ISSN 2616-5872 Vol.6, Issue 3: 42-50, DOI: 10.25236/AJEE.2024.060306

Spatiotemporal evolution and driving force of landscape fragmentation in semi-arid ecologically fragile region: A case study of Jingning County

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Abstract: *In order to explore the spatio-temporal evolution law and driving force of landscape fragmentation in semi-arid ecologically fragile area, the land use data transfer matrix, land use dynamic attitude, moving window method and geographical probe were used to study the landscape fragmentation and its driving force in Jingning County based on the land use data and socio-economic data in 2000 and 2020. The results show that: (1) Cultivated land and grassland are the landscape matrix of Jingning County, and the change among different classes is mainly manifested by the expansion of construction land and grassland. (2) The overall landscape fragmentation level of Jingning County showed an increasing trend from 2000 to 2020; The change was most obvious in the middle of the county, with new patches forming in some areas and the degree of fragmentation decreasing; The degree of fragmentation increased in areas close to towns and water systems. (3) Among the driving factors, GDP has the strongest explanatory power for the spatial differentiation of landscape fragmentation; Social and economic activities have a direct impact on the change of landscape types; The research results can provide scientific basis and methods for ecological protection and sustainable development in semi-arid ecologically fragile areas.*

Keywords: *Ecological fragile area, Landscape fragmentation, Evolution characteristics, Driving force*

1. Introduction

The structure and function of landscape patterns are impacted by landscape fragmentation, which is strongly linked to human activity and has a negative impact on sustainable development and environmental stability in the region. The sustainable growth of the ecosystem is determined by the shift in the landscape pattern, which indicates changes in the material and energy movement within the regional ecosystem. Thus, research on landscape fragmentation has enormous ecological implications. At present, the research on landscape fragmentation mainly takes river basins[1] and large and medium-sized cities as research areas[2][3], uses remote sensing technology and other technologies to acquire land use data in the study areas[4], focuses on the evolution of landscape pattern[5] or ecological assessment of the study areas[6], and mostly uses landscape pattern index method and moving window method to analyze the characteristics of landscape fragmentation from a macro perspective[7]. Principal component analysis and geographic detector are used to investigate the driving forces behind the evolution [8]. Research on the evolution characteristics of landscape pattern and the spatial characteristics of landscape fragmentation in small regions is seldom introduced by the thorough application of diverse approaches, and there are generally few pertinent studies on semi-arid ecologically sensitive places. Additionally, the majority of driving force research employs conventional techniques, and the geographical detector model is hardly ever applied as a novel statistical technique. China's semi-arid Jingning County is situated in the center of Gansu Province and has a highly sensitive biological environment. The construction of Jingning County's urbanization has accelerated, human activity interference has increased, the ecological environment has experienced significant changes, and the degree of landscape fragmentation has deepened as a result of the intensifying reform, opening up, and poverty alleviation. This study examined the causes of landscape fragmentation in semi-arid, ecologically fragile areas by analyzing the spatiotemporal evolution process and characteristics of landscape fragmentation using a variety of methods, including the moving window method, geographic detector, land use dynamic attitude, and land use data transfer matrix.2. Study the region and research method

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1.1 Overview of the study area

The construction of Jingning County's urbanization has accelerated, human activity interference has increased, the ecological environment has experienced significant changes, and the degree of landscape fragmentation has deepened as a result of the intensifying reform, opening up, and poverty alleviation. This study examined the causes of landscape fragmentation in semi-arid, ecologically fragile areas by analyzing the spatiotemporal evolution process and characteristics of landscape fragmentation using a variety of methods, including the moving window method, geographic detector, land use dynamic attitude, and land use data transfer matrix. There is an average of 450.8 mm of precipitation and 1469 mm of evaporation per year. All 160,900 rural individuals who currently fall below the federal poverty level will be raised out of it by 2020.

