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Analysis of Landscape Fragmentation Evolution Characteristics and Driving Factors in the Wei River Basin, China

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Abstract: Historically, the Wei River has served as part of the Yongji Canal section of the Grand Canal, playing a crucial role in connecting northern and southern China. However, with the acceleration of urbanization in China, issues such as excessive land development and ecological landscape fragmentation have emerged. Exploring the mechanisms of landscape fragmentation evolution in the Wei River basin and proposing optimization strategies is of significant importance for land use and ecological stability within small- to medium-sized river basins. This study selected land use data from the Weihe River basin between 2000 and 2020, using landscape pattern indices to analyze the trend of landscape fragmentation. The principal component analysis (PCA) and geographical detector methods were employed to explore the distribution characteristics and driving factors of landscape fragmentation. The research results indicate that: (1) The degree of landscape fragmentation in the Wei River basin has progressively intensified over time. The edge density index (ED), the landscape division index (DIVISION), the landscape shape index (LSI), and the Shannon diversity index (SHDI) have increased annually, while the contagion index (CONTAG) and area-weighted mean patch size (Area_AM) have continuously decreased; (2) Landscape fragmentation in the Wei River basin is characterized by stable changes in the source and tributary fragmentation areas, a concentrated distribution of fragmentation in the tributaries, and a significant increase in fragmentation in the main stream; (3) The analysis using the geographic detector method indicates that vegetation coverage (FVC), human activity intensity (HAI), and land use/land cover change (LUCC) are the main driving factors of landscape fragmentation in the Wei River basin. The findings explore the mechanisms of landscape fragmentation in the basin and provide a reference for land use planning and ecological restoration in the region.

Keywords: landscape pattern; landscape pattern index; degree of fragmentation; spatiotemporal pattern; geographical detector

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1. Introduction

The Wei River basin is part of the Zhang-Wei River system, a primary tributary of the Hai River basin. It plays a critical role in agricultural production, water supply security, and regional ecological balance in Henan Province, China [1]. The basin is rich in natural resources, encompassing diverse landscapes such as farmland, water bodies, urban areas, and vegetation, which provide crucial support for the ecosystem. With the intensification of urban expansion and the increasing pollution caused by human activities [2], the degree of landscape fragmentation in the basin has deepened [3]. Currently, there is a lack of research on the mechanisms of landscape pattern fragmentation and evolution in the environmental management of this basin. This study focuses on the evolution characteristics and driving factors of landscape fragmentation in the Wei River basin, aiming to optimize the rational allocation and utilization of land resources in the basin and enhance the stability of the ecosystem.

Human activities are not only regulated by and influenced by landscapes, but they may also induce changes in landscapes, further promoting the diversification of landscape element configuration and composition, thereby forming different landscape patterns [4,5]. The changes in landscape patterns caused by urbanization are primarily manifested as landscape fragmentation. This change is closely related to the increase in human activities and the alteration of landscape functions, with human activities serving as the key driving force behind this transformation [6,7]. Fragmentation leads to a reduction in patch size, an increase in habitat isolation, and an expansion of edge distances, resulting in changes in the internal relationships within ecosystems, which in turn affect the growth environments of species [8]. Therefore, the study of landscape fragmentation has become a major focus in the field of landscape ecology.

The basin is one of the earliest geographic units of human activity and remains one of the most strained areas in terms of the relationship between humans and the environment. With the acceleration of urbanization, significant changes in land use have occurred, leading to alterations in landscape patterns. However, natural factors, such as annual average temperature, annual evaporation, and annual precipitation, directly influence soil water storage [9], thereby shaping the formation and changes in landscape patterns [10]. Landscape fragmentation, as the main trend of this change [11], is closely linked to both natural and human activity-induced disturbance factors [12]. In existing studies, some scholars have systematically analyzed changes in land use data using satellite imagery and geographic information system (GIS) technology, and have quantified the number of patches for various land types to assess land use changes and the degree of fragmentation [13]. Building on this, landscape pattern indices have been widely applied for the quantitative description of landscape fragmentation, with their evolution patterns being measured and analyzed across different scales (e.g., county, grid, etc.) [14,15]. However, landscape pattern indices often contain redundancy in the multidimensional data, which may lead to analysis biases and increased complexity. To reduce redundancy and improve accuracy, the principal component analysis (PCA) can be used in dimensionality reduction to extract the key features [8]. Under this premise, driving factors are typically studied using the geographic detector model, the spatial autoregressive model, and the geographically weighted regression (GWR) model [16,17], with the geographic detector model being widely used to identify and quantify the impacts of these driving factors [18]. The traditional geographic detector model is limited by the spatial scale, spatial data discretization methods, and the number of layers, which lead to a certain degree of subjectivity in the results [19]. To address this issue, Song and other researchers developed an optimal parameters-based geographic detector (OPGD) on the R platform, which resolves the problems of spatial scale data discretization and subjective selection [20]. An objective analysis of driving factors helps to reveal the main causes of landscape pattern changes and to identify the relationships and interaction patterns among various factors [21]. In particular, evaluating human activities, and understanding their spatial distribution, intensity changes, and temporal characteristics, is crucial in preventing potential ecological risks [22]. Understanding the evolution mechanisms of human activities and landscape fragmentation is crucial in ecosystem protection [23].

Although landscape fragmentation has been widely studied in terms of pattern changes, most studies have relied solely on landscape pattern indices from a single year to analyze the driving factors, using traditional geographic detector methods. This approach overlooks the continuity of landscape fragmentation and the objectivity in the analysis of the driving factors. Additionally, there has been limited research on the quantification of human activity intensity and its application in driving factor analysis, resulting in a lack of in-depth exploration of the relationship between human activities and landscape fragmentation in existing studies. This study takes the Wei River basin as a case study, employing the principal component analysis based on multi-temporal landscape pattern indices, combined with the optimal parameters of the geographic detector model, and integrating a human activity intensity quantification model, thereby enriching the research methodology. This method accurately preserves the temporal continuity of landscape fragmentation, enhances the objectivity of the driving factor analysis, and provides a scientific reference for land use optimization and ecological restoration in the Wei River basin.

2. Materials and Methods

2.1. Study Area

The Wei River originates from Nanling, Duohuo Town, Lingchuan County, Shanxi Province, China. It flows to Xuwan Cang Village, Guantao County, Hebei Province, where it converges with the Zhanghe River to form the Zhang-Wei River (Figure 1). The Wei River has a total length of 394 km and a drainage area of 19,451 km^2 [24]. It is located in the southern part of the North China Plain, at the eastern foot of the Taihang Mountains, primarily covering the northern part of Henan Province. To the south, it borders the Yellow River; to the north, it connects with the Zhanghe River; and to the east, it is adjacent to the eastern line of the Grand Canal [25]. The basin can be divided into three parts: the source area, which includes the Dasha River, the Shimen River, and others, features significant topographical relief, and is primarily composed of plains and mountains, with the mountain areas designated as nature reserves; the tributary area, which includes the Qi River, the Tang River, the Anyang River, and others, and exhibits notable elevation variations, with both mountain ranges and plains. The eastern part is relatively higher in elevation, while the western part is lower; and the main river area, which includes the Wei River and the Communist Canal, is characterized by flat terrain and is predominantly plain. The Wei River basin is located in a temperate continental monsoon climate zone, with significant seasonal variations. The spring is dry and windy, with frequent sandstorms; the summer is hot and experiences abundant rainfall, making it prone to both droughts and floods; the autumn has long sunshine hours; while the winter is cold with little wind and snowfall [26].

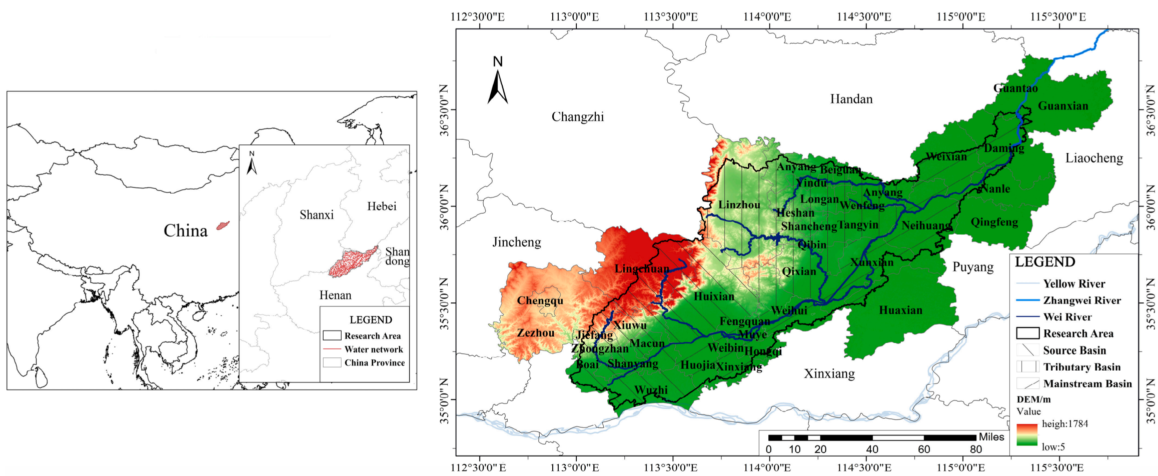

Figure 1. Study area of the Wei River basin.

