International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 2434-2447

https://doi.org/10.70517/ijhsa464206

Research on Protection Strategies and Modernization Development Pathways for Cultural Landscape Heritage in the Yellow River Basin

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Abstract This study focuses on the synergistic pathways for the protection of cultural landscape heritage and modernization in the Yellow River Basin, integrating cultural heritage preservation strategies with spatial quantification techniques to establish a comprehensive research framework. Through the analysis of 662 traditional villages and multi-period remote sensing imagery from 2016 to 2024, combined with spatial syntax theory, landscape dynamics models, and a pattern index system, empirical research was conducted. Spatial structure quantification reveals that the overall integration degree of scenic areas in the Yellow River Basin is 0.62, with significant regional differences—Region A has the highest integration degree (1.13) but the lowest comprehensibility (0.36), and a collaboration degree of only 0.47 (below the 0.5 threshold), indicating spatial cognitive barriers caused by the deterioration of historical relics. Region D achieved an understandability of 0.95, confirming the strong correlation between local and overall structures. Landscape dynamic monitoring indicates that the number of patches increased by 128.7% between 2016 and 2024, from 57,239 to 130,912, with patch density rising to 9.25 patches/km², and the maximum patch index (LPI) increasing to 77.17%, highlighting a trend toward fragmentation. Geographical name cultural research found that human landscape-related names accounted for 61.93%, surname-based names for 31.42%, natural landscape-related names for 38.07%, and geographical orientation-related names for 17.07%. Kernel density analysis revealed that terrain-related villages exhibit a clustered distribution with a nearest neighbor index K = 0.92, while surname-based names show uniform dispersion with K = 1.07.

Index Terms Yellow River Basin, cultural landscape heritage, spatial syntax, landscape pattern index

I. Introduction

Currently, China is actively building a socialist ecological civilization and spiritual civilization, accelerating the development and innovation of cultural undertakings [1]. People's ecological and environmental awareness is constantly increasing, which requires that social production and life adhere to the principle of integrated ecological and economic development, establish a harmonious relationship between humans and nature, and continue the long history of human civilization [2], [3]. The Yellow River is the cradle of Chinese civilization and is thus referred to as China's “mother river,” nurturing generation after generation of Chinese people. Yellow River culture encompasses the collective material and spiritual wealth created by the people of the Yellow River basin through centuries of river management efforts [4]. Additionally, as the birthplace of Chinese civilization, the Yellow River basin is rich in cultural heritage, ranging from the scattered Paleolithic cultural sites discovered through archaeology, to the Neolithic Peiligang Culture, Yangshao Culture, and Longshan Culture, from the records of the Three Sovereigns and Five Emperors and Yu the Great, to the capital sites of the Xia, Shang, and Zhou dynasties, Confucian classics, the works of the Hundred Schools of Thought from the Pre-Qin period, and numerous texts from later eras, from the Han-Wei Luoyang Old City to the Jiayuguan Pass, from the Longmen Grottoes to the Mogao Caves, from the Twenty-Four Solar Terms to Chinese silk weaving techniques, from ancient zither art to traditional timber-frame construction techniques—these are all prominent components of the Yellow River cultural landscape heritage and constitute an invaluable treasure in the history of Chinese culture [5]-[8].

Cultural heritage serves as the spiritual carrier of a nation's culture and stands as a testament to history [9]. The widespread application of high-tech technologies such as digital technology, multimedia information technology, geographic information systems, and broadband network technology in the field of cultural heritage protection has significantly enhanced the expressive power of various cultural heritage sites while also opening up broader prospects for the development of the cultural tourism industry [10]-[13].

Remote sensing technology can comprehensively, swiftly, and objectively detect and reflect the spatial attributes and distribution patterns of cultural landscape heritage [14]. For example, in 2013, Banerjee, R, and Srivastava utilized remote sensing technology and geographic information systems (GIS) to monitor and study changes in land cover of cultural landscape heritage in central India, achieving the digital collection of cultural landscape heritage [15]. In the same year, Hadjimitsis et al. combined satellite remote sensing and GIS to protect cultural landscape heritage sites in Cyprus from human-induced and natural disasters, addressing the challenges faced by traditional on-site observation methods [16]. In 2017, Agapiou explored the application of remote sensing big data in archaeology and cultural heritage protection, presenting two specific case studies: one using Landsat data to detect buried Paleolithic cultural heritage in Greece, and the other using DMSP-OLS nighttime light time series to monitor urban expansion near World Heritage sites [17]. Moise et al. used Albaruluria as an example to explore the potential of satellite remote sensing technology in assessing and monitoring cultural heritage sites, finding that the technology can provide reference suggestions for sustainable landscape management and conservation measures [18]. Overall, remote sensing technology is widely used to obtain spatial data at the macro scale.

Using 3D laser scanning technology to collect three-dimensional spatial information of the target area not only improves data quality, collection efficiency, and accuracy but also enables the visualization of data [19]. For example, in 2014, Zhang et al. explored the application of 3D laser scanning technology in the surveying of historical architectural landscapes, using Shang Shu Di in Fujian Province, China, as a case study. They outlined its numerous advantages over traditional conservation methods and discussed the technical challenges associated with data management and software-related issues [20]. In 2018, Naranjo et al. employed panoramic spherical photography and ground-based laser scanning technology to describe and document the cultural landscape heritage of Cáceres, aiming to develop a reliable cultural heritage modeling method [21]. In 2022, Parfenov et al. explored the potential of 3D laser scanning technology for the digital reconstruction and replication of cultural heritage, emphasizing its role in cultural landscape heritage conservation through a case study in St. Petersburg [22]. In the same year, Jia et al. proposed a method for protecting and managing China's ancient imperial gardens using 3D laser scanning technology. This method includes creating information models and management platforms to enhance the efficiency and accuracy of heritage conservation and management [23]. In 2024, Llabani and Abazaj comprehensively explored the application of ground-based laser scanning technology in the three-dimensional documentation of cultural heritage, conducting a detailed analysis using the Tirana Clock Tower as an example, and highlighting the implications of this technology for future cultural landscape heritage conservation efforts [24]. Overall, three-dimensional laser scanning technology is widely used to obtain spatial data at the microscopic scale and is commonly employed for surveying, simulation, and reconstruction.

