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Original Paper

Analysis of Habitat Quality Changes and Their Driving Factors in Rock Desertification Control Areas of Guizhou Province

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Abstract

Habitat quality affects the functioning of ecosystems, and analyzing its evolution characteristics and driving factors is important for regional ecological management. This study, based on multi-source remote sensing data and using methods such as the InVEST model and geographic detectors, explores the spatial and temporal evolution of habitat quality in the rocky desertification control area and quantifies the influence of various driving factors. The study found that: (1) from 2000 to 2024, the overall habitat quality in Guizhou's rocky desertification control area showed a slow upward trend, with significant spatial heterogeneity in its distribution.(2) during 2000-2024, the habitat quality level remained generally high, with areas of high-quality habitat gradually expanding and poorly rated habitat areas gradually improving through management.(3) from 2000 to 2024, habitat quality in the study area was driven by both natural and human factors, with human activity gradually becoming the dominant influence. Evaluating the habitat quality in Guizhou's rocky desertification control area allows us to quantify the impact of ecological management on regional habitat quality, providing a theoretical basis and data support for rocky desertification control.

Keywords

habitat quality, evolution characteristics, driving factors, stone desertification restoration areas

Introduction

Habitat quality refers to the ecosystem's ability to provide suitable conditions for the survival and continuous development of individuals and populations within a certain spatial and temporal range [1]. As a core indicator to measure an ecosystem's capacity to offer suitable living conditions, it directly reflects the health and service functions of the ecosystem, and is an important basis for regional ecological protection and restoration efforts [2].

In karst areas, vegetation degradation and soil erosion caused by rocky desertification severely threaten ecosystem stability and the sustainable development of human society [3], becoming a major factor affecting regional habitat quality. Guizhou, located at the center of China's southwest karst region, has extensive exposed carbonate rock [4], with strongly developed karst and serious rocky desertification [5], and its ecological environment is fragile. At the same time, the region has rich ecosystem diversity. Analyzing the evolution of habitat quality and its driving factors is of great significance for identifying ecological degradation risks and protecting biodiversity in karst areas.

Currently, research on habitat quality mainly focuses on administrative regions, river basins, and geomorphological units. At the administrative region level [6-15], studies mainly discuss the spatiotemporal distribution characteristics, spatial autocorrelation patterns, and driving factors of habitat quality in areas like Shanxi Province, Chengdu City, and Hubei Province. At the river basin scale [16-22], research mainly analyzes the temporal and spatial evolution patterns, clustering characteristics, and spatial differentiation driving factors of habitat quality in basins such as the Yellow River, Songhua River, and Nu River. For geomorphological units [23-27], studies mainly explore the spatial differentiation patterns of habitat quality in the Loess Plateau, Qinghai Plateau, Altay region, and examine the separate impacts of natural factors and human activities on habitat quality. Overall, existing studies have revealed the spatiotemporal evolution characteristics and driving mechanisms of habitat quality at different spatial scales, providing important scientific support for regional ecological protection and land space optimization.

The karst rocky desertification control area in Guizhou is located in a transitional zone where the Yunnan Plateau slopes toward the hills of Guangxi and the Sichuan Basin. The habitat quality here shows obvious edge effects and gradient features. Previous studies haven't done enough to detail this spatial heterogeneity, and questions like how habitat quality has changed due to rocky desertification control, and whether natural factors or human activities are the main drivers of these changes, still need answers.

In summary, taking the Guizhou rocky desertification control area as the study area, this study combines the InVEST model with geographic detectors to investigate the evolution characteristics and driving factors of habitat quality in the Guizhou rocky desertification control area, aiming to achieve three objectives: (1) identify trends in habitat quality changes and assess the long-term effectiveness of rocky desertification control projects.(2) classify and quantify trends in habitat quality area changes at different levels and their spatial distribution patterns, revealing the impact of land use changes on habitat quality under the context of rocky desertification control.(3) quantitatively analyze the effects of natural environmental factors and human-driven factors on habitat quality, and identify the interactions between different factors, providing scientific decision-making support for differentiated ecological management in the transition zone from the Karst Plateau to hilly areas.