2.2. Data Sources and Preprocessing

To accurately analyze the evolution characteristics of landscape fragmentation in the Wei River basin, this study selected land use data for the years 2000, 2010, and 2020. The data were obtained from the Resource and Environmental Science and Data Center, Chinese Academy of Sciences [27], with a spatial resolution of 1 km. The administrative boundaries of the study area were sourced from the Resource and Environmental Science and Data Center, Chinese Academy of Sciences [28]. The digital elevation model (DEM) data for the study area were obtained from the Geospatial Data Cloud [29], with a spatial resolution of 30 m. These data were used to extract key topographical factors such as elevation, watershed, and terrain relief in the study area, thereby accurately reflecting the topographical features of the Wei River basin. The forest vegetation coverage (FVC) data were obtained from the Geographic Data Sharing Infrastructure, Global Resources Data Cloud [30], with a spatial resolution of 1 km. These data represent the percentage of the total area of the statistical region covered by the vertical projection of vegetation leaves, stems, and branches onto the ground. The road density and population density data were obtained from OpenStreetMap and LandScan [31,32], respectively. The data from these platforms are open and accurate, and are widely used in relevant research. The normalized difference vegetation index (NDVI) [33], nighttime light data [34], and annual average precipitation data [35], along with the climate data, were obtained from the same platform as the land use data. The spatial resolution of the nighttime light data is 0.04°, while the spatial resolution of the other data is 1 km. Subsequent operations, including manual visual interpretation, clipping, and reclassification, were performed using the ArcGIS 10.8 software to ensure that the data accuracy exceeded 85%. Based on the land use/cover change (LUCC) classification standards and the actual land use conditions of the Wei River basin, the study area was divided into six categories: cultivated land, forest land, grassland, water bodies, built-up land, and unused land [36].

2.3. Research Methods

2.3.1. Landscape Pattern Indices

This study followed the method proposed by Liang et al. [37] and used the FRAGSTATS 4.2 software to calculate the landscape pattern indices of the Wei River basin for the years 2000, 2010, and 2020. The following indices were selected to describe the landscape fragmentation degree of the Wei River basin: the edge density (ED), the landscape shape index (LSI), the area-weighted mean patch size (Area_AM), the contagion index (CONTAG), the landscape division index (DIVISION), and the Shannon diversity index (SHDI) (Table 1).

Table 1. Significance of landscape pattern indices in the Wei River basin.

Number	Landscape Pattern Indices	Indicator Types	Rationale for Selection
1	ED	Positive indicators	The landscape edge density reflects the complexity of the patch shapes. The smaller its value, the shorter the boundary length per unit area, indicating a simpler patch shape.
2	LSI	Positive indicators	The landscape shape index can fully characterize the complexity of patch shapes in the landscape. The more complex the shape of the landscape patches, the higher the value of this index, indicating a greater degree of fragmentation.
3	Area-AM	Negative indicator	At the patch type level, it is the area-weighted average of the area of patches of a certain type. At the landscape level, it is the area-weighted average of the areas of all the patches within the landscape.

Table 1. *Cont.*

Number	Landscape Pattern Indices	Indicator Types	Rationale for Selection
4	CONTAG	Negative indicator	Contagion is used to measure the degree of aggregation or the expansion trend of the patch types in the landscape, reflecting the spatial structure of the landscape pattern. The larger the value, the higher the aggregation degree between patches, indicating a lower degree of landscape fragmentation.
5	DIVISION	Positive indicators	This landscape pattern index refers to the degree of separation in the distribution of different elements within a specific landscape type. The greater the separation degree, the more dispersed the landscape is spatially, indicating a more complex distribution and a higher degree of fragmentation.
6	SHDI	Positive indicators	The Shannon diversity index is an important indicator of landscape heterogeneity and can more accurately identify the spatially uneven distribution of different patch types within the landscape.

2.3.2. Principal Component Analysis

The selected landscape pattern indices in the study area effectively reflect the characteristics of landscape fragmentation; however, the fragmentation information provided by the relevant indices overlaps and intersects to some extent [37]. Therefore, this study employs the SPSS 27 software and principal component analysis (PCA) to reduce the dimensionality of multiple variables into a set of new, non-overlapping principal components to characterize the degree of landscape fragmentation in the basin. After standardizing the measurement data, they are substituted into the principal component calculation formula. The resulting values not only represent the degree of fragmentation in the basin but also serve as the dependent variable in the geographical detector model [37]. This study classifies the degree of fragmentation into five levels [38], namely slight fragmentation (0–0.05), moderate fragmentation (0.05–0.17), moderate to severe fragmentation (0.17–0.33), severe fragmentation (0.33–0.52), and extreme fragmentation (0.52–1).

2.3.3. Optimal Parameters-Based Geographical Detector (OPGD)

This study uses an objective and quantitative approach to assess the relationship between spatial heterogeneity features and influencing factors. Based on the geographical detector method, it analyzes the driving factors of landscape fragmentation in the Wei River basin. This method is a set of statistical tools used to detect spatial heterogeneity and reveal the underlying driving factors. It primarily includes risk detection, factor detection, ecological detection, and interaction detection [39]. The core idea is based on the assumption that if a certain independent variable has a significant impact on the dependent variable, then the spatial distribution of the independent variable and the dependent variable should exhibit similarity [40,41]. Compared with the traditional geographical detector model, the advantage of the optimal parameters-based geographical detector (OPGD) is that it uses five classification methods—equal interval, natural breaks, quantile, geometric interval, and standard deviation—which improve the objectivity of the spatial heterogeneity Q value [20]. The calculation formula for the geographical detector is as follows:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{i=1}^{L} N_i \sigma_i^2 \quad (1)$$

In the geographical detector model, q represents the spatial heterogeneity of a certain indicator, $q \in [0, 1]$; N denotes the total number of samples in the study area; σ_i^2 represents the variance of the indicator; i = 1, 2, . . . L, i represents the sub-region or partition, and L represents the number of partitions or sub-regions. The value of q reflects the degree of spatial heterogeneity. A larger q indicates stronger spatial stratification and heterogeneity, while a smaller q suggests greater randomness in the spatial distribution. When q = 0, it indicates the absence of spatial heterogeneity in the study area; when q = 1, it indicates perfect spatial heterogeneity [42].

The interaction detector is used to reveal the relationships between different driving factors. Its core purpose is to evaluate whether the explanatory power of the two factors on the dependent variable is enhanced or weakened when they interact [40]. The relationships between factors can be classified into five types: dual-factor enhancement, non-linear enhancement, mutual independence, non-linear weakening, and single-factor non-linear weakening (Table 2).

Table 2. Basis for judging factor interactions.

Interaction Type	Criteria for Judgment
Dual-factor enhancement	$q(X1 \cap X2) > Max(q(X1), q(X2))$
Non-linear enhancement	$q(X1 \cap X2) > q(X1) + q(X2)$
Non-linear weakening	$q(X1 \cap X2) < Min(q(X1), q(X2))$
Single factor non-linear weakening	$Min(q(X1), q(X2)) < q(X1 \cap X2) < Max(q(X1), q(X2))$
Independence	$q(X1 \cap X2) = q(X1) + q(X2)$

This study analyzes the spatial heterogeneity of landscape fragmentation in the watershed from three dimensions: natural factors, human factors, and their combined effects (Figure 2). It selects data from 11 driving factors, including vegetation cover, elevation, precipitation, road density, population density, and human activity intensity [37,43].

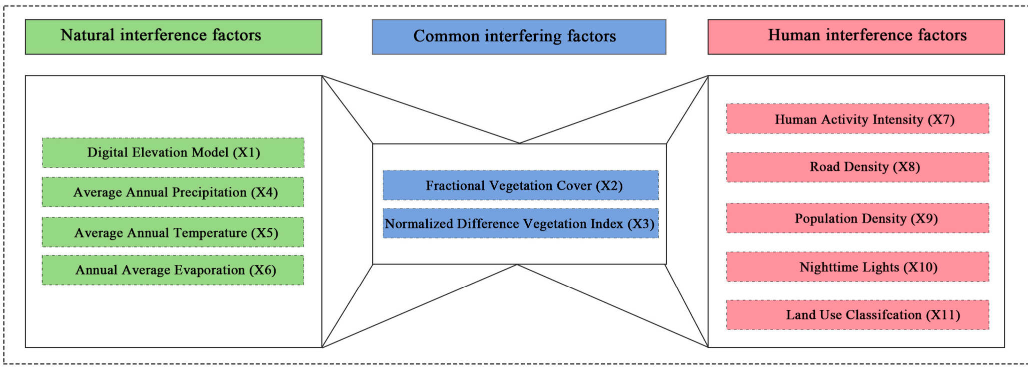

Figure 2. Division of independent variables in the geographic detector.