Virtual reality (VR) technology generates three-dimensional virtual environments with simulation and interactivity by integrating multiple display and control systems [25]. In 2021, Fidas and Sylaiou explored the application of VR technology in cultural heritage institutions, aiming to enhance user engagement and provide support [26]. In 2022, Rauscher and Humpe examined the application of VR technology in disseminating cultural landscape heritage, finding that fun and entertainment are key factors driving user acceptance of the technology. However, due to the technology's immaturity, its practical application remains lagging [27]. In 2024, Izaguirre et al. explored the use of VR technology to enhance the protection and academic research of cultural landscape heritage, detailing the creation process of VR experiences and evaluating their effectiveness through pilot tests [28]. Overall, VR technology enables the comprehensive display and promotion of cultural landscape heritage in digital media, contributing to its protection and preservation.

In summary, the rapid development of digital technology has led to significant progress in the collection, storage, and dissemination of landscape heritage information. Strengthening the protection and management of cultural landscape heritage in the Yellow River basin is urgent, and digital preservation is an inevitable trend. However, further in-depth research and practical exploration are needed to determine how to maximize the value of cultural landscape heritage through digital technology and stimulate public interest and enthusiasm for understanding and participating in the protection of cultural landscape heritage.

The article systematically constructs an integrated research framework that combines cultural heritage preservation strategies with spatial quantification technology, aiming to revitalize intangible cultural heritage resources through digital means. By integrating spatial syntax, dynamic monitoring, and pattern analysis, it provides practical pathways for the protection of landscape heritage in the Yellow River basin. At the cultural heritage preservation level, a dual-track strategy is proposed: on one hand, establishing a digital repository of intangible cultural heritage symbols, utilizing network technology to analyze landscape semantics and dissemination pathways, thereby achieving the collective creation and sharing of intangible cultural heritage resources by all citizens. On the other hand, it creates a “project-based intangible cultural heritage landscape belt” based on a “two-layer four-part classification system” (traditional performing arts, fine arts, production and living knowledge, and festival arts), combined with project carriers such as educational tourism and cultural and creative industries, to activate social participation in living inheritance. In terms of spatial analysis technology, the spatial syntax theory is introduced to analyze cultural spatial structures: regional centrality is identified through integration, the probability of human traffic flow is quantified through selectivity, spatial cognitive efficiency is assessed through comprehensibility, and the fit between local and overall structures is verified through coordination. Furthermore, spatial transformation models are used to monitor landscape dynamics, the dynamic degree formula is applied to calculate the rate of change in green spaces, and transfer matrices are employed to reveal the patterns of land use type transformations.

II. Methods for protecting cultural landscape heritage in the Yellow River basin and spatial quantification analysis techniques

II. A. Pathways for the Preservation and Development of Cultural Heritage in the Yellow River Basin through Landscape Design

II. A. 1) Establish a digital symbol library of intangible cultural heritage elements

First, guided by the important concept of a cyber power and in the context of the new era, establishing a digital repository of intangible cultural heritage landscape elements can serve as a medium for constructing interaction between intangible cultural heritage and the internet. The repository can be constructed by professionals and non-professionals alike, allowing people to spontaneously expand the digital repository. Second, the shaping of landscape environments can also be achieved through digital technologies, which can analyze issues such as the semantic meaning, timeliness, and effectiveness of intangible cultural heritage information landscapes. These analyses can serve as the basis for proposing solutions and provide pathways for the continuous development and effective dissemination of intangible cultural heritage information within landscape spaces.

II. A. 2) Establish a project-based intangible cultural heritage landscape belt

When designing the intangible cultural heritage landscape of the Yellow River Basin, it is also necessary to create material and intangible cultural landscapes from the perspective of developing social dynamics (the landscape environment must attract people in order to be fully and effectively utilized). Therefore, promoting the development of social dynamics through the establishment of project-based intangible cultural heritage landscape belts is one of the landscape design strategies. At the outset of designing the intangible cultural heritage landscape belt, it is necessary to categorize the intangible cultural heritage categories in the Yellow River Basin (the basis for project positioning). This can be done by applying the “two-layer, four-division” method based on the forms of expression and value orientations of intangible cultural heritage projects, initially classifying them into four major categories: traditional performing arts, traditional fine arts and crafts, traditional production and living knowledge and skills, and traditional festivals and arts. These four major categories can then be further subdivided. Concurrently, when categorizing relevant intangible cultural heritage categories, it is important to integrate the national conditions of the new era, multi-dimensional perspectives, and multi-dimensional values to create project-based landscape belts, such as practical teaching base projects, study-travel tourism projects, and cultural creativity industry projects, to support the living protection and inheritance of intangible cultural heritage in the Yellow River basin.

II. B. Spatial syntax variables

The effectiveness of the above cultural landscape protection strategies depends on a scientific analysis of spatial structure. Therefore, spatial syntax theory is introduced to quantify the spatial organization characteristics of the Yellow River intangible cultural heritage landscape belt in terms of four core variables: integration, selectivity, comprehensibility, and coordination.

