Landscape Ecological Risk Assessment and Driving Factor Analysis in the Shule River Basin Based on the Geodetector Model (Postprint)

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Abstract

The Shule River Basin, located at the westernmost end of the Hexi Corridor, is a typical arid inland river basin with an extremely fragile ecological environment and serves as one of China' s important ecological barriers. Using Fragstats software at patch and landscape scales, combined with land use data from 2000-2018, this study evaluated and analyzed the spatiotemporal variation characteristics of landscape ecological risk in the Shule River Basin, and quantitatively analyzed the driving factors of landscape ecological risk using geographic detectors. The results indicate: (1) The main landscape types in the Shule River Basin are unused land and grassland, with relatively high values for Number of Patches (NP), Landscape Shape Index (LSI), Largest Patch Index (LPI), and Aggregation Index (AI); from 2000 to 2018, the Contagion Index (CONTAG) decreased, while Shannon' s Diversity Index (SHDI) and Shannon' s Evenness Index (SHEI) increased slowly, indicating severe landscape fragmentation in the basin. (2) The spatial distribution of landscape ecological risk in the Shule River Basin exhibits a pattern of high in the north and low in the south; from 2000 to 2018, the landscape ecological risk in the basin showed a gradual decreasing trend, with the areas of relatively high risk and high risk decreasing significantly. (3) Human disturbance degree is the primary factor influencing the spatial distribution of landscape ecological risk, followed by Normalized Difference Vegetation Index (NDVI), while population density has the minimal impact; the influences on landscape ecological risk are all two-factor enhancement or nonlinear enhancement, with non-significant differences primarily observed between natural factors, while significant differences exist between natural and anthropogenic factors. Therefore, landscape ecological risk index evaluation and driving factor analysis for the basin are essential.

Full Text

Landscape Ecological Risk Assessment and Driving Factor Analysis of the Shule River Basin Based on the Geographic Detector Model

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Abstract

The Shule River Basin, located in the westernmost part of the Hexi Corridor, is a typical arid inland river basin with an extremely fragile ecological environment and serves as one of China' s important ecological barriers. Using Fragstats software at both patch and landscape scales, this study evaluates and analyzes the spatiotemporal variation characteristics of landscape ecological risk in the Shule River Basin based on land use data from 2000 to 2018. The geographic detector model is employed to quantitatively analyze the driving factors of landscape ecological risk in the basin. The results indicate: (1) The main landscape types in the Shule River Basin are unused land and grassland, which exhibit high values for number of patches (NP), landscape shape index (LSI), largest patch index (LPI), and aggregation index (AI). The contagion index (CONTAG) showed a declining trend, while Shannon' s diversity index (SHDI) and Shannon' s evenness index (SHEI) increased slowly, indicating severe landscape fragmentation. (2) The spatial distribution of landscape ecological risk in the Shule River Basin presents a pattern of higher risk in the north and lower risk in the south, with an overall declining trend from 2000 to 2018, particularly in high-risk and relatively high-risk areas. (3) Human disturbance is the primary factor influencing the spatial distribution of landscape ecological risk, followed by normalized difference vegetation index (NDVI), while population density has the weakest influence. The impacts on landscape ecological risk exhibit double-factor enhancement or nonlinear enhancement. No significant differences are found among natural factors, whereas significant differences exist between natural and anthropogenic factors. Therefore, conducting landscape ecological risk assessment and driving factor analysis is crucial for watershed management.

Keywords: landscape ecological risk; landscape pattern; geodetector; Shule River Basin

Introduction

Landscape ecological risk refers to adverse effects arising from the interaction between landscape patterns and ecological processes, primarily manifested as impacts of human activities or natural disasters on landscape composition, structure, and function [1-3]. Watersheds are important comprehensive geographical units connecting surface water, land cover, and natural-social systems [4], and represent the most significant geographical landscapes. Watershed conservation is essential for achieving sustainable regional socio-economic development [5]. Both natural factors and human activities have profoundly influenced landscape patterns, making watershed-scale landscape ecological risk assessment a critical research component for ecological protection and a hotspot in ecological risk evaluation [6].