2.3.4. Human Activity Intensity (HAI)

This study references the work of Chen et al., based on the land use framework, combining population density data and nighttime light data to quantify the human activity intensity (HAI) expression model [44]. The weights for each land use type are determined by comprehensively referencing the relevant literature [43,45]. The human activity intensity (HAI) expression model is as follows:

$$HAI = aLU + bPD + cNL \tag{2}$$

In the formula, HAI is a comprehensive indicator used to measure the frequency and intensity of human activities in a specific area. This indicator typically relies on normalized land use and land cover change data (land use and land cover change, LU, population density data (population density, PD), and nighttime light data (nighttime light, NL), to reveal the spatial distribution characteristics of human activities. In this model, the weights for a, b, and c are set to 0.4, 0.3, and 0.3, respectively [44].

3. Results

3.1. Landscape Pattern Index Calculation

3.1.1. Based on Land Use Classifications

Based on the land use data of the Wei River basin for 2000, 2010, and 2020 (Table 3, Figure 3), the proportion of cultivated land decreased from 59.68% in 2000 to 57.37% in 2020. However, cultivated land remains the dominant land use type in the basin. From 2000 to 2020, the proportion of forest land increased slightly, rising from 13.53% to 13.59%, indicating a steady growth trend. The proportion of grassland decreased slightly, from 11.18% in 2000 to 11.10% in 2020, reflecting a generally stable land use and conservation strategy. The proportion of water bodies increased during the same period, rising from 0.84% to 0.91%, indicating a slight expansion of the water areas. The proportion of built-up land increased from 14.74% in 2000 to 17.01% in 2020, reflecting the high demand for land resources driven by rapid urbanization and population growth. At the same time, the proportion of unused land remained at a low level of 0.02%, indicating that the wasteland and undeveloped areas experienced almost no change during this period. The analysis shows a significant decline in the proportion of agricultural land and a marked increase in the proportion of built-up land, reflecting the rapid urbanization and industrialization in the basin. The changes in the forestland, grassland, and water areas have remained relatively stable, indicating that their environments have been effectively maintained. However, with the continued increase in built-up land, the rational allocation and utilization of land resources may face greater pressure. Therefore, there is an urgent need to strengthen the protection of the ecological environment in the Wei River basin.

Table 3. Area proportion of land use types in the Wei River basin.

Year	Cultivated Land	Forest Land	Grassland	Water Bodies	Construction Land	Unused Land
2000	59.68%	13.53%	11.18%	0.84%	14.74%	0.02%
2010	58.90%	13.53%	11.17%	0.86%	15.52%	0.02%
2020	57.37%	13.59%	11.10%	0.91%	17.01%	0.02%
Change	−2.31%	0.06%	−0.08%	0.07%	2.27%	0.00%

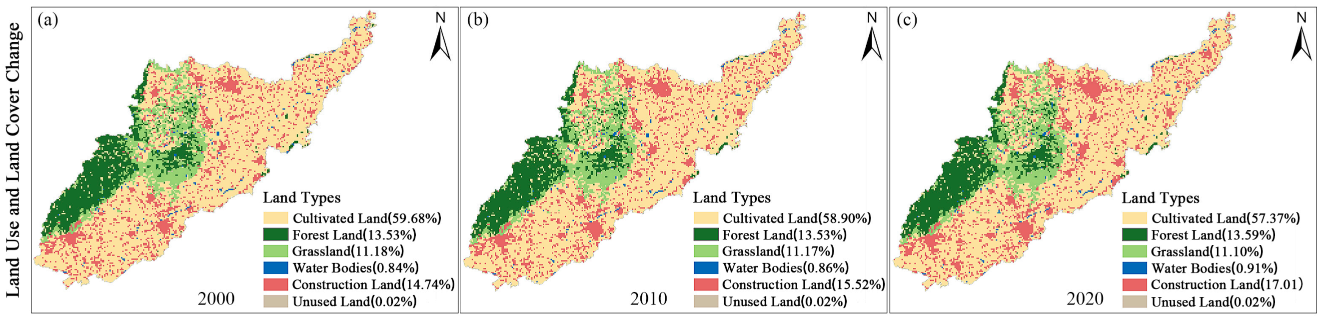

Figure 3. Land use type distribution map of the Wei River basin. (**a**–**c**) represent the land use data for the Wei River Basin in 2000, 2010, and 2020, respectively. Note: The percentages represent the proportion of each land use type's area relative to the total area of the basin.

During the time span from 2000 to 2020, the indices of various land use types exhibited different trends of change (Table 4), with significant variations observed in both the cultivated land and the construction land (Figure 4). The fragmentation trend in the cultivated land is reflected in the decrease in Area_AM from 1,222,003.07 m^2 to 1,171,948.85 m^2, the increase in ED from 4.3197 m/hm^2 to 4.4001 m/hm^2, the rise in DIVISION from 0.6667 to 0.6927, and the increase in LSI from 22.4236% to 23.1689%. These changes indicate a growing complexity in the shape of the cultivated land, an increase in the edge length, strengthened regional fragmentation, and a reduction in connectivity. The expansion of the construction land is quantitatively confirmed by the increase in ED from 3.2610 m/hm^2 to 3.3780 m/hm^2, while its shape complexity remains stable. The decrease in LSI from 32.2544% to 31.0244% indicates a trend towards landscape simplification. Area_AM increases to 7558.51 m^2, intuitively reflecting an expansion in area. Although the degree of fragmentation has slightly decreased, with the DIVISION value approaching 1, it suggests that the fragmentation of the construction land still exists, though to a lesser extent.

Table 4. Changes in the type horizontal index of the Wei River basin from 2000 to 2020.

Year	Landscape Index	Landscape Types					
		Cultivated Land	Forest Land	Grassland	Water Bodies	Construction Land	Unused Land
2000	ED	4.3197	1.1057	1.5718	0.2678	3.2610	0.0059
	LSI	22.4236	12.0734	17.8384	10.8214	32.2544	1.75
	Area_AM	1,222,003	148,756	117,497	273	4308	150
	DIVISION	0.6667	0.9908	0.9940	1	0.9997	1
2010	ED	4.2954	1.1034	1.5736	0.2732	3.2500	0.0059
	LSI	22.3816	12.0826	17.8586	10.8929	31.3761	1.75
	Area_AM	1,203,949	148,554	117,317	295	5526	150
	DIVISION	0.6760	0.9908	0.9940	1.0000	0.9996	1
2020	ED	4.4001	1.0879	1.5668	0.2860	3.3780	0.0059
	LSI	23.1689	11.8091	17.7879	11.0000	31.0244	1.75
	Area_AM	1,171,948	149,570	116,650	297	7558	150
	DIVISION	0.6927	0.9907	0.9941	1.0000	0.9994	1

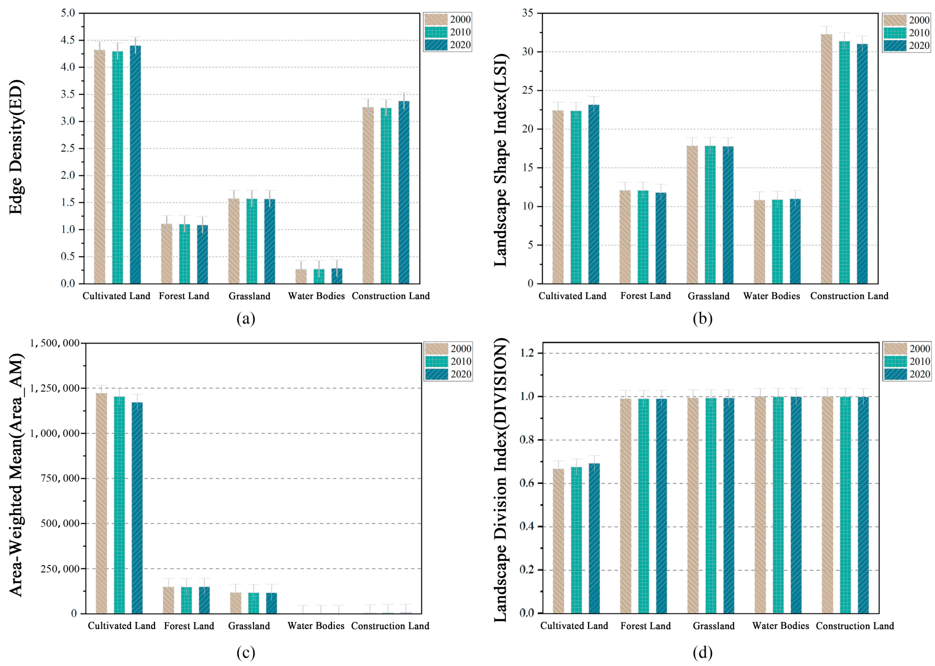

Figure 4. Changes in the land type index of the Wei River basin from 2000 to 2020. (**a**) trend of the ED index for each land use type, (**b**) trend of the LSI index for each land use type, (**c**) trend of the Area_AM index for each land use type, and (**d**) trend of the DIVISION index for each land use type.