II. B. 1) Integration

Integration reflects the syntactic permeability of spatial units to surrounding spatial units, i.e., idealized spatial accessibility, reflecting the “relative centrality” between spaces. Sometimes redundant nodes appear, which are standardized and converted using relative asymmetry values. To ensure a positive correlation with actual meaning, the reciprocal of the above standard values is taken, yielding the integration value. Global integration refers to the degree of aggregation or dispersion of spatial units within the entire spatial system, relative to the entire model, block, or city, and describes the spatial organizational characteristics at the highest level of the overall system. Local integration is generally defined as the integration within three steps, expressing the connectivity between a spatial unit and other spatial units within a relative region, and can be used for pedestrian flow analysis. Within the entire system, if the global integration of certain axes is dominant, these syntactic axes form the global integration core (representing the overall center of the region) and the three-step integration core (representing the center within the local region), which are the most accessible areas. Therefore, when utilizing this information, it is important to analyze the connections and differences between global and local integration.

II. B. 2) Selectivity

Selectivity refers to the frequency with which a certain element in a spatial system serves as the shortest topological distance between two nodes. It examines the advantages of spatial units as the shortest travel paths and reflects the likelihood of spatial traversal. Spaces with higher selectivity are more likely to be traversed by people.

II. B. 3) Understandability

Comprehensibility is the correlation coefficient between connectivity and global integration, also represented by the coordinate system of X and Y. The magnitude of its value measures the ease with which the system under study is understood by the people who use it. A higher value indicates that the system is easier for people to perceive and understand, while a lower value indicates that it is harder to understand. Comprehensibility is used to describe the relationship between the whole and the parts within a system. Specifically, it assesses whether the information obtained by individuals in a particular local space can assist them in deriving and constructing an understanding of the overall spatial structure. Spatial syntax distinguishes between the whole and the parts as two distinct concepts, corresponding to the travel radii for vehicular or pedestrian movement. By understanding the relationship between the whole and the parts, one can assess travel relationships across different scales and analyze the space. Therefore, within the same system, if the overall variables and local variables of certain spaces are in a direct proportional relationship, these spaces have high understandability. Thus, through the cognitive understanding of a local space within the system, one can infer the overall spatial structure of the system. Conversely, with low understandability, people find it difficult to infer the overall spatial structure from local spaces.

II. B. 4) Degree of synergy

In the research system, global integration is generally used to evaluate the spatial structure of the cognitive system at the macro level, while local integration is used to understand the local structure within a certain radius of activity in the system. Synergy is used to measure the correlation between the two, thereby assessing their similarity. The degree of synergy is represented by the coordinate system X and Y, where the scatter points in the coordinates represent the elements in the research system. Typically, the Y variable is set as the local integration degree, and the X variable is set as the global integration degree to calculate the fit between the local and global spatial structures, also known as the degree of synergy, expressed as R^2. A fit R^2 above 0.5 indicates that the global integration and local integration have good synergy, with the spatial structures aligning well, making it easier to infer the global space from the local space. A fit R^2 above 0.7 indicates that the local integration and global integration have a good fit trend, i.e., high correlation.

II. C. Calculation methods related to spatial conversion

Spatial syntax reveals static structural characteristics, while the dynamic evolution of landscape space needs to be tracked through dynamic degrees and transition matrices.

II. C. 1) Dynamic degree calculation

The rate of change in various types of green space is reflected through dynamic degree, calculated using the following formula:

$$K = \frac{S_{ib} - S_{ia}}{S_{ia}} \times \frac{1}{T} \tag{1}$$

In Equation (1): S_{ia} and S_{ib} represent the areas of green space type i at the beginning and end of the study period, respectively; T is the number of years in the study period; and K is the rate of change of this type of green space during the study period. The dynamics of green space in each region are classified into four categories based on the natural breakpoint method.

II. C. 2) Spatial transfer matrix

The transfer matrix reflects the dynamic changes in the conversion between various land uses during the study period. The calculation formula is as follows:

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix} \tag{2}$$

In equation (2): S_{ij} is the area matrix of the spatial transfer from type i to type j during the period from the beginning to the end of the study; n is the number of green space types.

II. D.Quantitative indicators of landscape patterns

Based on an understanding of the dynamic transformation patterns of spatial dynamics, it is necessary to further assess landscape stability systematically from the patch to the landscape scale. The Fragstats 4.2 analysis software can calculate three categories of indices at the patch level, patch type level, and landscape level, respectively reflecting the structural characteristics of individual patches within the landscape, the structural characteristics of different patch types, and the overall structural characteristics of the landscape. Referring to previous research findings, this study selected the following indices at the patch type level: patch area (CA), patch number (NP), patch density (PD), largest patch index (LPI), and landscape shape index (LSI). At the landscape level, the following indices were selected: contiguity index (CONTAG), Shannon diversity index (SHDI), Shannon evenness index (SHEI), and Aggregation index (AI) at the landscape level. Landscape pattern indices were calculated using landscape pattern analysis software, with the calculation model as follows.

II. D. 1) Plaque type hierarchy

(1) Plaque area (CA)

$$CA = \sum_{j=1}^{n} a_{ij} \cdot \frac{1}{10000} \tag{3}$$

Here, a_{ij} represents the area of patch ij, where i is the patch type and j is the number of patches. CA represents the sum of the areas of all patches of a certain patch type, which is the basis for calculating other indicators. $CA > 0$, and the unit is hm^2.

(2) Number of patches (NP)

$$NP = \sum_{i=1}^{n} n_i \tag{4}$$

Here, n_i represents the number of patches of the i th landscape type, NP is the total number of patches of all landscape elements in the study area, $NP \geq 1$, and is an integer. The larger the value, the higher the landscape fragmentation.