Scholars have extensively explored theories and methods of landscape ecological risk assessment at various scales, including national [7-9], township [10], and watershed [11-13] levels, establishing a preliminary research framework. Most studies have focused on quantifying and analyzing landscape patterns, using results to directly or indirectly reflect landscape ecological risk. However, research on driving forces has primarily employed qualitative approaches, lacking quantitative methods. The geographic detector model, proposed by Wang Jinfeng et al. [14], is a statistical method that quantitatively expresses spatial heterogeneity by analyzing differences between intra-layer and inter-layer variance. This approach can detect both numerical and categorical data, quantitatively explore interactions between driving factors, and determine whether each factor' s influence on the spatial distribution of landscape ecological risk is significantly different. Compared with other spatial heterogeneity detection tools, the geographic detector offers higher explanatory efficiency and has been widely applied to quantitatively study driving factors of climate change [15], vegetation dynamics [16], settlement distribution [17], and even COVID-19 spread [18]. However, its application in analyzing landscape ecological risk drivers remains limited.

The Shule River Basin is a typical arid inland river basin with a vulnerable ecological environment. Recent climate change and human activities have led to increasing landscape fragmentation [19], further intensifying landscape ecological risk. This study investigates the spatiotemporal evolution characteristics of landscape ecological risk in the basin and quantifies the contributions of different driving factors, aiming to provide a scientific basis for controlling landscape ecological risk escalation and optimizing watershed management for coordinated sustainable development.

1 Study Area

The Shule River Basin is located in China' s arid northwest region, representing the only inland river flowing from east to west in the Hexi Corridor' s westernmost part, between 92°22 ~98°35 E and 38°05 ~42°45 N, with a total area of 1.12$\times10^{5}$ km^2. Originating from the Gang' erxiaoheliling Peak in the Qilian Mountains, the river flows through Subei Mongolian Autonomous County, Dunhuang City, Yumen City, and Guazhou County. The basin' s topography is characterized by higher elevations in the south and lower in the north, with altitudes ranging from 802 to 5,504 m. The region experiences low precipitation and high evaporation, adjacent to deserts in the east, with water supply primarily from glacier melt and precipitation. The upper reaches feature high elevations and steep terrain with permanent glaciers and snow, while the middle and lower reaches have flat terrain with coexisting oases and deserts. Unused land accounts for over 60% of the area, with severe land desertification. According to the 2018 Gansu Provincial Water Resources Bulletin, the basin had a population of 5.36\$×10$^{\{5\},GDPof14.79\times10}${9}\$ yuan, and cultivated land area of 3.67\$×10^{4}\$ hm^2.

[Figure 1: see original paper]

2 Data and Methods

2.1 Data Sources and Processing

Land use data for 2000, 2005, 2010, 2015, and 2018, along with county-level administrative boundary vector data, were obtained from the Resource and Environmental Data Cloud Platform of the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (http://www.resdc.cn/Default.aspx), with a spatial resolution of 30 m and Krasovsky_{1940}_{Albers} projection coordinate system. The accuracy of cultivated land, urban and rural residential land, grassland, forest land, and water bodies was \$ \$90%, while unused land accuracy was \$ \$85%. Following the national land use classification standards and appropriate merging, six landscape types were identified: cropland, forest, grassland, water, residential land, and unused land.

Eight driving factors were selected: three climatic factors (annual precipitation, annual maximum temperature, annual minimum temperature), three surface factors [elevation (X1), slope, normalized difference vegetation index (NDVI)], and two anthropogenic factors (population density and human disturbance). Population density data were obtained from Worldpop (http://www.worldpop.org/). Annual precipitation and temperature data were sourced from the National Earth System Science Data Center. NDVI data were acquired from the Resource and Environmental Data Cloud Platform, while slope data were derived from elevation data. In ArcGIS, elevation, precipitation, NDVI, temperature, and human disturbance were classified into 6 categories using the natural breaks method, population density into 6 categories using the quantile method, and slope into 7 categories (0°-3°, 3°-8°, 8°-15°, 15°-25°, 25°-35°, >35°) according to the Comprehensive Control Planning for Soil and Water Conservation (GB/T 15772-2008).

2.2 Research Methods

2.2.1 Landscape Pattern Indices Landscape pattern indices can reveal underlying patterns and significance from disordered landscape patches, using quantitative indicators to reflect landscape composition, structure, and spatial distribution [20]. Referencing existing domestic and international research and considering the distribution of landscape elements in the Shule River Basin [21-23], this study selected seven indices at the landscape element level focusing on quantity, edge, distribution, aggregation, connectivity, and diversity: number of patches (NP), largest patch index (LPI), aggregation index (AI), Shannon' s diversity index (SHDI), landscape shape index (LSI), Shannon' s evenness index (SHEI), and contagion index (CONTAG). These were calculated using Fragstats software (Table 1).