1. Materials and Methods

1.1 Study Area

Guizhou Province is located in southwest China (Figure 1), between 103°36'-109°35' east longitude and 24°37'-29°13' north latitude, with an average elevation of about 1,100 meters. It has a subtropical humid monsoon climate. The terrain decreases from the northwest to the southeast and is mainly mountainous and hilly, with some valleys, basins, and plateaus [28]. The karst exposure area is 109,084 km², accounting for 61.9% of the province's total land area [29]. Karst features are widespread, with a complete range of types and noticeable regional differences, forming a unique karst ecosystem [30]. The southwestern karst area is centered on the Yunnan-Guizhou Plateau, covering about 540,000 km². Due to the ancient and hard nature of carbonate rocks, the influence of monsoon climate's water and heat, and high human activity, the area is highly ecologically vulnerable [31]. Guizhou falls in a subtropical karst plateau mountainous area, with carbonate rock outcrops covering 130,000 km², making up 73% of the province's land area and appearing in 95% of counties and cities [32]. As the province with the largest karst area in China, its soil and vegetation are sensitive to outside influences, easily damaged, and very hard to restore, making it a typical fragile carbonate ecological zone [33].

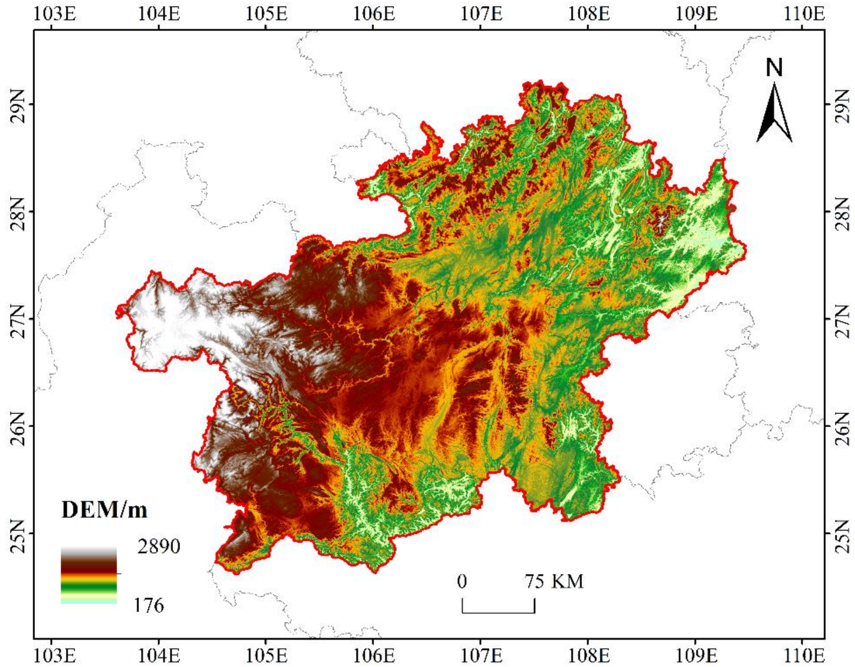


Figure 1. Overview of the Study Area

1.2 Data Source

This study uses land use data systems to assess the spatial and temporal evolution patterns of habitat quality in key rocky desertification areas of Guizhou and combines natural and human-related data to analyze the driving factors: DEM data is used to extract slope and aspect to analyze the influence of terrain, precipitation and temperature data are used to reflect water and heat conditions, and NDVI is used to analyze the dynamic changes in vegetation cover, nighttime light and population distribution data are used to quantitatively describe the impact of human activities on habitat quality. All data have been processed through unified projection transformation, resampling, and normalization to ensure that the combined driving mechanisms of landforms, climate, and human activities on habitat quality can be analyzed on the same spatial and temporal scale (Table 1).