1.2 Data source and processing

This study obtained the land use data of Jingning County in 2000 and 2020 from the Resources and Environmental Sciences and Data Center, Chinese Academy of Sciences (http://www.resdc.cn/). The data has a spatial resolution of 1km and an overall accuracy of over 90%. According to the Classification of Land Use Status (GB/T21010-2017) and the research objectives, the land use data is divided into 6 categories: cultivated land, forest land, grassland, water area, construction land, and unused land. The DEM used in this study is ASTER GDEM data with a spatial resolution of 30m, obtained from the Geospatial Data Cloud (http://www.gscloud.cn). This data is suitable for general readers and has a professional tone and style. The study has also corrected any spelling errors and supplemented missing information. Data reflecting the topography of the study area, such as slope and slope direction, are extracted using the ArcGIS10.2 surface analysis. The Data Center for Resources and Environmental Sciences and Chinese Academy of Sciences (http://www.resdc.cn/) is the source of the data on annual precipitation, average temperature, water system, soil, and traffic. GIS is used to convert the data into raster data with a consistent range. The Jingning County, Gansu Province, Civil Economic and Social Development Bulletin (http://www.gsjn.gov.cn) is the source of the GDP and other annual data for various years.

1.3 Research Methods

1.3.1 Land use data transfer matrix

The land use data transfer matrix can further illustrate the transformation features among various types and quantitatively reflect the transformation among land use types. The formula for calculation is displayed in equation (1).

$$S_{ij} = \begin{bmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & \ddots & \vdots \\ S_{n1} & \cdots & S_{nn} \end{bmatrix} \quad (1)$$

S represents the area of the study area, n represents the number of land types, i and j represents the land use types at the beginning and end of the study[7].

1.3.2 Dynamic attitude of land use

Dynamic attitude of land use is used to describe quantitatively the change of land use type. The single dynamic attitude of land use represents the average annual change rate of a certain type of land use transformation in a specific region. Its mathematical expression is formula (2).

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\% \quad (2)$$

K is the dynamic attitude of a single land use in the study period; U_a and U_b represents the area of the land use type at the beginning and end of the study respectively, and T represents the length of the study period[9].

1.3.3 Moving window method

The moving window method is mostly applied to small- and medium-scale landscape pattern analysis. In order to achieve the quantification and spatial visualization of the local landscape pattern index and better reflect the dynamic process of landscape pattern change, a single input grid is statistically calculated for the selected landscape index in the window. The resulting grid map then reveals the spatial differentiation of landscape internal change.[7].

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1.3.4 Geographic detector

Geographical probe model (http://www.geodetector.org/) is the detection and the method of using space differentiation and reveals the driving factors[10]. Factor detection and interactive are used in this study. The model is shown in formula (3).

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{3}$$

(1) Factor detection. Probe the spatial differentiation of attribute Y; And the extent to which factor X explains the spatial differentiation of attribute Y.

Where: q represents spatial differentiation, L represents the number of partitions, $h = 1,2,\ldots,L$; N_h and N represent the number of samples for classification h and the whole region, respectively; And $\sigma_h^2$and σ^2represent the variance of Y values for class h and the whole region, respectively. The range of q is $[0,1]$, and the larger the value of q, the stronger the spatial differentiation of Y; If the classification is generated by the independent variable X, a larger q value also indicates that the independent variable X has a stronger explanatory power for the attribute Y.

(2) Reciprocal probing

Analyze the interaction between variables X, and evaluate whether the interaction of two factors will increase or weaken the explanatory power of variable Y, and compare the q values under different X and the q values under the combined action.

2. Results and analysis

2.1 Dynamic change characteristics of land use types

In order to analyze the evolution of landscape pattern and the spatiotemporal differentiation characteristics of landscape fragmentation, it is useful to examine the area proportion and change rate of various land use types. ArcGIS10.2 was used to extract land use vector data, which is shown in Figure 1. The land use data transfer matrix from 2000 to 2020 was created by analyzing the land use data of the study region in 2000 and 2020 (Table 1). The dynamic attitude and transfer rate of each land use category were computed based on the calculation formula (Table 2).