In summary, the landscape pattern changes of the cultivated land and construction land are significant. The fragmentation and marginalization of cultivated land have intensified, leading to weakened regional connectivity. Meanwhile, the expansion of the construction land and the growth of the patch area reflect the accelerated urbanization process. In contrast, the landscape pattern changes of the forest land, grassland, and water bodies are relatively small. Over time, the land use pattern in the Wei River basin has become more fragmented and regionally isolated, with significant changes observed in the cultivated land and construction land. This phenomenon indicates a significant effect of landscape fragmentation in the watershed, particularly the fragmentation of the cultivated land and built-up areas. In contrast, the fragmentation of the forest land, grassland, and water bodies is relatively lower.

3.1.2. Landscape Pattern Index Trends

From 2000 to 2020, the positive indices ED, LSI, DIVISION, and SHDI in the Wei River basin consistently increased, while the negative indices CONTAG and Area_AM continued to decrease. This indicates a significant escalation in landscape fragmentation, showing a positive correlation with time (Table 5). Specifically, the increase in the ED index in the Wei River basin indicates a relative increase in the boundary length between ecological units in the landscape. At the same time, the rise in the LSI index reflects a growing irregularity in patch shapes and an increase in their geometric complexity. Furthermore, the increase in the DIVISION index reveals a strengthening of landscape heterogeneity, indicating that different types of patches have become more unevenly distributed in space. The rise in the SHDI points to an increase in the diversity of the patch types within the landscape, reflecting a more complex landscape structure and heightened heterogeneity. Conversely, the decrease in the CONTAG value suggests the continued presence of many small patches in the basin's landscape, with a weakened spatial aggregation of different patch types, resulting in a more fragmented overall landscape pattern. The reduction in the Area_AM index reflects a gradual decline in the average patch area, leading to an increase in the number of small patches. The analysis of these landscape pattern indices shows a significant increase in the degree of landscape fragmentation in the Wei River basin from 2000 to 2020.

Table 5. Changes in the landscape index of the Wei River basin from 2000 to 2020.

Year	ED	LSI	Area_AM	CONTAG	DIVISION	SHDI
2000	5.2659	21.7618	763,240.1992	47.6282	0.6513	1.1478
2010	5.2508	21.7061	743,120.0219	47.1924	0.6605	1.1590
2020	5.3623	22.1182	706,994.9100	46.2382	0.6770	1.1794
Change	+1.7977%	+1.6113%	−7.9555%	−3.0061%	+3.7961%	+2.6793%

3.1.3. Spatiotemporal Distribution Characteristics of Landscape Pattern Indices

As shown in Figures 5 and 6, the spatial distribution of the landscape pattern indices in the Wei River basin exhibits consistency. High-value areas of ED, LSI, DIVISION, and SHDI correspond to low-value areas of CONTAG and Area_AM. In the study area, regions with higher levels of landscape fragmentation are mainly located in the northern part of the central tributary area. This region features significant topographic relief and includes various land use types, such as cultivated land, forest land, grassland, and urban residential land. In addition, the landscape fragmentation degree is also relatively high in areas such as Linzhou City in the western part of the tributary and Huixian City in the eastern part of the headwater region. Through the analysis over time, it is observed that the spatial distribution of most landscape indices has shown little change, while the landscape fragmentation degree in a few areas has exhibited an increasing trend. Specifically, the ED in Qixian County and Xinxiang County shows an increasing trend, indicating that the boundary length of landscape patches in these areas is expanding. At the same time, the LSI in Qixian County is also rising, suggesting that the number of landscape patches in this region is increasing over time, and the shape of the patches is shifting from regular to irregular. The DIVISION index in Huojia County and Neihuang County has increased, reflecting a greater degree of fragmentation and the dispersion of landscape patches in these areas. Meanwhile, the rise in SHDI in Qibin District indicates an increase in the number of heterogeneous patches, with a corresponding intensification of fragmentation.

Through a comparative analysis, the landscape fragmentation in the Weihe River basin is mainly concentrated in its tributary areas, particularly in the Linzhou, Qibin, Heshan, and Longan regions, where the fragmentation trend is most pronounced.

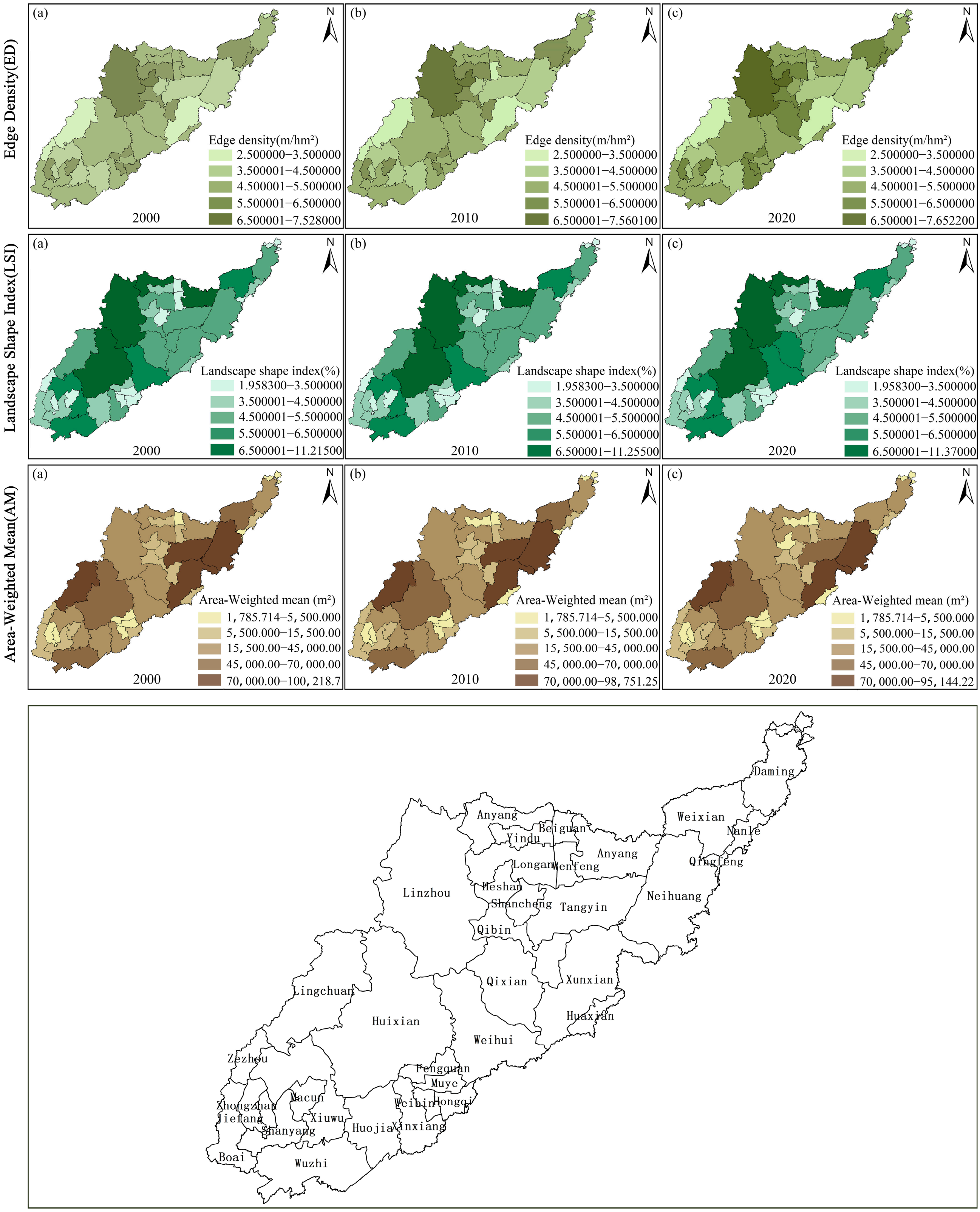

Figure 5. Spatial distribution maps of ED, LSI, and Area_AM in the Wei River basin. (**a**–**c**) represent the county-level spatial distribution of landscape pattern indices in the Wei River Basin for 2000, 2010, and 2020, respectively.