Table 1. Data Source

Data Type	Time Range	Data Source	Resolution	Website
Land Use	2000-2024	Earth Resource Data Cloud	1km	https://www.gis5g.com
Guizhou Rocky Desertification Distribution		Resource and Environmental Science Data		https://www.resdc.cn
DEM		Geospatial Data Cloud	30m	https://www.gscloud.cn
Precipitation	2000-2024	Plateau Science Data Center	1km	https://data.tpdc.ac.cn
Temperature	2000-2024	Plateau Science Data Center	1km	https://data.tpdc.ac.cn
Nighttime Lights	2000-2024	Plateau Science Data Center	1km	https://data.tpdc.ac.cn
NDVI	2000-2024	NASA MOD13A3 Data	1km	https://doi.org/10.5067/MODIS/MOD13A3.006
Population Distribution	2000-2024	LandScan（ORNL）	1km	https://landscan.ornl.gov

1.3 Research Methods

1.3.1 InVEST Model

Using the Habitat Quality module in the InVEST model, this module is based on parameters that describe threat attributes from land use satellite remote sensing products, as well as the habitat and sensitivity to threats provided by each land use type [34]. Its values range from 0 to 1, with numbers closer to 1 indicating a healthier ecosystem and higher biodiversity in the study area [35]. The formula for calculating habitat quality is:

$$Q_{xj} = H_j\left[1-\left(\frac{D_{xj}^z}{D_{xj}^z+k^z}\right)\right] \quad (1)$$

In the equation: Q_{xj} is the habitat quality index of plot x for land use type j, H_j is the habitat suitability of land use type j, D_{xj} is the overall threat level of plot x for land use type j, k is the half-saturation constant, set at 0.5, z is the normalization constant, usually 2.5. The calculation formula for D_{xj} is:

$$D_{xj} = \sum_{r=1}^{R}\sum_{y=1}^{Y_r}\left(\frac{w_r}{\sum_{r=1}^{R} W_r}\right) r_y i_{rxy} \beta_x S_{jr} \quad (2)$$

In the formula: R is the number of threat factors; r is the selected threat factor, y is all the grids for threat factor r, Y_r is the number of grids of the threat factor in the land use type map; W_r is the weight of the threat factor, r_y is the intensity of the threat factor, i_{rxy} is the impact of threat factor r from grid x on grid y, β_x is the accessibility level of grid x; S_{jr} is the sensitivity of land use type j to threat factor r. Here, i_{rxy} is divided into linear decay and exponential decay, with the calculation formula as follows:

linear decay：

$$i_{rxy} = 1 - \left(\frac{d_{xy}}{drmax}\right) \quad (3)$$

Exponential decay：

$$i_{rxy} = exp\left[-\left(\frac{2.99}{d_{rmax}}\right) d_{xy}\right] \quad (4)$$

In the formula: d_{xy} is the linear distance between grid x and grid y; d_{rmax} is the maximum distance that threat factor r can act. Referring to relevant literature[36][37]and considering the actual situation of the study area, this study selects farmland, urban land, rural residential areas, other construction land, and unused land as threat factors. Based on actual conditions, the maximum impact distance and weight of different threat factors are determined (Table 2), as well as the habitat suitability of different land use types and their sensitivity to threat factors (Table 3).

Table 2. Weighting of Risk Factors

Threat Factor	Distance from Threat Factor / km	Weight	decaying linear correlation
Farmland	1	0.7	Linear
Urban land	8	1	Exponential
Rural residential areas	6	0.8	Exponential
Other construction land	4	0.4	Linear
Unused land	4	0.4	Linear