Table 1: Land use data transfer matrix of Jingning County from 2000 to 2020

Year	Land use type	2020						
		Arable Land	Woodland	Grassy	Waters	Land for construction	Unused land	Total
2000	Arable Land	967.566	13.050	221.791	4.802	28.996	2.987	1239.192
	Woodland	11.099	36.439	4.266	0.048	1.320	-	53.172
	Grassy	204.595	6.627	587.047	3.700	8.495	1.071	811.535
	Waters	3.146	0.118	1.663	11.793	0.533	0.293	17.546
	Land for construction	15.594	0.939	6.298	0.312	37.526	0.092	60.762
	Unused land	2.080	0.089	1.101	0.207	0.278	3.109	6.863
	Total	1204.080	57.262	822.165	20.862	77.149	7.551	2189.069

Table 1 clearly shows that there has been a clear conversion from 2000 to 2020 in all classes in Jingning County. There were increases of 4.06, 10.63, 3.361, 16.387, and 0.688 km^2 in forest land, grassland, water area, building land, and unused land among them. The cultivable land area shrank by 35.112 square kilometers. The primary changes in Jingning County's land use between 2000 and 2020 are the growth of construction, water, and forest land areas and the decrease of farmed land. These changes are indicative of the significant influence that growing human activity has on the transformation of land types. The afforestation area and forest stock have expanded in tandem due to the outstanding outcomes of the farmland-to-forest initiative. On the other hand, the water environment management project has successfully enhanced the Hulu River basin's water ecological environment; Meanwhile, the impoverished towns in Jingning County's northwest have accomplished amazing things in terms of focused poverty alleviation, developing a "Jingning model" that works for the community, encouraging urban renewal and bolstering urban construction in the central urban area, and encouraging the simultaneous development of ecology and economy.

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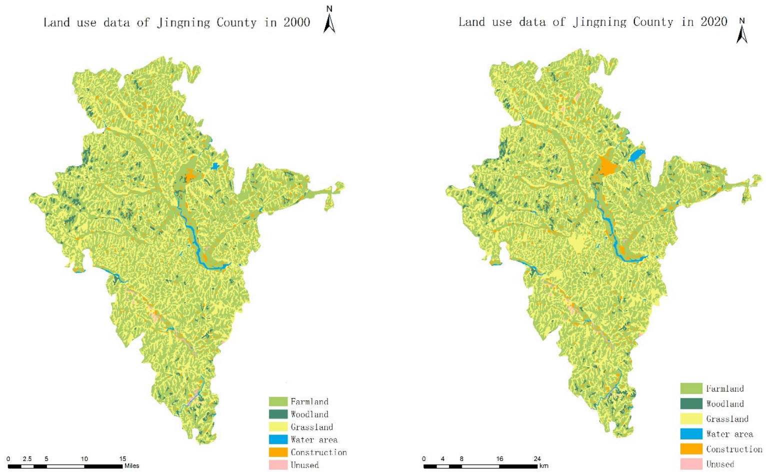

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Figure 1: Spatial distribution of land use types

Table 2: Dynamic attitude of land use change

Landscape type	2000		2020		2000-2020.
	Landscape area CA/(ha)	Percentage/ (%)	Landscape area CA/(ha)	Percentage/ (%)	Dynamic attitude of single land use (%)
Arable land	123988.41	56.61%	120408.03	55.00%	0.14%
Woodland	5317.65	2.43%	5726.16	2.62%	0.38%
Grass	81189.72	37.07%	82216.53	37.56%	0.06%
Waters	1756.17	0.80%	2086.20	0.95%	0.94%
Construction land	6076.17	2.77%	7714.89	3.52%	1.35%
Unused	686.34	0.31%	755.10	0.34%	0.50%

Table 2 shows that, although there have been only minor changes, cultivated land and grassland have remained the two most prevalent landscape types in Jingning County between 2000 and 2020. Cultivated land makes up the largest portion of this matrix, while unused land makes up the smallest. There was a 1638.72 hectare increase in construction land and a 330.03 hectare increase in water area; the corresponding dynamic rates of single land use were 1.35% and 0.94%. Rapid population growth and an acceleration of the urbanization process were caused by the comprehensive execution of programs including river management, farmland restoration to forests, and poverty alleviation. The number of urban construction projects rose.

2.2 Basic characteristics of landscape pattern index

Total Area (TA), Number of Patches (NP), Patch Density (PD), Landscape Shape Index (LSI), Interspersion Juxtaposition Index (IJI), Landscape Division Index (DIVISION), Shannon's Diversity (SHDI), and Aggregation Index (AI) were chosen to characterize the degree of landscape fragmentation by taking into account the ecological significance of the landscape pattern index as well as the actual conditions of the study area. Table 3 provides an overview of the fundamental features of landscape fragmentation at the overall level. The landscape index is calculated at the landscape level using the FRAGSTATS software in conjunction with the landscape pattern index.