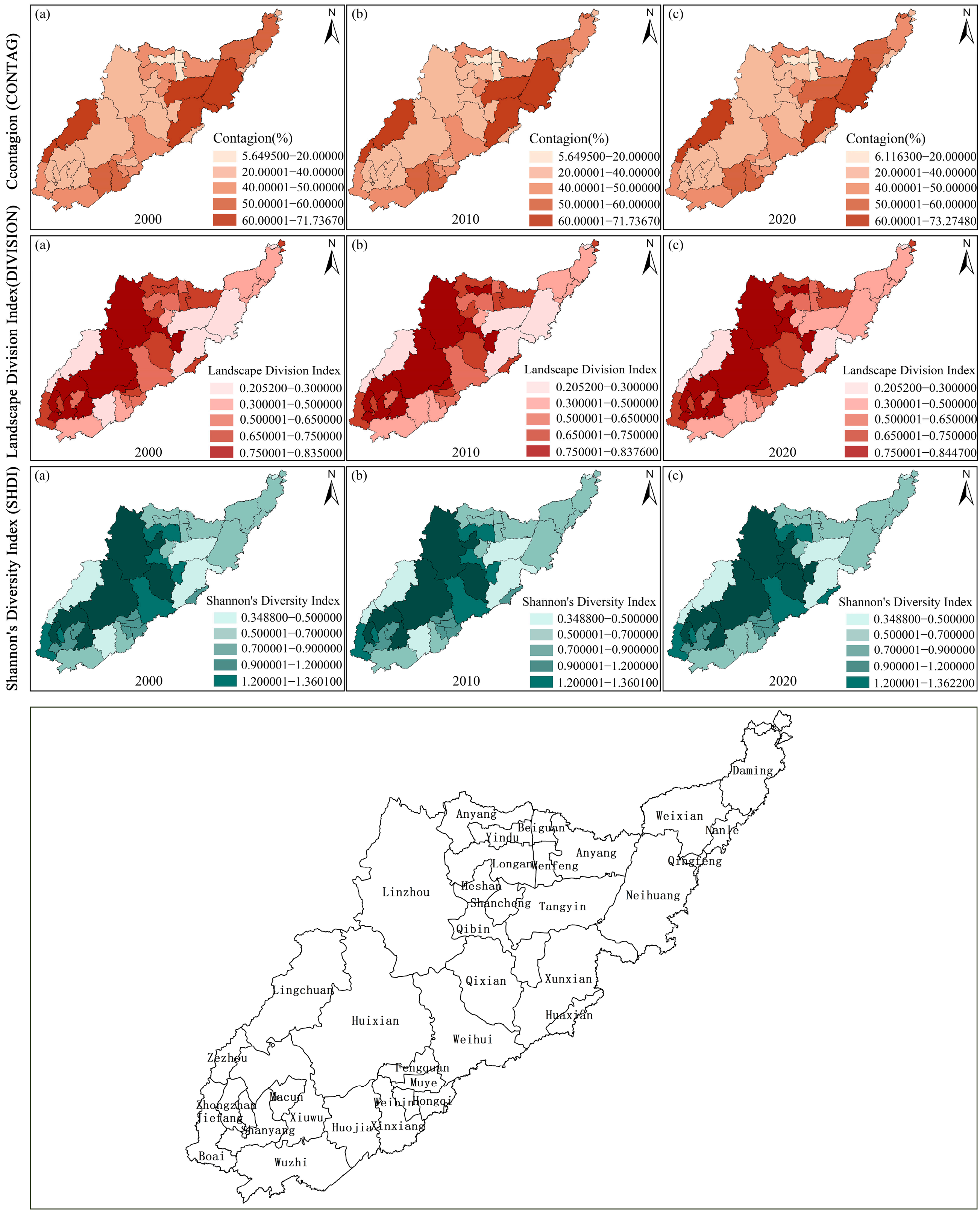

Figure 6. Spatial distribution maps of CONTAG, DIVISION, and SHDI in the Wei River basin. (**a**–**c**) represent the county-level spatial distribution of landscape pattern indices in the Wei River Basin for 2000, 2010, and 2020, respectively.

3.2. Comprehensive Analysis of Landscape Fragmentation

3.2.1. Principal Component Variables of Comprehensive Landscape Fragmentation

This study first conducted an independent principal component analysis (PCA) for the data at three time points—2000, 2010, and 2020—ensuring that the KMO value for each period was greater than 0.5, which meets the prerequisite conditions for factor analysis. To ensure the continuity of landscape fragmentation evolution, the data from the three periods were combined in a comprehensive analysis, resulting in the principal component analysis results for the landscape indices of the Wei River basin (Table 6).

Table 6. Principal components of the landscape index in the Wei River basin, 2000–2020.

Year	KMO	Bartlett	Landscape Index	Common Factor Variance		Component	Initial Eigenvalue			Component Matrix
				Initial	Extract		Total	Variance Percentage	Cumulative Percentage of Variance	1
2000	0.733	0.000	ED	1	0.992	1	5.444	90.731	90.731	0.996
			LSI	1	0.992	2	0.530	8.836	99.567	0.996
—			Area_AM	1	0.956	3	0.020	0.339	99.906	−0.978
			CONTAG	1	0.582	4	0.006	0.094	100.0	0.763
			DIVISION	1	0.958	5	0.000	0.000	100.0	0.979
2020			SHDI	1	0.963	6	0.000	0.000	100.0	0.981

From the analysis results, the KMO value for the period from 2000 to 2020 was 0.733. To enhance the rationality of the comprehensive landscape fragmentation analysis in the Wei River basin, the first principal component, which accounts for 90.731% of the variance, was selected as the representative indicator. The expression for the comprehensive variable of landscape fragmentation is as follows:

$$F = Z_{ED} \times 0.426 + Z_{LSI} \times 0.426 - Z_{Amera\_AM} \times 0.419 + Z_{CONTAG} \times 0.327 + Z_{DIVISION} \times 0.419 + Z_{SHDI} \times 0.420 \quad (3)$$

In the formula, the composite variable F is constructed by dividing the corresponding component matrix coefficients by the root 5.444. Z_{ED}, Z_{LSI}, Z_{Area_AM}, Z_{CONTAG}, $Z_{DIVISION}$, and Z_{SHDI} represents the standardized values of the landscape index.

3.2.2. Temporal and Spatial Distribution of Comprehensive Landscape Fragmentation

Through the analysis of the spatial—temporal distribution pattern of the comprehensive landscape fragmentation from 2000 to 2020 in the Wei River basin (Figure 7), it is evident that the overall fragmentation degree in the basin has significantly intensified. From a temporal perspective, both the number of areas with severe and extreme fragmentation in the Wei River basin have shown an increasing trend, indicating that the degree of landscape fragmentation has intensified. From a spatial perspective, highly fragmented areas are primarily concentrated in the northern part of the basin's middle section, where the topography is more undulating, and exhibit a tendency to spread towards the eastern part (Figure 8). In contrast, the degree of fragmentation in the western part of the basin has changed relatively little, while the fragmentation in the eastern and southern regions has significantly increased. Overall, the degree of landscape fragmentation in the basin is generally high, highlighting the urgent need for effective measures to protect the ecological environment of the Wei River basin.

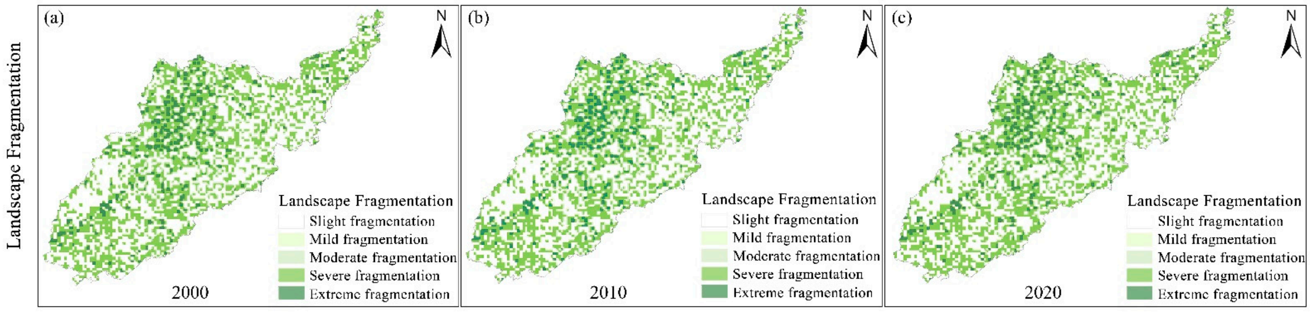

Figure 7. Spatiotemporal distribution pattern of comprehensive landscape fragmentation in the Wei River basin from 2000 to 2020. (**a**–**c**) represent the spatial distribution of comprehensive landscape fragmentation in the Wei River Basin for 2000, 2010, and 2020, respectively.