Table 3. Sensitivity to Stressors

Land Use Types	Habitat suitability	farmland	urban land	rural residential areas	other construction land	unused land
Paddy Field	0.4	0	0.7	0.6	0.6	0.5
Dry Land	0.3	0	0.7	0.6	0.6	0.5
Forest Land	1	0.7	0.8	0.3	0.3	0.6
Shrubland	0.8	0.8	0.6	0.4	0.4	0.6
Sparse Woodland	0.7	0.7	0.7	0.5	0.5	0.6
Other Forest Land	0.6	0.6	0.7	0.5	0.5	0.6
High-Coverage Grassland	0.8	0.8	0.5	0.7	0.7	0.5
Medium-Coverage Grassland	0.7	0.7	0.7	0.5	0.5	0.3
Low-Coverage Grassland	0.6	0.5	0.7	0.5	0.5	0.4
Rivers and Channels	0.8	0.8	0.6	0.6	0.8	0.3
Lakes	0.9	0.7	0.7	0.7	0.4	0.5
Reservoirs and Ponds	0.6	0.7	0.6	0.7	0.5	0.5
Tidal Flats	0.5	0.6	0.8	0.7	0.5	0.5
Urban Land	0	0	0	0	0	0
Rural Residential Area	0	0	0	0	0	0

Other Built-up Land	0	0	0	0	0	0
Bare Rock	0.1	0.1	0.1	0.1	0.1	0.1

1.3.2 GeoDetector Model

Geographical detectors identify the driving mechanisms of geographical elements by $q$uantifying spatial heterogeneity and can be used to determine the driving factors of spatial differentiation in habitat quality, including single-factor detection and interaction-factor detection. The larger the q value, the stronger the explanatory power of that factor for the spatial distribution of carbon storage. Interaction-factor detection can determine the type of synergistic effect of factors X_1 and X_2 on Y, with five result categories: nonlinear weakening, single-factor nonlinear weakening, two-factor enhancement, independence, and nonlinear enhancement [38].

The calculation formula is as follows:：

$$q = 1 - \frac{1}{N\beta^2}\sum_{h}^{L} N_h\delta_h^2 = 1 - \frac{SSW}{SST} \qquad (5)$$

$$SSW = \sum_{h=1}^{L} N_h\delta_h^2, SSW = N\delta^2 \qquad (6)$$

In the formula, q represents the explanatory power of the factor, ranging from 0 to 1; h is the level of the factor; N_h and N are the number of units in the level and the whole area, respectively; δ_h^2 and δ^2 are the variances of the Y values in level h and the entire area, respectively; SSW and SST are the sums of within-level variance and the total variance for the whole area, respectively.

(Table 4)Types of Interactions and Criteria for Judging Interaction Type Criteria: Nonlinear Decrease $q(x_1 \cap x_2) < Min(q(x_1),(x_2))$,Single Factor Nonlinear Decrease $Min(q(x_1),q(x_2)) < q(x_1 \cap x_2) < Max(q(x_1),q(x_2))$,Independent $q(x_1 \cap x_2) = q(x_1) + (x_2)$, Two-Factor Enhance -ment $q(x_1 \cap x_2) > Max(q(x_1),q(x_2))$,Nonlinear Enhancement $q(x_1 \cap x_2) > q(x_1) + (x_2)$ .In the table, $Min(q(x_1),q(x_2))$ represents the smaller of $q(x_1)$ and $q(x_2)$; $Max(q(x_1),q(x_2))$ represents the larger of $q(x_1)$ and $q(x_2)$; $q(x_1) + q(x_2)$ is the sum of $q(x_1)$ and $q(x_2)$; and $q(x_1 \cap x_2)$ represents the interaction between $q(x_1)$ and $q(x_2)$.