Table 3: The overall horizontal landscape pattern index of Jingning County from 2000 to 2020

Year	TA/(ha)	NP	PD/(/ha-2)	LSI	IJI/(%)	DIVISION	SHDI	AI/(%)
2000	219014.46	1621.00	0.74	60.54	28.15	0.94	0.94	92.51
2020	218906.91	1809.00	0.83	63.12	30.49	0.95	0.97	92.19

Table 3 shows that while TA falls between 2000 and 2020, NP and PD grow, suggesting that in the study area, human intervention with the landscape is continually getting worse and that patch diversification and land use fragmentation are becoming more and more intense. The study area's landscape dispersion was strengthened, community diversity and landscape segmentation were reinforced, and LSI and IJI increased, suggesting that the landscape edge evolved from regular to irregular, indicating that human activities caused the encroachment of building land on other land use types. DIVISION and SHDI showed a slightly increasing trend. A small decline in the degree of landscape patch aggregation was indicated by the AI, which went from 92.51 to 92.19. This suggests that landscape dispersion increased following human activity or other ecological processes.

In conclusion, the study area's TA and AI values decreased between 2000 and 2020, while the values of NP, PD, LSI, IJI, DIVISION, and SHDI increased to varying degrees, exhibiting a similar trend of change. These findings reflect the area's increasing patch quantity and density, intensifying landscape type complexity, and weakening of patch aggregation. It suggests that the study area's landscape integrity is declining and its degree of fragmentation is rising.

2.3 Spatial distribution characteristics of landscape fragmentation

The spatial distribution of landscape fragmentation in Jingning County from 2000 to 2020 is shown in Figure 2. As can be seen from Figure 2, the landscape fragmentation pattern shown by the 5 types of landscape indices has obvious dispersion and heterogeneity.

(1) In 2000, the distribution characteristics of PD high value were higher in the north than in the south, but there was a high value accumulation area in the southernmost Inda Town. The distribution of low value was affected by water area and traffic. The high value area is dotted, and the high value is dense in Shipu Town, Hongsi Town, Xixiang Town, Ganguou Town, Xindan Town and Shuangxian Town in the western boundary, which indicates the high degree of landscape fragmentation, mainly because of the terrain change and the complex land use type. The low-value areas show that the number of patches is small and the landscape integrity is high. In 2018, the size of high values increased, and the distribution of high and low values was roughly the same. In central Ganguou Town and Zhiping Town, the low-value areas of grassland showed obvious flake expansion, indicating that the degree of landscape fragmentation decreased, mainly because of the implementation of the policy of returning farmland to forest and grassland in Jingning County. In Chengguan Town, the construction land shrank and the fragmentation degree increased, mainly because of the continuous advancement of urbanization, resulting in urban building land; The area increases, the landscape tends to be complicated.

(2) LSI and AI high and low value distribution is opposite. LSI measures the irregularity of landscape type shape and is proportional to the fragmentation of landscape. AI reflects the degree of plate type aggregation, which is inversely proportional to the degree of landscape fragmentation, and the larger the value, the more concentrated the patches in the landscape. The distribution of LSI and AI is closely related to annual precipitation. In the southern regions with high annual precipitation, Shengou Town, Lidian Town, Yuwan Town, Jiahe Town and Renda Town, the high AI values and low LSI values are densely distributed in a dot pattern, indicating that more patches in the landscape are distributed in the south. In the north, the distribution of low LSI and high AI values in traffic, water and construction land is strongly correlated. LSI has high value gathering areas in the northernmost Sanhe Township and Yuan 'an Township. In the western boundary, the high-value areas of Shipu Town, Hongsi Town, Xixiang Town, Ganguou Town, Xindan Town and Shuangxian Town are densely distributed, which indicates that the landscape fragmentation degree is high. Compared with 2000, LSI low value distribution tends to be discrete in 2020 in the Cucuhe River basin and around major transportation networks, mainly due to the dispersion and complexity of landscape types caused by road construction and watershed development. In general, LSI high values increased, AI low values decreased, and the overall landscape fragmentation degree increased in the characterization study area.