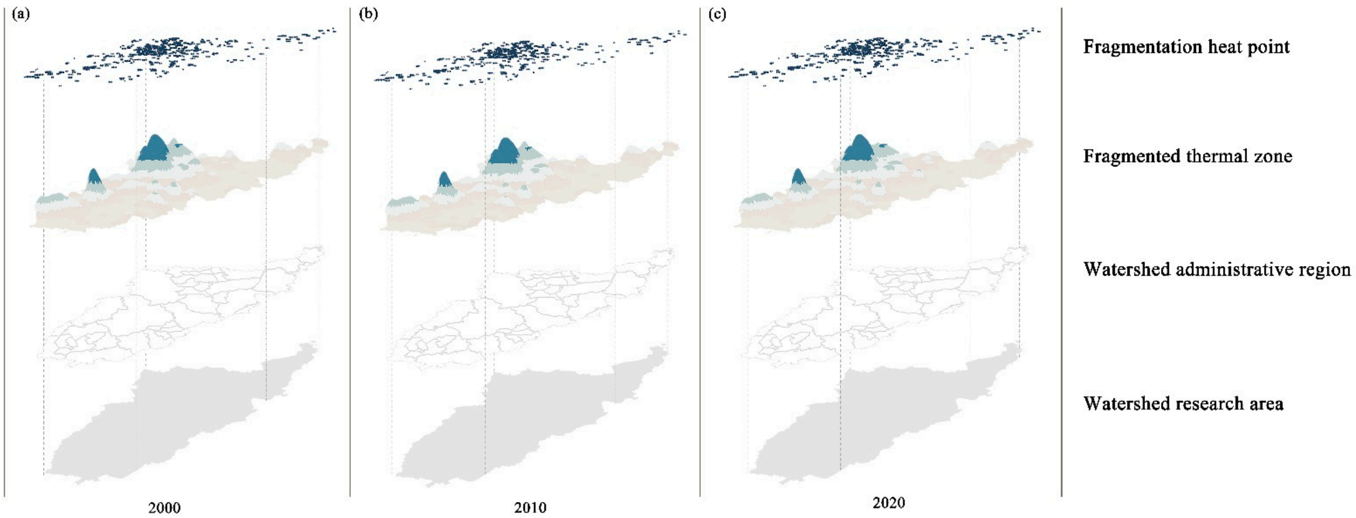

Figure 8. Spatial distribution map of hotspots of comprehensive landscape fragmentation in the Wei River basin from 2000 to 2020. (**a**–**c**) represent the concentrated areas of moderate and severe comprehensive landscape fragmentation in the Wei River Basin for 2000, 2010, and 2020, respectively.

In the study of landscape fragmentation in the Wei River basin, it was found that the degree of fragmentation in the headwater area remained relatively stable, while the fragmentation in the tributary areas showed a geographic distribution pattern with higher levels in the western part and lower levels in the eastern part. Meanwhile, the degree of landscape fragmentation in the main channel area has shown a tendency to increase. Based on the spatiotemporal distribution characteristics of landscape fragmentation in the headwater, tributary, and main channel areas (Figure 9), the fragmentation degree in the headwater area is generally above moderate, with heavy and extreme fragmentation primarily concentrated in the northeastern part. In the tributary zones of the Wei River basin, most regions in the western part have reached a state of extreme landscape fragmentation, with no signs of a decrease in fragmentation observed during the study period. Furthermore, this extreme fragmentation is predominantly concentrated in the western regions, exhibiting a trend of expansion towards the east. In the main stem zones, areas with a higher degree of fragmentation are mainly located in the northeastern part, where a significant shift from moderate to severe fragmentation has been observed.

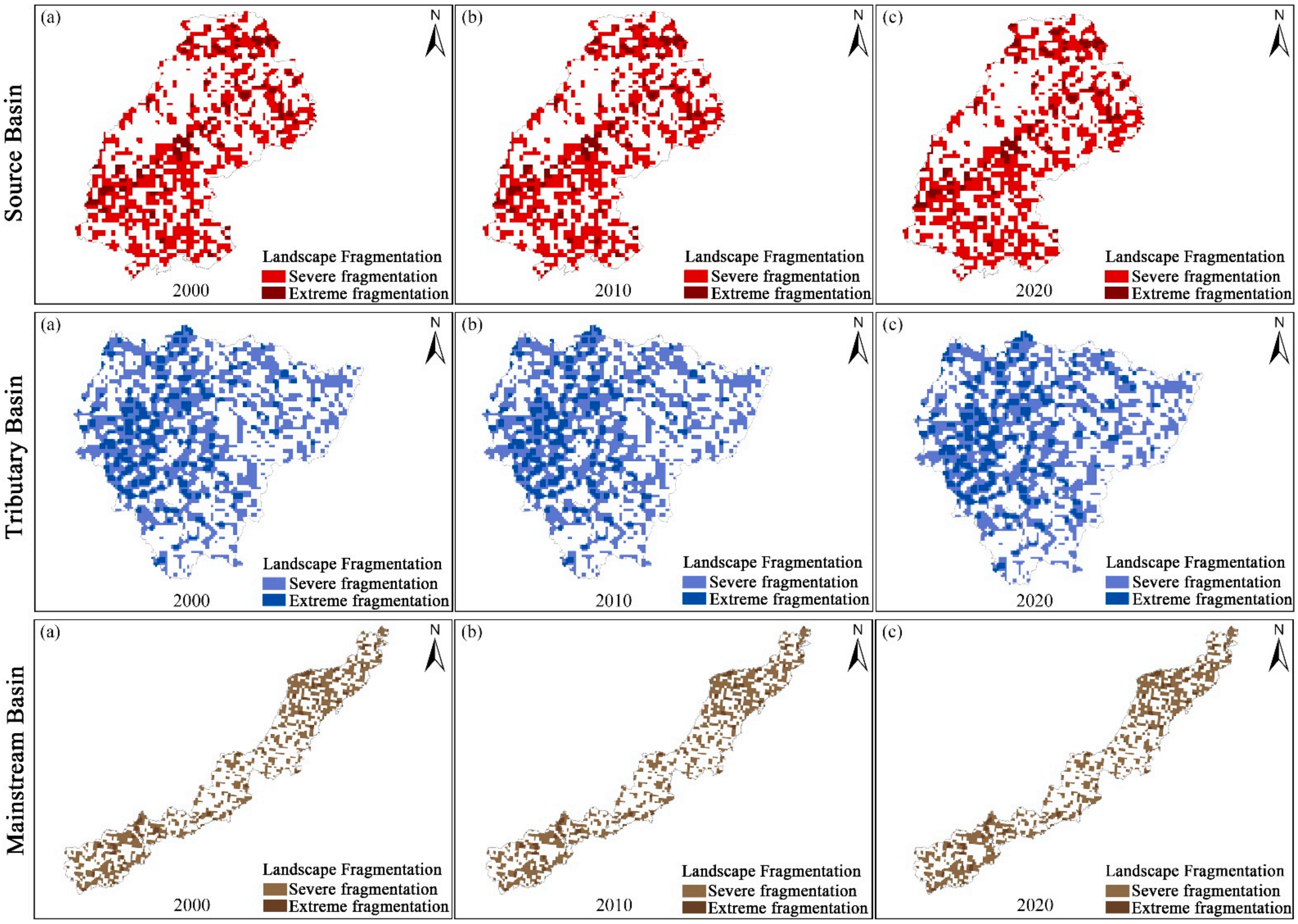

Figure 9. Spatiotemporal distribution pattern of landscape fragmentation in each sub-basin of the Wei River from 2010 to 2020. (**a**–**c**) represent the spatial distribution of moderate and severe comprehensive landscape fragmentation in the headwaters, tributaries, and main stream of the Wei River Basin for 2000, 2010, and 2020, respectively.

3.3. Analysis of Driving Factors of Landscape Fragmentation

3.3.1. Optimal Discretization Analysis

The results of the OPGD optimization parameter discretization indicate that vegetation coverage (X2) and human activity intensity (X7) are the primary driving factors of landscape fragmentation, while the Q-values of the other factors did not exceed the 0.1 threshold. An analysis using the geographical detector revealed significant variations in the Q-values of vegetation coverage (X2) and human activity intensity (X7) across different discretization levels (Figure 10). In the geometric interval classification method, the Q-value of vegetation cover (X2) reaches its maximum at five classification levels. In contrast, in the natural break classification method, the Q-value of human activity intensity (X7) is highest at ten classification levels, exhibiting a fluctuating upward trend. The results indicate that the driving effects of the influencing factors on landscape fragmentation exhibit a certain degree of complexity across different discretization levels.