(3) Patch density (PD)

$$PD = \frac{N}{A} \cdot 10000 \cdot 100 \tag{5}$$

Here, N denotes the number of landscape type patches, A is the total area of all landscape types, PD is the number of patches per unit area of landscape elements within the study area, reflecting the density of patches; the larger the value, the smaller the number of patches and the higher the landscape fragmentation. $PD \geq 0$, with units of $/100\mathrm{hm}^2$.

(4) Maximum Patch Index (LPI)

$$LPI = \frac{\max_{j=1}^{n}\left(a_{ij}\right)}{A} \times 100 \tag{6}$$

Here, a_{ij} represents the area of patch ij, A is the total area of patches, LPI is the ratio of the maximum patch area to the total landscape area in a certain type of landscape, which is the core index for identifying dominant patches, $0 \leq LPI \leq 100$, and the unit is 100%.

(5) Landscape shape index (LSI)

$$LSI = \frac{0.25E}{\sqrt{A}} \tag{7}$$

Here, E is the total length of all patch boundaries in the landscape, A is the total patch area, LSI indicates the degree of deviation between the shape of a patch of a certain landscape type and a square of the same area. The larger the value, the more complex the patch shape; conversely, the smaller the value, the simpler the patch shape. $LSI \geq 1$.

II. D. 2) Landscape Levels

(1) Shannon Homogeneity Index (SHEI)

$$SHEI = \frac{-\sum_{i=1}^{m}\left(p_i \ln\left(p_i\right)\right)}{\ln m} \tag{8}$$

Here, m is the number of landscape element types, p_i is the area proportion occupied by the i th landscape type, SHEI reflects the uniformity and dominance of landscape element type distribution, and the closer the value is to 1, the more balanced the landscape type distribution is, $0 \leq SHEI \leq 1$.

(2) Shannon Diversity Index (SHDI)

$$SHDI = -\sum_{i=1}^{m} p_i \times \ln(p_i) \tag{9}$$

Here, m is the number of landscape element types, p_i is the area proportion occupied by the i th landscape type, SHDI reflects the diversity and heterogeneity of landscape element types, and the larger the value, the greater the landscape diversity, and vice versa, the smaller the diversity, $0 \leq SHDI$.

(3) Contagion index (CONTAG)

$$CONTAG = \left(1 + \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{R_i K_{ij} \ln(K_{ij})}{2\ln(n)}\right) \times 100 \tag{10}$$

Here, n is the number of patches of a certain patch type, K_{ij} is the probability of adjacency between patch types i and j, CONTAG is an indicator reflecting the aggregation and extension of different patch types in the landscape. A higher value indicates that a major patch type in the landscape has formed good connectivity, while a lower value indicates poor connectivity and high fragmentation in the landscape. $0 \leq CONTAG \leq 100$.

(4) Aggregation Index (AI)

$$AI = \left[\frac{g_{ii}}{\max \rightarrow g_{ii}}\right](100) \tag{11}$$

Here, g_{ii} is the similar adjacent patch of the corresponding landscape type, AI reflects the degree of aggregation of landscape patches, the larger the value, the more aggregated the landscape, the smaller the value, the more dispersed the landscape, $0 \leq CONTAG \leq 100$.

III. Quantitative Analysis of Spatial Characteristics of Cultural Landscapes in the Yellow River Basin and Research on Village Place Name Culture

Based on the framework for constructing cultural landscape protection strategies and spatial quantification techniques, this chapter focuses on specific cases in the Yellow River basin. It analyzes the spatial structure of scenic areas through spatial syntax, diagnoses multi-scale dynamic evolution through landscape pattern indices, and reveals the spatial distribution characteristics of cultural landscapes through statistical classification of place names.

III. A. Analysis of the spatial characteristics of scenic spots in the Yellow River Basin based on spatial syntax theory

First, the landscape network within the study area was divided into spatial units, with clear boundaries defined for each unit. The study area was divided into four sections, A, B, C, and D, based on the Yellow River basin. Next, the axis representation method was used to convert the actual spatial structure into an axis diagram that could be quantitatively analyzed. Finally, based on the axis model, Depthmap software was used to calculate various spatial syntax parameters and analyze the layout and structural characteristics of the landscape space.

Based on the spatial layout characteristics of the Yellow River Basin scenic area and field survey data, the transportation network of the scenic area is abstracted using axes, transforming the actual road system into a quantifiable analytical model composed of 814 spatial connection elements.

III. A. 1) Spatial Form Attributes

The axis diagram was exported from CAD software into a specific file format and then imported into Depthmap software for spatial syntax analysis. Quantitative analysis was conducted based on indicators such as integration, comprehensibility, and selectivity to analyze the spatial morphology and structural characteristics of scenic spots in the Yellow River basin, as shown in Table 1.

Table 1: The spatial form characteristics of the scenic areas in the Yellow River Basin

	Global	Local area			
		Region A	Region B	Region C	Region D
Topological distance R	-	4	8	12	16
Number of axes	814	308	177	201	128
Integration degree	0.62	1.13	0.82	0.74	0.58
Connectivity	2.51	1.96	2.34	2.88	3.49
Control degree	0.56	0.42	0.35	0.70	0.66
Depth value	18.27	14.09	22.73	9.74	16.28
Comprehensibility	-	0.36	0.53	0.67	0.95
Collaboration degree	0.81	0.47	0.58	0.75	0.68

Table 1 data shows that there are significant regional differences in the spatial structure of scenic spots in the Yellow River Basin. The overall integration index is 0.62, indicating that the overall spatial accessibility of scenic spots is at a moderate level. By region, Region A has the highest integration index of 1.13, with the strongest spatial centrality, making it the core activity area; Regions B (0.82) and C (0.74) follow; Region D has the lowest integration index (0.58), indicating a pronounced spatial marginality.