(3) In 2000, the high values of DIVISION and SHDI were mainly distributed in the southern mountainous areas with scattered construction land distribution, mainly due to the diversity of land use types in these areas; The low values were mainly distributed in river basin and Chengguan town. In 2020, the distribution will be roughly the same. On the basis of the original distribution, the low-value areas in Ganguou Town and Zhiping Town will expand in a flake. The terrain in these areas will be flat and the ecological optimization of returning farmland to grassland will be implemented. The low-value areas in Chengguan Town and river basin shrank, and the landscape connectivity declined, mainly due to the continuous advancement of river development, infrastructure construction and urbanization process, indicating that economic development, human activity intensity and natural development have an impact on the diversification of landscape use types.

2.4 Analysis of the driving forces of spatial-temporal landscape fragmentation

The natural environment in Jingning County limits the social economy and impedes its growth. Along with the advancement of poverty alleviation in recent years, the advancement of the social economy has

ISSN 2616-5872 Vol.6, Issue 3: 42-50, DOI: 10.25236/AJEE.2024.060306

coincided with the devastation of the natural ecology through the building and upgrading of transportation networks, infrastructure, and industrial structures. There are overlapping impacts when using the landscape index PD, LSI, AI, and SHDI to define the results of landscape fragmentation; as a result, approximate fragmentation results are achieved.

Table 4: Factor detection

Driver Factors	Transportation	Water system	Soil type	Slope	Slope	Population	GDP	Average temperature	Annual precipitation	elevation
q values	0.0038	0.0624	0.0183	0.0103	0.0148	0.0019	0.3304	0.0025	0.0193	0.0085

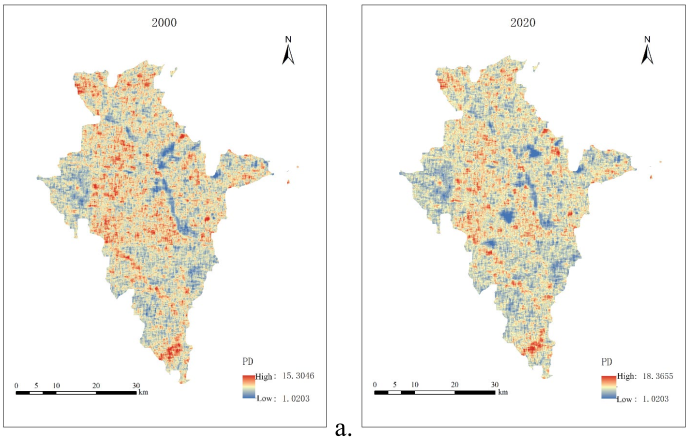
Landscape fragmentation is influenced by both physical geography and socio-economic factors. Six natural environmental factors, such as soil type, slope, slope direction, average temperature, annual precipitation and elevation, and four socio-economic factors, such as traffic, water system, population and GDP, were selected. First, 223 sample points were determined by ArcGIS. After the analysis variables of geographical detector were processed, each driving factor was graded, as shown in figure 3. The explanatory power between the changes of landscape fragmentation degree and landscape pattern index in the study area and the selected driving factors, namely the size of q value, was explored by using the geographic detector model, and Table 4 was obtained. And the interaction among the factors was explored through the interactive probe, and Table 5 was obtained.

Table 5: Interactive detection

Driver Factors	Transportation	drainage	Soil type	Slope	Slope	Population	GDP	Average temperature	Annual precipitation	Elevation
Transportation	0.0038									
Water System	0.0908	0.0624								
Soil	0.0333	0.3333	0.0183							
Slope	0.0256	0.1667	0.1111	0.0103						
Slope	0.0370	0.2501	0.0714	0.0500	0.0148					
Population	0.0112	0.0998	0.0385	0.0196	0.0303	0.0019				
GDP	0.5002	1.0000	1.0000	1.0000	1.0000	0.3334	0.3304			
Air temperature	0.0156	0.0713	0.0666	0.0232	0.0303	0.0093	0.3334	0.0025		
Precipitation	0.0293	0.0908	0.0998	0.0666	0.1110	0.0243	0.5002	0.0269	0.0193	
Elevation	0.0217	0.3333	0.0767	0.0400	0.0555	0.0164	1.0000	0.0185	0.0712	0.0085

Factor detection is capable of analyzing how much the spatial differentiation of landscape fragmentation is explained by driver factors. Table 4 displays the acquired results. It is evident that, compared to other driving factors, GDP has a significantly larger explanatory power for the regional differentiation of landscape fragmentation in the research area, with population having the lowest explanatory power.