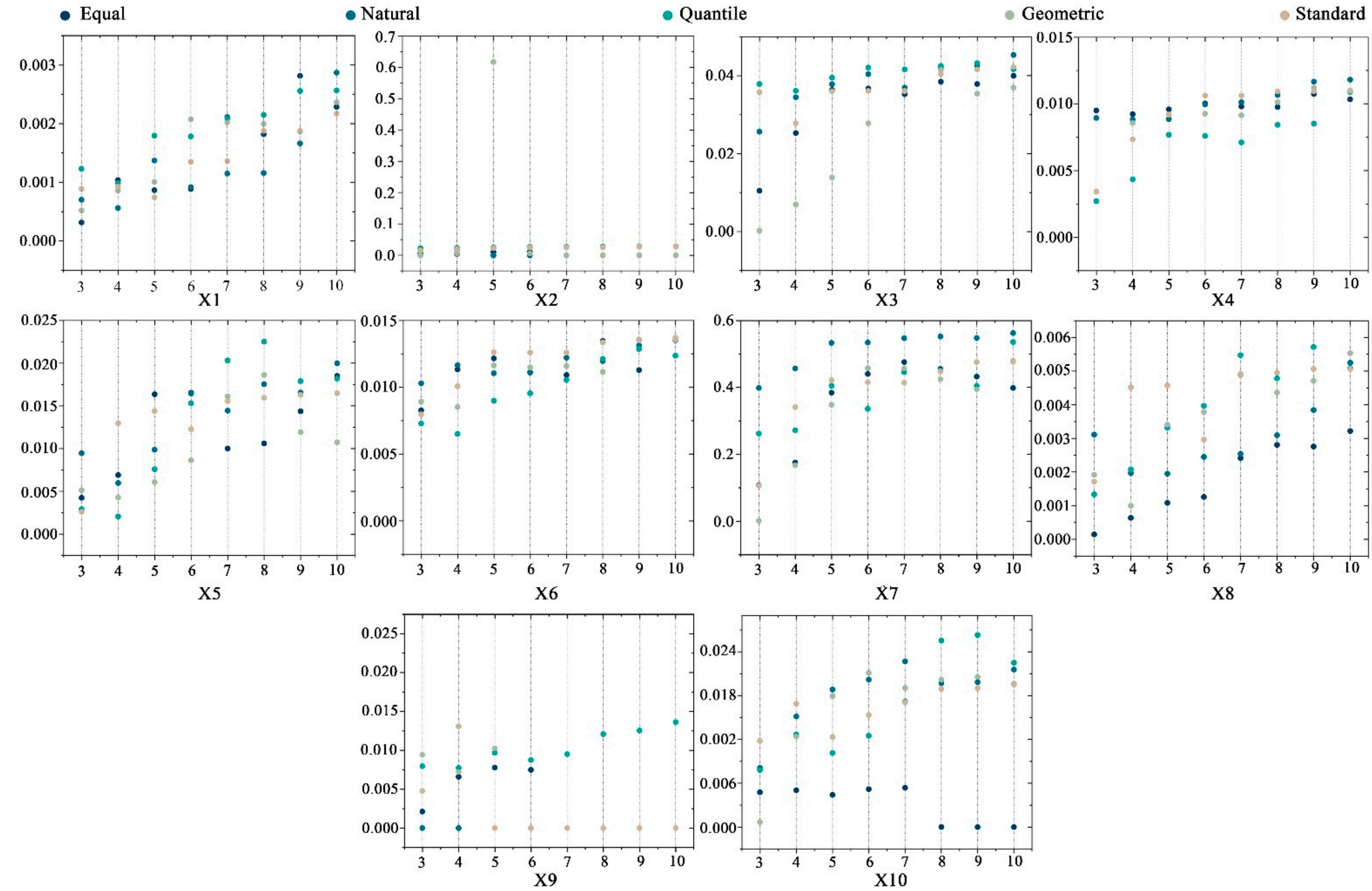

Figure 10. Optimal parameter discretization results of OPGD. Note: Digital Elevation Model (X1), Fractional Vegetation Cover (X2), Normalized Difference Vegetation Index (X3), Average Annual Precipitation (X4), Average Annual Temperature (X5), Annual Average Evaporation (X6), Human Activity Intensity (X7), Road Density (X8), Population Density (X9), Nighttime Lights (X10), and Land Use Classification (X11).

3.3.2. Factor Detector

The dynamic changes in landscape fragmentation in the Weihe River basin are influenced by multiple factors (Figure 11), with vegetation cover (X2) and human activity intensity (X7) being the key driving factors. From the perspective of global driving factors, vegetation coverage (X2) has the most significant impact on the spatial differentiation of landscape fragmentation in the basin compared with the other factors. Its Q-value reaches 0.6167, indicating that vegetation coverage plays a dominant role in the spatial differentiation of landscape fragmentation, with a greater explanatory power than other factors. Although population density (X9), nighttime light (X10), and land use classification (X11) did not show significant impacts in the single-factor variable analysis, the combined human activity intensity (X7), formed by these three indicators, plays a significant role in driving landscape fragmentation. Its correlation coefficient Q-value reaches 0.5623, indicating that human activity intensity has a moderate explanatory power in the spatial differentiation of landscape fragmentation.

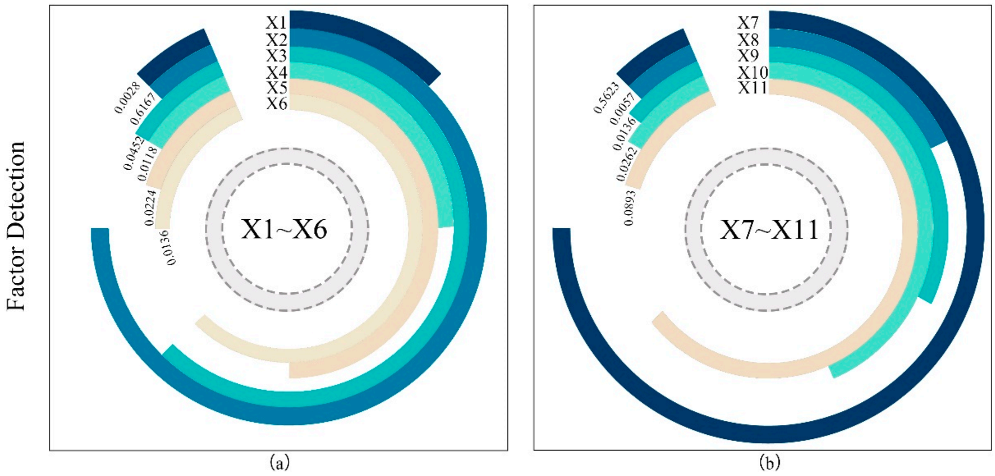

Figure 11. Single-factor detection of the geographic detector in the Wei River basin. (**a**) represents the factor detector results for the driving factors: Digital Elevation Model (X1), Fractional Vegetation Cover (X2), Normalized Difference Vegetation Index (X3), Average Annual Precipitation (X4), Average Annual Temperature (X5), and Annual Average Evaporation (X6). (**b**) represents the factor detector results for the driving factors: Human Activity Intensity (X7), Road Density (X8), Population Density (X9), Nighttime Lights (X10), and Land Use Classification (X11).

3.3.3. Interaction Detector

According to the interaction detection results (Figures 12 and 13), all the factors in the Wei River basin study area, except for vegetation coverage (X2), exhibit a non-linear amplification effect in their interaction contribution rates, indicating that these factors play a significant driving role in the process of landscape fragmentation in the basin. In the interaction detection analysis, human activity intensity (X7) exhibits interaction results exceeding 0.6 with the normalized difference vegetation index (NDVI) (X3), annual average temperature (X5), nighttime light (X10), and land use classification (X11), while interactions with the other factors all exceed 0.5. This indicates that human activity intensity is a key driver of landscape fragmentation in the Wei River basin. The interaction of land use classification (X11) with other factors explains more than 0.1 of the spatial heterogeneity, thereby influencing the degree of landscape fragmentation in the study area to some extent.

