of Dafeng District, Yancheng City." *Chinese Journal of Ecology* 38 (3): 828-37.

[26] Yin, H. W., Kong, F. H., Qi, Y., Wang, H. Y., Zhou, Y. N., and Qin, Z. M. 2011. "Developing and Optimizing Ecological Networks in Urban Agglomeration of Hunan Province, China." *Acta Ecologica Sinica* 31 (10): 2863-74.

[27] Li, H., Zheng, Y. T., Huang, H., and Chen, F. P. 2024. "Construction of Lushan Ecological Network Based on MSPA and MCR Model." *Journal of Central South University of Forestry & Technology* 44 (2): 98-107.

[28] You, Z., and Jiang, Q. F. 2018. "Construction and Management Model of Ecological Network System in the Yangtze River Economic Belt." *Journal of Nantong University (Social Sciences Edition)* 34 (3): 37-44.

[29] Li, Z. Q., and Zhou, W. Q. 2021. "Quantifying Within-City Landscape Dynamics at the Block Level: A Case Study of Shenzhen." *Acta Ecologica Sinica* 41 (6): 2180-9.

[30] Zheng, H., Gao, J. X., Xie, G. D., Zou, C.-X., and Jin, Y. 2019. "Ecological Corridor." *Journal of Ecology and Rural Environment* 35 (2): 137-44.