An analysis of the interaction between several driving factors and their impact on the spatial differentiation of fragmentation was done by interactive detection. Table 5 displayed the outcomes. The relationship between GDP and the water system, soil, slope, slope direction, and elevation is shown to have the most explanatory power for the regional differentiation of fragmentation. This was followed by the relationship between GDP and traffic, which once more demonstrated the function of GDP driving variables. It demonstrates the significant impact of human intervention on landscape fragmentation.



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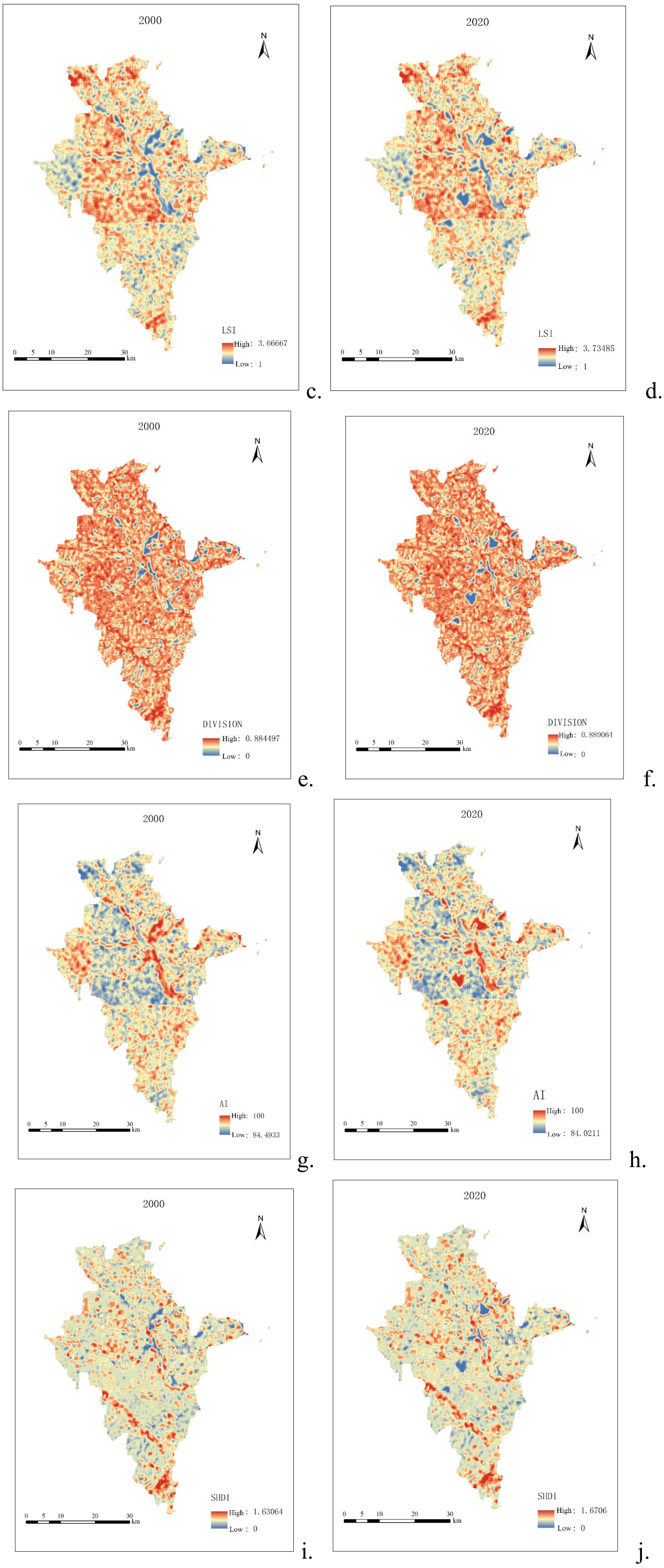

Figure 2: Spatial distribution of landscape fragmentation in Jingning County from 2000 to 2020