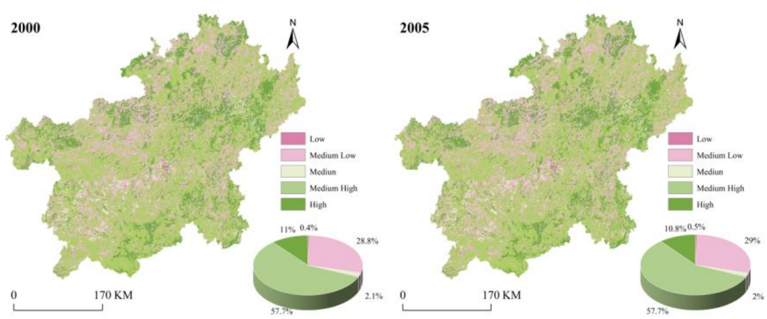
Table 4. Types of Interactions in the Interaction Detector

Interaction Types	Basis for judgment
Nonlinear Weakening	$q(x_1 \cap x_2) < Min(q(x_1), (x_2))$
Single-Factor Nonlinear Weakening	$Min(q(x_1), q(x_2)) < q(x_1 \cap x_2) < Max(q(x_1), q(x_2))$
Independent	$q(x_1 \cap x_2) = q(x_1) + (x_2)$
Two-Factor Enhancement	$q(x_1 \cap x_2) > Max(q(x_1), q(x_2))$
Nonlinear Enhancement	$q(x_1 \cap x_2) > q(x_1) + (x_2)$

2. Results Analysis

2.1 Spatiotemporal Distribution of Habitat Quality

The study area is mainly dominated by high and medium-high habitat quality levels (together accounting for over 65%), with an overall good ecological environment. The area of high-quality habitats has generally shown a fluctuating upward trend, reflecting the ongoing optimization of ecosystem structure and function. From 2000 to 2024, the habitat quality in the study area has generally remained high, with low-quality habitats decreasing and high-quality habitats gradually increasing. However, there were some fluctuations between 2015 and 2020, showing how habitat quality responds to human activities and ecological management measures. In terms of spatial distribution, medium and higher-quality habitats are concentrated in areas that were managed earlier and have better vegetation recovery; low and lower-quality habitats are mostly patchily scattered; overall, habitat quality shows obvious spatial heterogeneity. Over time, the low-quality patches have gradually decreased but are still fairly widespread, while high-quality habitats have struggled to form large, continuous areas.



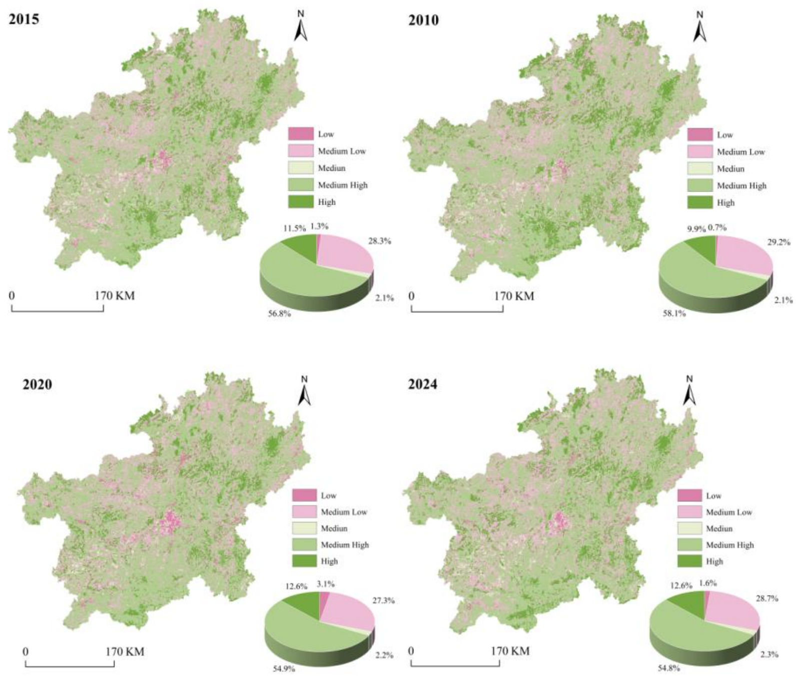


Figure 2. Spatiotemporal Distribution of Habitat Quality, 2000-2024

2.2 Analysis of Factors Driving Changes in Habitat Quality

2.2.1 Driver Factor Selection and Handling

The geographic detector aims to reveal spatial differentiation and its driving mechanisms, where the independent variables are required to be categorical. This study selected 8 independent variables: X_1 (elevation), X_2 (slope), X_3 (aspect), X_4 (population density), X_5 (average temperature), X_6 (average precipitation), X_7 (NDVI), and X_8 (nighttime lights), and these variables were reclassified.