2.2.2 Construction of Landscape Ecological Risk Index The Shule River Basin was divided into 10 km$\times$10 km square grid evaluation units using equal intervals. The ecological risk index was calculated for each unit and assigned to the unit' s center point, followed by Kriging interpolation to map landscape ecological risk across the basin.

Drawing on relevant studies [24-26], landscape disturbance index was established using landscape fragmentation, separation, and fractal dimension indices, with weights of 0.5, 0.3, and 0.2 assigned respectively. The landscape ecological risk index was then calculated (Table 2).

2.2.3 Landscape Ecological Risk Classification Using the natural breaks method in ArcGIS, landscape ecological risk levels were classified into five categories: low, relatively low, moderate, relatively high, and high.

2.2.4 Human Disturbance Index To analyze the impact of human disturbance on landscape ecological risk, the human disturbance index was calculated based on landscape types and local conditions, referencing previous research [27]:

UI = Σ(i=1 to m) (Ii × Si) / S

where UI is the human disturbance index of a grid unit; Ii is the disturbance index of landscape type i; Si is the area of landscape type i (km^2); S is the total area of the grid unit (km^2); and m is the number of landscape types.

2.2.5 Geographic Detector The geographic detector, proposed by Wang Jinfeng [14], is a statistical method with four functions: factor detection, interaction detection, ecological detection, and risk detection. It has been applied across multiple disciplines. This study employed the first three detectors. The principle involves dividing a region into subregions; if the sum of variances within subregions is less than the overall variance, the region exhibits heterogeneity. If the spatial distributions of two variables are similar, they are likely associated. The q statistic quantifies these relationships.

Factor Detector: This explores the spatial heterogeneity of the dependent variable (Y) and the degree to which independent variables (X) explain this heterogeneity:

$q = 1 - (\Sigma(h=1 \text{ to } L)\ Nh\sigma h^2) / (N\sigma^2) = 1 - SSW/SST$

where h is the stratum number; L is the total number of strata; Nh and N are the numbers of grid cells in stratum h and the entire region, respectively; σh^2 and σ^2 are the variances of landscape ecological risk in stratum h and the entire region, respectively; SSW and SST are the within-sum-of-squares and total sum of squares, respectively. The q value ranges [0,1], with higher values indicating stronger explanatory power.

Interaction Detection: This determines the interaction strength between different factors through spatial overlay analysis, quantifying the degree to which combined factors influence landscape ecological risk.

Ecological Detection: This compares factors pairwise to determine whether their impacts on the spatial distribution of landscape ecological risk are significantly different.

3 Results and Analysis

3.1 Landscape Pattern Analysis

As shown in Table 3, except for grassland, other landscape types had 100-300 patches, while grassland had 1,000-1,500 patches. This is because grassland is widely distributed from plains to high-altitude areas, exhibiting both point and areal patterns with high fragmentation. Other landscape elements have smaller areas and more concentrated distributions. Although unused land has the largest area, its NP value is relatively small due to concentrated distribution. The LPI of unused land exceeds 60%, while grassland' s LPI is around 30%, with other land use types ranging 0.03-0.44, reflecting the dominance of unused land and grassland as primary landscape types. The LSI values are highest for grassland and unused land due to their irregular shapes, while construction land and water bodies show more regular shapes due to human planning constraints. The AI values indicate that unused land has the highest aggregation (~95%), while other landscape elements range 29.17-87.32.

Table 4 shows that the contagion index (CONTAG) of landscape types in the Shule River Basin declined from 2000 to 2018, indicating increasing landscape fragmentation due to population growth, land reclamation, and abandonment. Meanwhile, Shannon' s diversity index (SHDI) and Shannon' s evenness index (SHEI) increased slowly but remained low, suggesting uneven patch distribution.

3.2 Landscape Ecological Risk Analysis

Spatially, the landscape ecological risk in the Shule River Basin showed consistent patterns from 2000 to 2018 (Figure 2), with higher risk levels in the north and lower levels in the south. The northern region is dominated by unused land with single landscape types, poor resistance to disturbance, and fragile ecological conditions. The southern region, near the Qilian Mountains, has abundant water resources and diverse landscape types (grassland, water, forest) with strong water conservation capacity, higher elevation, and less human disturbance, resulting in lower risk levels.