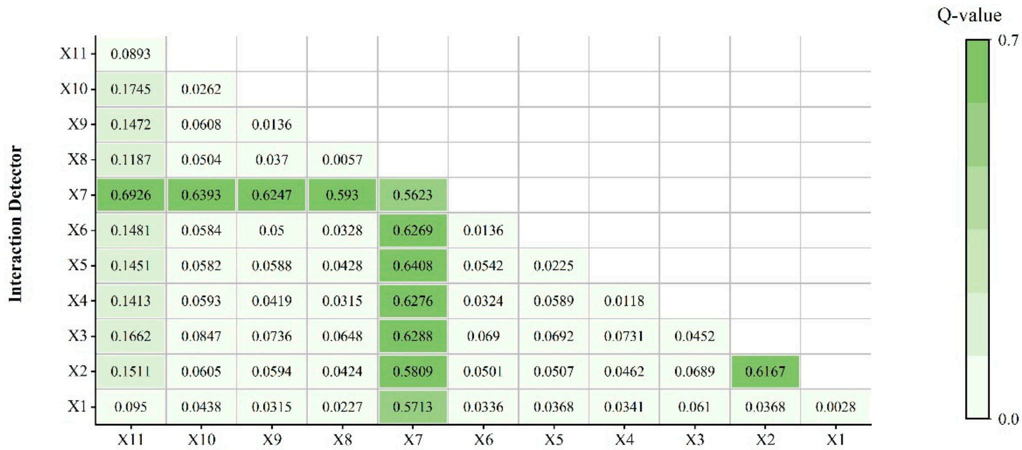

Figure 12. Interaction detection results of the geographic detector in the Wei River basin. Note: Digital Elevation Model (X1), Fractional Vegetation Cover (X2), Normalized Difference Vegetation Index (X3), Average Annual Precipitation (X4), Average Annual Temperature (X5), Annual Average Evaporation (X6), Human Activity Intensity (X7), Road Density (X8), Population Density (X9), Nighttime Lights (X10), and Land Use Classification (X11).

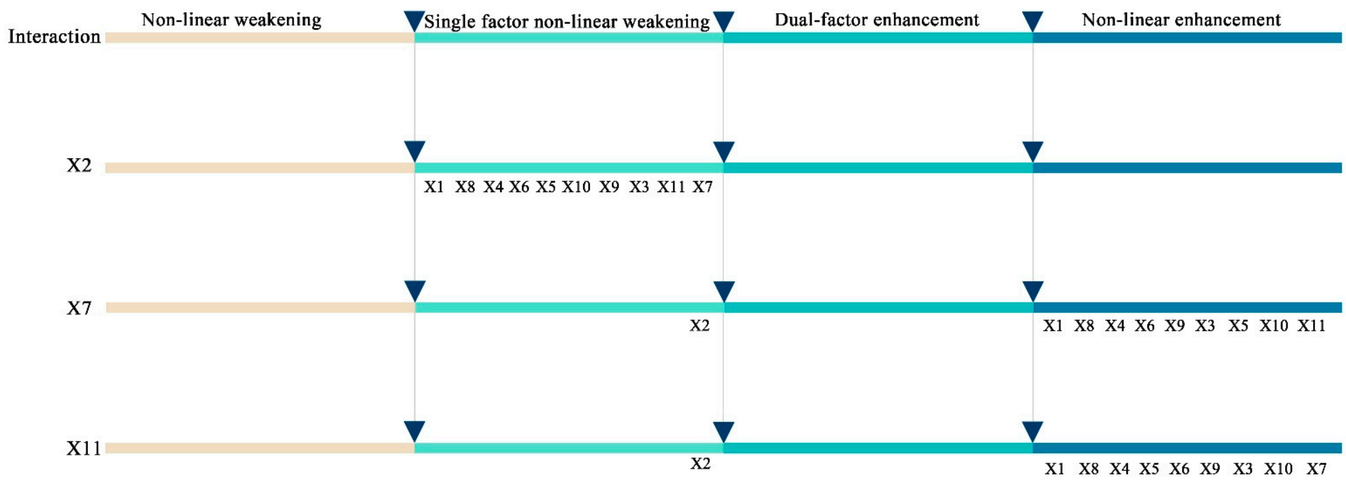

Figure 13. Interaction detection types of major driving factors. Note: Digital Elevation Model (X1), Fractional Vegetation Cover (X2), Normalized Difference Vegetation Index (X3), Average Annual Precipitation (X4), Average Annual Temperature (X5), Annual Average Evaporation (X6), Human Activity Intensity (X7), Road Density (X8), Population Density (X9), Nighttime Lights (X10), and Land Use Classification (X11).

4. Discussion

From 2000 to 2020, the trend of landscape fragmentation in the Wei River basin has significantly intensified. This phenomenon is closely related to multiple factors, including the acceleration of urbanization, increased land resource utilization intensity, and human activities. The study found that: (1) The change in vegetation coverage is one of the key factors driving landscape fragmentation in the Wei River basin. The scarcity of vegetation cover leads to alterations in biological habitats [46], resulting in reduced ecological resilience and increased ecological vulnerability [47]. The destruction of native vegetation leads to soil exposure to rainwater and wind, thereby increasing the risk of soil erosion [48]. However, changes in soil erosion are closely related to the evolution of landscape patterns [49]; (2) The intensity of human activities is a key driver of landscape fragmentation in watershed areas. With the acceleration of urbanization, land development activities fragment arable land into smaller plots, resulting in abandoned or unused land [50]. This leads to a reduction in the habitat area, an increase in the number of ecological patches, and an intensification of isolation between patches [51], thereby affecting species distribution, population dynamics, species interactions, and ecosystem functions [52]; (3) Land use classification is an important factor influencing landscape fragmentation in the Wei River basin. Land use changes, driven by economic development and social demands, have triggered adjustments in the spatial structure of the landscape [53]. Such changes in the spatial structure further affect the composition of biological communities, leading to alterations in their structure [54].

The innovation of this study lies in combining multi-temporal landscape pattern index data for the principal component analysis and applying the OPGD method for optimal discretization. This approach maintains the continuity of landscape fragmentation in the Wei River basin, enhances the objectivity of discretization classification, and addresses the issues of insufficient spatiotemporal coherence and subjectivity in discretization commonly found in landscape fragmentation research. By combining land use data, population density data, and nighttime light data to quantify human activity intensity, this study reveals its key driving role in landscape fragmentation, advancing the application of human activity intensity in the analysis of landscape fragmentation drivers.

The intensification of landscape fragmentation in the Wei River basin is driven by multiple factors. To promote landscape conservation and sustainable development, the following recommendations are proposed: (1) Conduct dynamic land use studies to optimize land use structure and reduce fragmentation risk; (2) Use tools such as landscape ecological risk indices to assess ecological risks, refine risk zoning, and clarify risk distribution. These studies will help to mitigate landscape fragmentation issues and provide scientific support for land use optimization and ecological restoration.

5. Conclusions

This study, based on remote sensing monitoring data on land use in the Wei River basin for the years 2000, 2010, and 2020, utilized the FRAGSTATS 4.2 software to assess the spatiotemporal evolution characteristics of landscape fragmentation in the Wei River basin and applied the geographical detector technique to identify key driving factors. The main conclusions are as follows:

(1) The degree of landscape fragmentation in the Wei River basin has significantly intensified, and this trend is positively correlated with time. The increasing trends of the edge density index (ED), the landscape shape index (LSI), the landscape division index (DIVISION), and the Shannon diversity index (SHDI) reveal a gradual increase in the complexity and diversity of landscape patches. The continuous decline in the contagion index (CONTAG) and the area-weighted mean patch size (Area_AM) indicates a weakening in the patch connectivity within the region, which may further exacerbate the fragmentation and dispersion of the landscape.

(2) The degree of landscape fragmentation in the Wei River basin is relatively high, with areas of high fragmentation primarily concentrated in the northern part of the central region. The fragmentation in the northern and central areas has evolved from severe to extreme, while the western region shows little change. In contrast, the eastern and southern regions exhibit a significant increasing trend. The fragmentation in the headwater areas remains relatively stable, whereas the fragmentation in the tributary zones is more concentrated, showing an expansion trend from west to east. The fragmentation degree in the northeastern part of the main stem has deepened. Overall, the degree of landscape fragmentation in the basin is high, with continuous landscape patches fragmenting into smaller and more isolated units, leading to increased habitat isolation, expanded edge effects, and a reduction in interactions between the various components of the ecosystem.

(3) Landscape fragmentation in the Wei River basin is driven by multiple factors, primarily including vegetation coverage, human activity intensity, and land use classification. Among these, vegetation coverage has the greatest impact, with an influence value of 0.6167, indicating its key role in maintaining landscape continuity. Secondly, the influence value of human activity intensity is 0.5623, indicating that it partially determines the degree of landscape fragmentation. The synergistic effect between human activity intensity and land use classification is significant, jointly contributing to the intensification of landscape fragmentation, with an explanatory power of 0.6926. Therefore, understanding these factors and their interaction mechanisms is crucial for developing effective ecological management strategies to protect and restore landscape continuity.

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Conflicts of Interest: The authors declare no conflicts of interest.

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