For the classification of each driving factor, the natural breaks method was used to divide elevation (X_1), population density (X_4), average temperature (X_5), average precipitation (X_6), and nighttime lights (X_8) into 6 categories; the equal interval method was used to divide slope (X_2) and NDVI (X_7) into 6 categories, and aspect (X_3) into 9 categories[39].

2.2.2 Single-factor Analysis

Using the geographic detector factor detection model, we analyzed the driving factors behind the spatial differentiation of ecological indicators in the study area for 2000, 2005, 2010, 2015, 2020, and 2024 (Table 5). The results show that different driving factors have obviously different explanatory power (q value) and significance levels (p value) for ecological spatial differentiation, and they display clear stage-related evolution patterns. Between 2000 and 2024, habitat quality in the study area was driven by both natural factors and human activities, with the driving mechanism showing a trend of shifting from being dominated by natural factors to being dominated by human activities.

Table 5. Results of the Analysis of Land Use Change Drivers

Driving factor	q-value					
	2000	2005	2010	2015	2020	2024
X_1	0.001682	0.00136	0.00239	0.003219*	0.004568*	0.003605*
X_2	0.009294*	0.011378*	0.011207*	0.01244*	0.013436*	0.015791*
X_3	0.002196	0.00161	0.001024	0.00122	0.00272	0.001217
X_4	0.011276*	0.011673*	0.011732*	0.023207*	0.035215*	0.049449*
X_5	0.00359	0.006388*	0.006611*	0.006046*	0.005024*	0.007035*
X_6	0.005476*	0.002794	0.002432	0.00386*	0.004157*	0.006238*
X_7	0.065131*	0.07188*	0.072784*	0.069715*	0.102601*	0.097017*
X_8	0.015143*	0.017767*	0.023452*	0.050422*	0.06843*	0.060315*

Note. *: $p<0.05$.

2.2.3 Interaction between Factors

The analysis of habitat quality factor interactions shows that from 2000 to 2024, the driving factors in the study area generally exhibited either double-factor enhancement or nonlinear enhancement effects, with the explanatory power of any two-factor interaction being higher than that of a single factor. In the early years (2000-2010), habitat quality was mainly controlled by natural factors such as terrain and climate, with interactions among elevation (X_1), slope (X_2), precipitation (X_6), and NDVI (X_7) being particularly prominent. The interactive explanatory power of human activity factors like population density (X_4) and nighttime lights (X_8) gradually increased. After 2015, the interaction q-values among population density (X_4), NDVI (X_7), and nighttime lights (X_8) significantly rose, reaching the highest level of the study period by 2024, indicating that the spatial differentiation of habitat quality in the study area gradually shifted from being dominated by natural factors to being driven by a combination of natural and human activities.