The connectivity index reflects the cross-connectivity of spatial units. Region D has the highest connectivity index (3.49), indicating a dense network of road intersections; Regions B (2.34) and C (2.88) are intermediate; Region A has the lowest connectivity index (1.96), indicating a relatively simple road network structure. Control indices exhibit different patterns: Region C has the highest control index at 0.70, indicating strong dominance over surrounding spaces; Region B has the lowest control index at 0.35, with weaker spatial autonomy.

Depth values reveal spatial penetration efficiency: Region C has the lowest depth value at 9.74, with the shortest optimal paths to other regions; Region B has the highest depth value at 22.73, with the lowest spatial penetration efficiency. The comprehensibility analysis shows that Region D has the best cognitive efficiency (0.95), with local spaces effectively reflecting the overall structure; Region A has a comprehensibility of only 0.36, with weak associations between local and overall spaces, which may lead to difficulties in visitor orientation.

The R^2 of coordination indicates that the global level has excellent coordination (0.81 > 0.7), suggesting that the overall spatial hierarchy of the scenic area is clear; however, the coordination of Region A is only 0.47 (<0.5), indicating poor alignment between local and overall structures, consistent with the low understandability conclusion, suggesting that this region may have spatial structural fractures or damage to historical remnants.

III. A. 2) Spatial comprehensibility analysis

In spatial syntax theory, comprehensibility reflects the degree of association between local spatial structures and the overall spatial structure. The higher the value, the more significant the spatial cognitive efficiency, meaning that the higher the comprehensibility, the easier it is for people to infer the general structure of the overall space based on local spatial structures. This study utilizes Depthmap software to select data on local integration and global integration at different R values. Through XY scatter plot analysis, it examines the comprehensibility of the scenic axis system in the Yellow River Basin, revealing the associative characteristics of spatial hierarchies within the scenic area. The spatial comprehensibility of the four regions (A, B, C, and D) at different R values is shown in Figures 1–4. Blue dots represent points with high comprehensibility (>0.5), while gray dots indicate points with comprehensibility below 0.5.

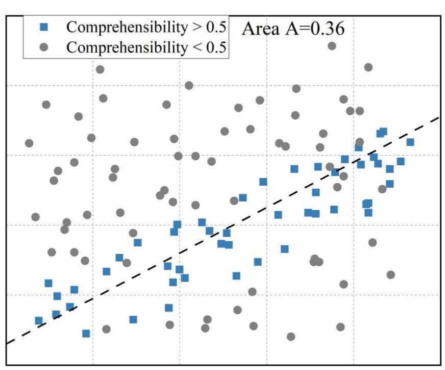

Figure 1: The spatial comprehensibility of Area A

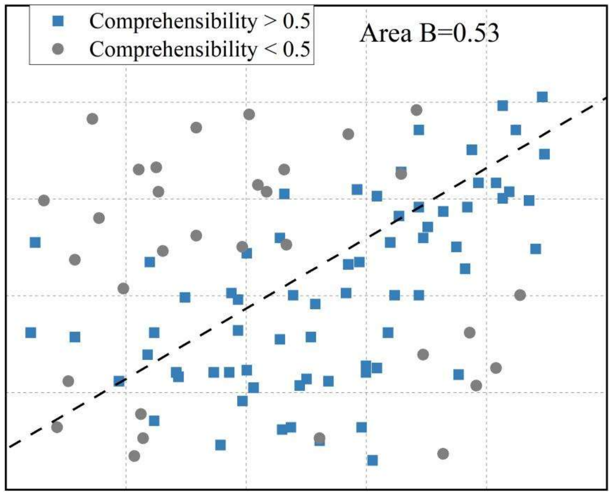

Figure 2: The spatial comprehensibility of Area B

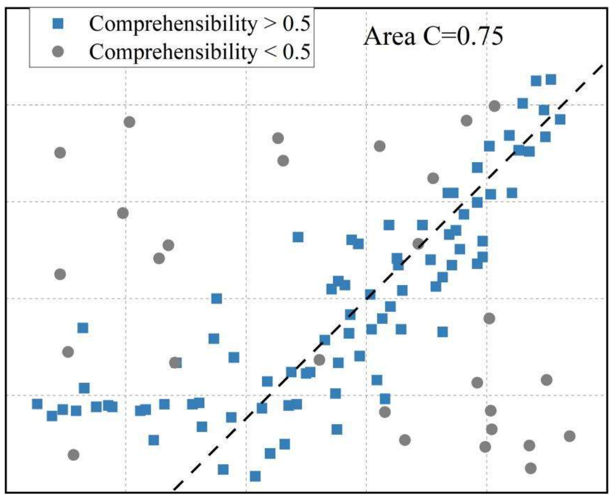

Figure 3: The spatial comprehensibility of Area C

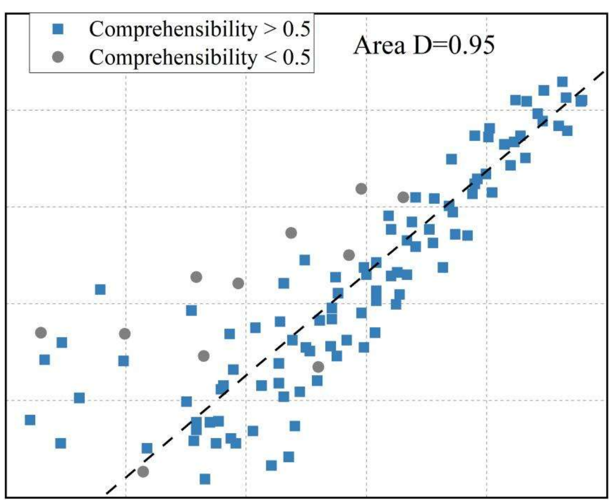

Figure 4: The spatial comprehensibility of Area D

Analysis indicates that the fit between the overall integration and local integration of the scenic area improves as the R value increases. When R = 4, the comprehensibility is only 0.36, reflecting the low cognitive efficiency of the spatial structure in Area A of the Yellow River Basin scenic area, where local spaces struggle to effectively represent the overall structural characteristics. Due to the long history of Area A and its location in the mountainous interior, some road systems have varying degrees of damage, resulting in insufficient spatial structural integrity, which is the primary cause of the low spatial comprehensibility of the scenic area. When the topological distance values for local integration increase, the comprehensibility is consistently above 0.5, indicating good overall fit and the ability to establish a coherent understanding of the entire scenic area's spatial form. For example, in spatial regions B, C, and D, the majority of points have comprehensibility values above 0.5, resulting in high overall spatial comprehensibility and the ability to derive the system's overall spatial structure.