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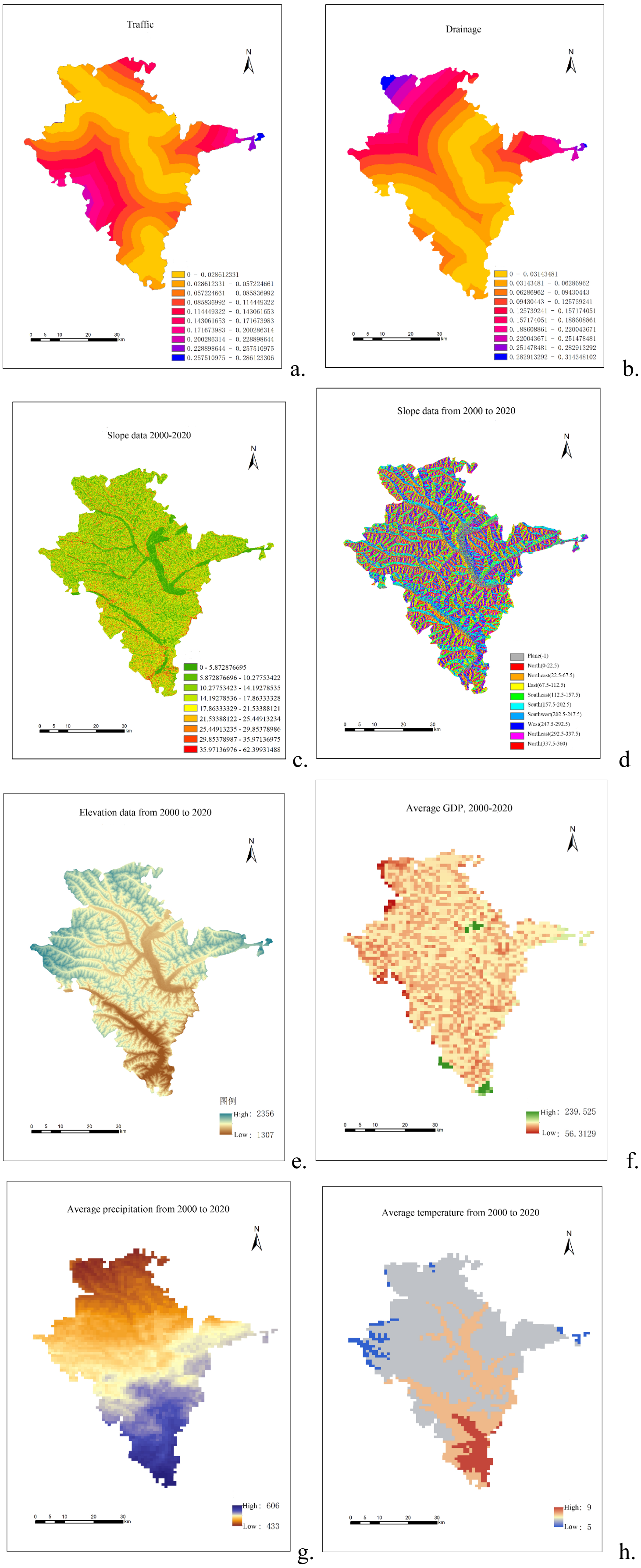

Figure 3: Driving factors

ISSN 2616-5872 Vol.6, Issue 3: 42-50, DOI: 10.25236/AJEE.2024.060306

3. Conclusion and discussion

(1) From 2000 to 2020, Jingning County's land use classifications underwent substantial changes. According to the land use data transfer matrix, the majority of the transferred area was from cultivated land to grassland. The dynamic attitude of land use suggests that human disturbance or natural environmental conditions have a significant impact on both cultivated and construction land.

(2) The degree of landscape fragmentation in Jingning County shown an overall upward trend between 2000 and 2020. The center of the county saw the most shift, with new patches emerging there and the level of fragmentation declining. The degree of fragmentation rose in the vicinity of water systems and settlements.

(3) The combined influence of social and environmental factors on landscape pattern is reflected in GDP, which has the highest explanatory power among all driving factors for the regional differentiation of landscape fragmentation. However, social factors remain the primary drivers of landscape pattern fragmentation.

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