Temporally, the overall risk level changed little from 2000 to 2010, mainly shifting between relatively high and high risk. Unused land and forest area decreased, while cropland, grassland, and construction land increased. Cropland expansion increased by 351.51 km^2 due to resettlement projects, causing risk to shift toward higher values.

From 2010 to 2018, the area of relatively high and high risk decreased significantly. The relatively high risk area decreased by 4,459.02 km^2, mainly in southwestern Yumen, while the high risk area decreased by 1,034.10 km^2, primarily in central Subei (south). The combined reduction was 4,396.46 km^2. Low, relatively low, and moderate risk areas increased by 2.88%, 1.09%, and 0.61% respectively, mainly in central Guazhou and central Subei (south). The southern region saw increased water, grassland, and forest areas due to strengthened ecological protection of the Qilian Mountains and water-saving strategies in downstream areas, such as irrigation system renovation and planting structure adjustment in Dunhuang, which curbed groundwater decline and reduced overall risk.

Overall, from 2000 to 2018, the low risk area increased by 1,131.19 km^2, relatively low risk increased by 2,226.52 km^2, moderate risk increased by 1,154.71 km^2, and relatively high risk decreased by 4,459.02 km^2, while high risk decreased by 2,231.55 km^2. The proportion of low, relatively low, and moderate risk increased by 1.01%, 0.92%, and 1.98% respectively, while relatively high and high risk decreased by 3.30% and 0.61% respectively.

[Figure 2: see original paper]

3.3 Analysis of Driving Factors for Landscape Ecological Risk Spatial Differentiation

Factor Detection Results: The factor detector reveals both the spatial heterogeneity of landscape ecological risk and the degree to which each factor explains this heterogeneity. For convenience, X1-X8 represent elevation, slope, precipitation, NDVI, maximum temperature, minimum temperature, population density, and human disturbance, respectively.

From 2000 to 2018, the q values ranked as: X8 > X4 > X5 > X3 > X1 > X6 > X2 > X7. Human disturbance (X8) ranked first in contribution, indicating it is the primary controlling factor of landscape ecological risk change in the Shule River Basin. NDVI (X4) was the second dominant factor, while population density (X7) was the weakest, with a contribution rate of only 0.43%. The dominant factors were elevation, precipitation, and maximum/minimum temperatures, while population density had minimal impact.

From 2000 to 2010, the area of high risk increased by 545.51 km^2 (0.49%), while low, relatively low, moderate, and relatively high risk areas decreased by 37.16 km^2, 5.03 km^2, 482.94 km^2, and 23.51 km^2 respectively. The q value ranking changed slightly compared to other periods, with NDVI (X4) dropping from third to fifth position.

From 2010 to 2018, low risk area increased by 1,154.71 km^2, relatively low risk by 2,226.52 km^2, and moderate risk by 1,154.71 km^2. The q value ranking differed from previous periods, with precipitation (X3) rising from fifth to third position. Comparing q values across periods shows that different factors vary annually. The q values of X1-X6 showed an "N-shaped" pattern, with minimum values in 2010 and maximum in 2015. X7 showed a "V-shaped" pattern, with the highest q value in 2000. X8 showed an "inverted V-shaped" pattern, with the highest q value in 2015. Overall, q values of all factors were similar in 2000 and 2018, with large fluctuations in 2010 and 2015, consistent with changes in risk level distribution maps.

[Figure 3: see original paper]

Interaction Detection Results: The interaction detection results (Table 6) show that interactions between any two selected factors are stronger than single factors, primarily exhibiting double-factor enhancement and nonlinear enhancement. This indicates that landscape ecological risk spatial differentiation results from multiple factors rather than single factors. The interaction between X1 X8 (elevation and human disturbance) was strongest, with q values reaching 0.91-0.93. Other factor pairs with q > 0.9 include X3 X8, X4 X8, and X5 X8. When human disturbance (X8) interacts with other factors, q values exceed 0.85, demonstrating that human disturbance combined with climate and surface factors has the greatest impact on landscape ecological risk distribution.