III. B. Analysis of landscape scale indices in the Yellow River basin

After identifying the spatial static structural characteristics, it is necessary to further track the dynamic processes of the landscape. Based on the spatial transformation model and pattern index system outlined in Sections 2.3–2.4, Fragstats 4.2 was used to calculate the patch type/landscape layer indices for the period 2016–2024, analyzing the evolutionary trajectory and ecological risks of the Yellow River Basin from 2016 to 2024. The landscape pattern index values for the Yellow River Basin in 2016, 2020, and 2024, as calculated using the Fragstats4.2 analysis software, are shown in Table 2.

Table 2: The values of landscape pattern indices of 2016, 2020 and 2024

		2016	2020	2024
Patch type hierarchy	CA/10,000km^2	46.01	43.47	42.86
	NP	57239	80832	130912
	PD	5.09	8.18	9.25
	LPI	59.32%	65.10%	77.17%
	LSI	84.20	88.49	90.11
Landscape level hierarchy	CONTAG	38.74	37.55	37.01
	SHDI	1.03	1.11	1.20
	SHEI	0.72	0.80	0.84
	AI	81.39	83.02	83.44

According to the quantitative results of landscape pattern index measurements, the Yellow River Basin exhibited a significant “fragmentation-diversification” trend between 2016 and 2024. The number of patches (NP) surged from 57,239 to 130,912, representing an increase of 128.7%, directly leading to a rise in patch density (PD) from 5.09 patches/km² to 9.25 patches/km², reflecting a continuous deepening of landscape fragmentation. Meanwhile, the largest patch index (LPI) jumped from 59.32% to 77.17%, indicating an enhanced dominance of dominant patches.

In terms of morphological complexity, the landscape shape index (LSI) increased from 84.20 to 90.11, confirming an increase in the tortuosity of patch boundaries, with human activity disturbances leading to an increasingly complex natural landscape morphology. The steady increase in the aggregation index (AI) from 81.39 to 83.44 reveals enhanced aggregation effects of patches within local areas.

Landscape diversity indices exhibit contradictory changes: the Shannon diversity index (SHDI) increased from 1.03 to 1.20, and the Shannon evenness index (SHEI) rose from 0.72 to 0.84, indicating a more balanced distribution of area among different landscape types. However, the CONTAG index decreased from 38.74 to 37.01, indicating a weakening of overall landscape connectivity, with dominant patches failing to effectively suppress the dispersal trend at the regional scale. This characteristic of increasing diversity but decreasing connectivity highlights that the Yellow River Basin is undergoing an ecological spatial restructuring process—where human-built land expansion coexists with the fragmentation of natural habitats—and urgently requires the optimization of spatial structure through ecological corridor construction.

The landscape-scale indices for the Yellow River Basin in 2016, 2020, and 2024, categorized by patch type (construction land, farmland, forest land, and water bodies), are shown in Table 3.

Table 3: The landscape-scale indices of Yellow River for different types of patches

Plaque type	Year	CA	NP	PD	LPI/%	LSI	AI
Construction land	2016	8.32	15,642	1.88	24.17	28.15	85.36
	2020	9.87	23,509	2.38	31.05	32.67	87.91
	2024	11.25	34,781	3.09	38.92	36.04	89.07
Farmland	2016	22.15	28,735	1.30	32.46	41.83	79.24
	2020	20.03	36,882	1.84	28.91	45.12	76.58

	2024	18.64	52,406	2.81	25.73	47.29	74.32
Forest land	2016	12.07	10,215	0.85	18.63	26.94	83.17
	2020	12.89	15,426	1.20	21.05	30.25	86.43
	2024	13.52	27,638	2.04	23.81	33.76	88.05
Water	2016	3.47	2,647	0.76	6.24	12.28	77.85
	2020	0.68	5,015	7.37	1.09	18.45	71.34
	2024	0.45	6,087	13.53	0.71	21.02	68.27

Based on the results of the patch type scale quantification in Table 3, the four landscape types in the Yellow River basin exhibit significantly differentiated evolutionary trajectories, reflecting a complex pattern of "expansion-contraction-restoration-degradation" coexisting:

The rigid expansion and internal optimization of construction land are reflected in the increase in patch area CA from 83,200 km² to 112,500 km² (+35.2%), confirming the rapid advancement of urbanization. The number of patches (NP) surged from 15,642 to 34,781 (+122.4%), and patch density (PD) increased from 1.88 patches/km² to 3.09 patches/km², revealing that urban sprawl exhibits a core contiguous-peripheral fragmented pattern. The largest patch index (LPI) increased from 24.17% to 38.92%, indicating contiguous development in the main urban area; the aggregation index (AI) rose from 85.36 to 89.07, reflecting improved internal connectivity due to enhanced infrastructure. The landscape shape index (LSI) increased from 28.15 to 36.04, with road network segmentation and satellite town development leading to increased boundary irregularity.