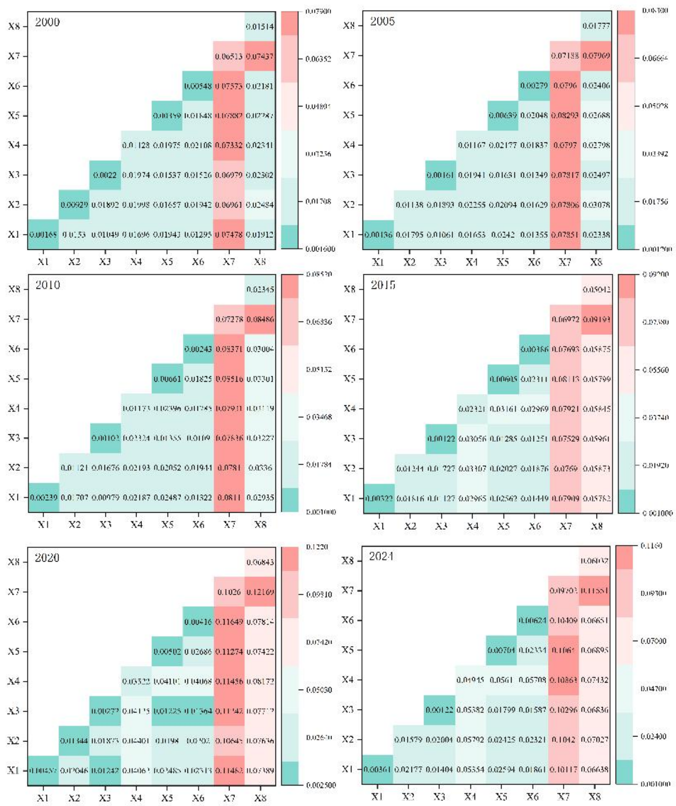


Figure 3. Interaction Analysis of Land Use Change Drivers

3. Discussion and Conclusion

3.1 Discussion

This study found that the pattern of habitat quality differentiation aligns with [3][40][41], which focused on regions in China, the Southwest Karst area, Bijie in Guizhou, and Jinsha County in Guizhou. These areas generally have higher overall habitat quality, but significant spatial heterogeneity, matching the study's finding that habitat quality overall shows a slow upward trend.

The results show that the habitat quality in the karst rocky desertification management areas of Guizhou has significant spatial heterogeneity, showing a 'high in the west and low in the east' distribution pattern that matches the terrain. This is mainly because the study area is located in a key zone where the Yunnan-Guizhou Plateau transitions to hills, with complex landforms (plateau mountains, hills, basins) forming different habitat foundations. Because different landform units have inherent differences in sensitivity to soil and water loss, soil thickness, and water and heat conditions, the ecological restoration benefits of rocky desertification management projects vary noticeably across space.

The ecological indicators in the study area are influenced by both natural factors and human activities. NDVI, as a core natural factor, sets the basic framework for the ecological pattern ($q > 0.065$), while slope provides a stable terrain constraint. In terms of evolution, the driving forces have shifted from being mainly natural to increasingly influenced by humans. Socioeconomic factors like nighttime lights and population density now play a much bigger role, showing that human activities are gradually having more impact on the ecological environment.

The InVEST model's assessment of habitat quality focuses on the impact of land use types on it and doesn't fully take into account the succession differences within the hierarchical structure of karst vegetation communities. When using geographic detectors to handle continuous driving factors, the q value is significantly influenced by the spatial classification method, which involves some scale effects. In the future, combining multi-temporal remote sensing data with field surveys could further explore the nonlinear lag effects between rocky desertification control projects and improvements in habitat quality.

3.2 Conclusion

This study takes the rocky desertification control areas in Guizhou Province as the research unit, combining the InVEST model with a geographic detector to analyze regional habitat quality and its driving factors, using multi-source remote sensing data from 2000 to 2024. The results show that:

(1) During the study period, habitat quality in the rocky desertification control areas gradually improved, but the overall improvement was limited and showed a highly spatially differentiated pattern. Analysis indicates that rocky desertification control projects played a leading role in converting low-quality habitats to medium and high-quality ones. However, due to the extremely high ecological sensitivity of karst habitats and disturbances from extreme climate events, the stability of high-value habitat areas remains fragile.

(2) From 2000 to 2024, the habitat quality in the study area generally remained at a high level, with areas of low-quality habitats being controlled and high-quality habitats steadily expanding. However, there were some stage-specific fluctuations between 2015 and 2020, reflecting the combined response of habitat quality to human activities and ecological management measures.

(3) The study area has established a compound driving system involving both natural factors and human activities. Spatiotemporal evolution analysis shows that the driving mechanisms exhibit clear reinforcing effects and aggregation characteristics, revealing that under the joint influence of long-term climate change and frequent human activities, the regional ecological space has achieved a systemic dynamic balance.

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