Ecological Detection Results: Ecological detection reflects whether each factor' s impact on landscape ecological risk spatial distribution is significantly different, further validating dominant factors and evaluating their mechanistic differences. The results show that human disturbance (X8) has significant differences with all other factors, while non-significant differences mainly occur among natural factors (Figure 5). For example, in 2000, X1 X3, X1 X5, and X1 X6 showed no significant differences; in 2010, X2 X6, X4 X5 showed no significant differences; in 2015, X1 X3, X1 X5, X2 X6, X2 X7, X3 X5 showed no significant differences; and in 2018, X6 X7, X1 X3, X1 X4, X1 X5, X2 X6, X3 X4, X3 X5, X4 X5 showed no significant differences. This pattern aligns with Pan Jinghu et al. [31], showing that from north to south, elevation increases, temperature decreases, precipitation increases, and landscape types transition from unused land, desert, and cropland to forest and grassland, with ecological risk decreasing accordingly.

[Figure 4: see original paper] [Figure 5: see original paper]

4 Discussion

4.1 Spatiotemporal Differentiation Characteristics of Landscape Ecological Risk

The spatial distribution of landscape ecological risk in the Shule River Basin shows a clear north-south gradient, corresponding to changes in elevation, temperature, and precipitation. From 2000 to 2010, the overall risk level changed little, mainly shifting between relatively high and high risk, with risk increases scattered sporadically and decreases concentrated in Dunhuang and Yumen. From 2010 to 2018, the combined area of relatively high and high risk decreased by 3.97%, indicating an overall improvement in the basin' s ecological environment. This aligns with findings from the Manas River Basin, another arid inland region [37]. High or relatively high risk is primarily associated with unused land and construction land, while low or relatively low risk is associated with forest, grassland, and water bodies, consistent with studies in the Bosten Lake Basin [39], Bailong River Basin [40], and Chaohu Basin [41], but differs from the Xi River Basin [42] where concentrated mining construction land in the north resulted in low risk due to low loss degree after human disturbance. The 10 km$×$10 km grid-based risk index effectively reveals landscape ecological risk patterns, showing that human impacts can be reflected in short-term risk changes. However, as watersheds are complex systems, the equal-interval grid approach lacks consideration of dry-wet transitions and farming-pastoral alternation, requiring future improvement.

4.2 Driving Factors

Factor analysis indicates that human disturbance is the main controlling factor for landscape ecological risk spatial differentiation, with population density having the weakest influence, consistent with Xi Shijun' s [43] study on karst mountain basins. Interaction results show double-factor and nonlinear enhancement, indicating that paired factor interactions are stronger than single factors, particularly for human disturbance interacting with other factors. Significant differences exist between human disturbance and natural factors, but not among natural factors themselves. Zheng Xu et al. [44] similarly found significant interactions between human disturbance intensity and other factors affecting water yield in the Shule River Basin. Therefore, controlling human disturbance is key to regulating landscape ecological risk. While policy factors have substantial impacts, their quantification is challenging due to data availability, representing an important direction for future research.

5 Conclusions

This study constructed a landscape ecological risk index and used geographic detectors to analyze driving factors in the Shule River Basin, yielding the following main conclusions:

(1) Analysis of patch-type landscape pattern indices from 2000 to 2018 shows that grassland has the highest number of patches (NP) and landscape shape index (LSI), while unused land has the highest largest patch index (LPI) and aggregation index (AI). This is because grassland and unused land are the dominant landscape types with large areas and wide distribution.

(2) The contagion index (CONTAG) of the Shule River Basin showed a declining trend from 2000 to 2018, while diversity index (SHDI) and evenness index (SHEI) increased slowly, indicating continuously increasing landscape fragmentation.

(3) Landscape ecological risk in the Shule River Basin exhibited a north-south gradient from 2000 to 2018. The proportions of relatively high and high risk decreased by 3.30% and 0.61%, respectively, while low, relatively low, and moderate risk increased by 1.01%, 0.92%, and 1.98%, respectively.

(4) Human disturbance is the primary factor affecting landscape ecological risk spatial distribution, followed by NDVI, while population density has the minimal impact. The influence of factors is not independent but results from combined effects. Interactions between any two factors are stronger than single factors, with human disturbance interactions showing significant enhancement effects, all exhibiting double-factor or nonlinear enhancement.

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Note: Figure translations are in progress. See original paper for figures.