The total arable land area decreased, with CA dropping from 221,500 km² to 186,400 km² (-15.8%), reflecting the impact of urban encroachment and ecological land conversion. NP increased from 28,735 to 52,406 (+82.4%), PD increased from 1.30 to 2.81 per km², with farmland being divided into small and micro-sized patches. LPI decreased from 32.46% to 25.73%, with a reduction in large-scale farmland; AI decreased from 79.24 to 74.32, with spatial dispersion weakening farming efficiency. LSI increased from 41.83 to 47.29, with irrigation channels and mechanized road networks further complicating the landscape structure.

Forest area (CA) increased from 120,700 km² to 135,200 km² (+12.0%), reflecting the implementation of the grain-for-green policy. NP surged from 10,215 to 27,638 (+170.6%), and PD increased from 0.85 per km² to 2.04 per km², reflecting the small-scale and dispersed nature of afforestation patches. LPI increased from 18.63% to 23.81%, indicating enhanced dominance of natural forest reserves; AI rose from 83.17 to 88.05, reflecting improved connectivity through ecological corridor construction. LSI increased from 26.94 to 33.76, driven by the addition of firebreaks and tourist trails, which increased boundary complexity.

The CA of water bodies dropped sharply from 34,700 km² to 04,500 km² (-87.0%), highlighting the water crisis. The NP increased from 2,647 to 6,087 (130.0%), the PD increased from 0.76/km² to 13.53/km², and the lake dried up and split into discrete pits. The LPI plummeted from 6.24% to 0.71%, and large water bodies disappeared; AI drops from 77.85 to 68.27, and hydrological connectivity collapses. The LSI rose from 12.28 to 21.02, and the boundary was fragmented due to broken channels and shrinking wetlands.

III. C. Classification of Traditional Village Names in the Yellow River Basin

Spatial evolution analysis reveals the reconstructive effects of human activities on natural landscapes, while place names, as the core carriers of cultural landscapes, can inform heritage protection strategies through their classification. By analyzing 662 traditional village place names, this study lays the foundation for subsequent research on spatial distribution.

Traditional village place names in the Yellow River basin are divided into two major categories: natural landscape-related and human landscape-related. Natural landscape-related place names are further categorized into geographical orientation, hydrological, plant and animal, and topographical types; human landscape-related place names are categorized into economic activity, historical and cultural, military-related, architectural and garden, surname-based, auspicious meaning, settlement, and numerical sequence types. The classification statistics of traditional village names in the Yellow River Basin are shown in Table 4.

Table 4: Statistics of Traditional Village Names of Yellow River Basin

Category	Frequency	Percentage	Type	Frequency	Percentage
Natural Landscape Category	252	38.07%	Geographical location	113	17.07%
			Hydrology	46	6.95%
			Plants and animals	43	6.50%
			Topography and landforms	50	7.55%
Cultural and Historical Landmarks Category	410	61.93%	Economic activities	17	2.57%

			Historical culture	22	3.32%
			Military-related matters	39	5.89%
			Architecture and gardens	45	6.80%
			Surnames and naming conventions	208	31.42%
			Good meanings	51	7.70%
			Settlements	17	2.57%
			Number sequences	11	1.66%

Among the 662 traditional village place names in the Yellow River basin, humanistic landscape-related place names dominate, accounting for 61.93%, significantly higher than the 252 natural landscape-related place names (38.07%). Specifically, humanistic landscape-related place names are centered around those named after surnames (31.42%, totaling 208), reflecting the profound influence of clan culture on village naming; followed by those with auspicious meanings (7.70%, 51) and architectural and garden-related names (6.80%, 45), highlighting the public's emphasis on auspicious symbols and artificial environments. Among natural landscape categories, geographical orientation-based names have the highest proportion (17.07%, 113), highlighting the tradition of topography-driven naming; hydrological categories (6.95%, 46), topographical and landform categories (7.55%, 50), and plant and animal categories (6.50%, 43) collectively reflect the natural ecological characteristics of the Yellow River basin.

III. D. Spatial Characteristics of Traditional Village Place Name Cultural Landscapes

The nearest index of traditional village names in the Yellow River basin is shown in Table 5.

Table 5: The nearest name similarity index of villages in the Yellow River Basin

Category	The nearest index K	Spatial distribution type	Type	The nearest index K	Spatial distribution type
Natural Landscape Category	0.92	Coagulability	Geographical location	0.91	Coagulability
			Hydrology	1.02	Uniformity
			Plants and animals	0.95	Coagulability
			Topography and landforms	0.92	Coagulability
Cultural and Historical Landmarks Category	0.96	Coagulability	Economic activities	1.35	Uniformity
			Historical culture	1.02	Uniformity
			Military-related matters	0.93	Coagulability
			Architecture and gardens	0.90	Coagulability
			Surnames and naming conventions	1.07	Uniformity
			Good meanings	1.13	Uniformity
			Settlements	1.06	Uniformity
			Number sequences	0.93	Coagulability

Both natural landscape and cultural landscape categories exhibit clustered distributions, with nearest neighbor indices K of 0.92 and 0.96, respectively, where $K < 1$, indicating that place names are significantly spatially clustered, driven by geographical environment and historical settlement patterns. Within the natural landscape subcategories, geographical orientation ($K = 0.91$), flora and fauna ($K = 0.95$), and topography ($K = 0.92$) all exhibit high clustering, while the hydrological category approaches uniform distribution ($K = 1.02$), possibly due to the linear extension characteristics of river networks. Among the human landscape subcategories, military-related ($K=0.93$), architecture and gardens ($K=0.90$), and numerical sequences ($K=0.93$) exhibit clustered distributions; while economic activity ($K=1.35$), surname naming ($K=1.07$), and auspicious meanings ($K=1.13$) are uniformly distributed ($K>1$), reflecting the widespread coverage of economic activities and clan expansion.

The specific kernel density maps of natural and human landscape categories in the Yellow River Basin are shown in Figures 5 and 6.

It can be seen that both types are agglomerated, with nuclear densities mostly concentrated in the 80-100 range. Among them, natural landscape villages are mainly concentrated in the left and middle parts of the Yellow River basin, while cultural landscape villages are mostly concentrated in the lower right corner. Topographical and surname-named villages were selected as the focus of the study, and their distribution and nuclear density maps are shown in Figures 7 and 8.

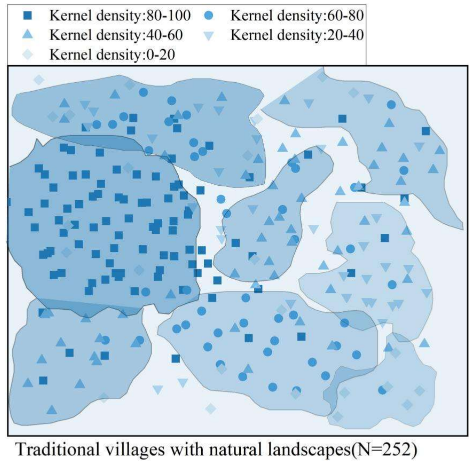

Figure 5: The density of natural landscapes in the Yellow River Basin

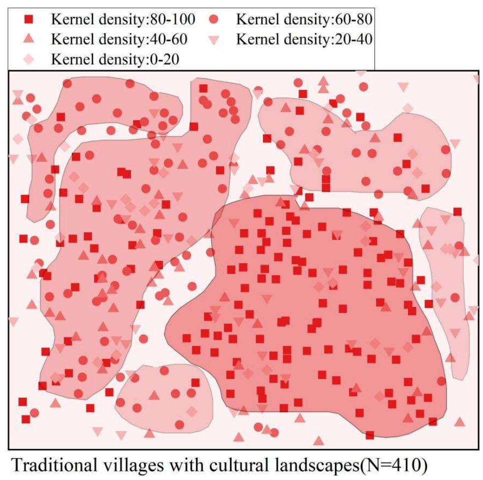

Figure 6: The density of cultural landscapes in the Yellow River Basin

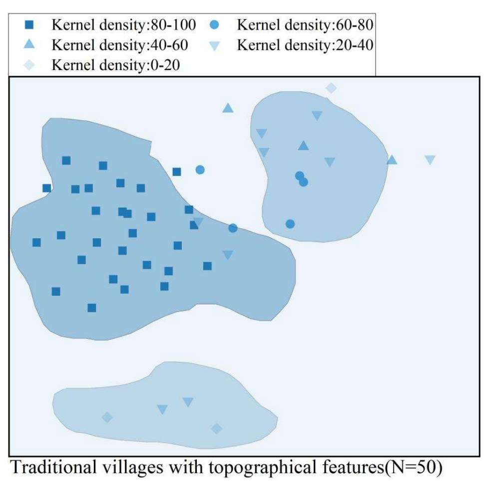

Figure 7: The density of topographical features in the Yellow River Basin

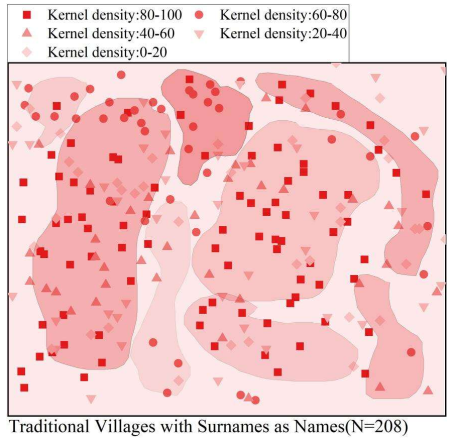

Figure 8: The density of Surnames as Names in the Yellow River Basin

It can be seen that there are 50 traditional villages classified as topographical and geographical, also of the cohesive type. Their spatial layout is similar to that of natural landscape-related place names, with a higher concentration in the southwest and fewer in the eastern regions. This aligns well with the topographical orientation of the Yellow River basin and reflects the associated landscape characteristics.

Villages named after surnames exhibit a uniform distribution pattern in the Yellow River basin and are relatively numerous, indicating that clan-based villages, though widely present, have a relatively dispersed spatial distribution. This may be related to historical migration and geographical adaptability.

IV. Conclusion

This study addresses the contradiction between the protection of cultural landscape heritage and modernization in the Yellow River Basin. It employs spatial syntax, dynamic monitoring, and landscape pattern indices to conduct a multidimensional quantitative analysis.

(1) Spatial structural characteristics: The overall integration of the scenic area is 0.62, but the comprehensibility of region A is only 0.36 and the coordination is 0.47, revealing directional obstacles caused by damage to historical remains.

(2) Landscape dynamic evolution shows a 128.7% increase in patch numbers (from 57,239 to 130,912), with a patch density of 9.25 patches per km², indicating worsening fragmentation. The expansion of construction land by 35.2% (from 8.32 to 11.25 million km²) and the shrinkage of water bodies by 87.0% (from 3.47 to 0.45 million km²) highlight the human-land conflict; the Shannon Diversity Index (SHDI) has risen to 1.20, but the Contagion Index (CONTAG) has dropped to 37.01, reflecting the degradation of ecological connectivity;

(3) In the distribution of place names, humanistic landscape-related place names account for 61.93%, surname-based place names account for 31.42%, natural landscape-related place names account for 38.07%, and geographical orientation-related place names account for 17.07%;

(4) Kernel density analysis shows that terrain-related villages exhibit clustered distribution with a nearest neighbor index K=0.92, while surname-based place names exhibit uniform dispersion with K=1.07.

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