Vulnerability of Lake Basin Landscape Patterns in Semi-arid Regions and Their Influencing Factors: A Case Study of Liangcheng County (Postprint)

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Abstract

Based on six-phase landscape type data from 1980 to 2020, we analyzed the lake basin landscape and its change process in Liangcheng County; using the landscape sensitivity index and landscape adaptability index, we constructed a comprehensive landscape vulnerability index to analyze the spatio-temporal differentiation of landscape pattern vulnerability and its influencing factors at the county scale. The research shows: (1) Over the past 40 a, the changes in landscape types in Liangcheng County have shown significant differences. Except for unused land, the dynamic degrees of cropland, forestland, and grassland were the largest from 1980 to 1995, the dynamic degrees of all landscape types were relatively large from 1995 to 2010, and the dynamic degrees of water bodies and construction land were the largest from 2010 to 2020. (2) From 1980 to 2020, the landscape pattern vulnerability of the entire county was mainly at medium and relatively high levels, accounting for over 70% of the area; high-value areas were concentrated in the central and southeastern parts of Liangcheng, while low-value areas were located in Daihai Lake and its northern region; the comprehensive landscape vulnerability index exhibited a trend of first decreasing, then increasing, and then decreasing again, indicating that the regional ecological environment has begun to improve. (3) The ecological environment vulnerability in the study area varied significantly among different landscape types and terrains. Scattered forestlands and grasslands had relatively high vulnerability, while water bodies had the lowest; areas with elevation <1300 m and slope <5° had the lowest landscape pattern vulnerability, while areas with elevation of 1700-1900 m and slope of 25°-40° had the highest. (4) Total population, water area, and cropland area were the main influencing factors of lake basin landscape pattern vulnerability; compared with climatic factors, human activities had a greater impact on the ecological environment of the study area.

Therefore, optimizing landscape structure, reducing excessive disturbance, and protecting water resources and aquatic environment are the main measures to reduce landscape pattern vulnerability and strengthen ecological conservation and construction in Liangcheng.

Full Text

Landscape Pattern Vulnerability and Its Influencing Factors in Semi-Arid Lake Basins: A Case Study of Liangcheng County

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Abstract

Based on six periods of landscape type data from 1980 to 2020, this study analyzes the lake basin landscape and its change process in Liangcheng County. A comprehensive landscape vulnerability index was constructed using landscape sensitivity index and landscape adaptability index to examine the spatiotemporal differentiation of landscape pattern vulnerability and its influencing factors. The results show that: (1) Landscape type changes in Liangcheng County were significantly different across periods. Except for unused land, cultivated land, forestland, and grassland showed the largest dynamic degree during 1980–1995; all landscape types exhibited large dynamic degrees during 1995–2010; and water bodies and construction land showed the largest dynamic degree during 2010–2020. (2) From 1980 to 2020, the landscape pattern vulnerability was dominated by medium and relatively high grades, covering over 70% of the area. High-value zones were concentrated in central and southeastern Liangcheng, while low-value zones were located in Daihai Lake and its northern region. The landscape vulnerability integrated index showed a trend of first decreasing, then increasing, and finally decreasing again, indicating that the regional ecological environment began to improve. (3) The vulnerability of the ecological environment differed significantly among different landscape types and terrains. Scattered forestland and grassland showed higher vulnerability, while water bodies had the lowest. Landscape pattern vulnerability was lowest in areas below 1300 m elevation and with slopes less than 5°, and highest in areas at 1700–1900 m elevation with slopes of 25°–40°. (4) Total population, water area, and cultivated land area were the main factors affecting lake basin landscape pattern vulnerability. Compared with climatic factors, human activities had a greater impact on the ecological environment. Therefore, optimizing landscape structure, reducing excessive disturbance, and protecting water resources and aquatic environments are the primary means to reduce landscape pattern vulnerability and strengthen

ecological protection in Liangcheng County.

Keywords: lake-basin landscape; landscape pattern vulnerability; landscape pattern vulnerability integrated index; influencing factors; Liangcheng County

1. Introduction

Landscape pattern represents the comprehensive product of different landscape patches 镶嵌组合 (mosaicking) in space and time, reflecting the interaction between landscape spatial heterogeneity and ecological processes, which is crucial for maintaining ecosystem stability. With rapid population growth and socioeconomic development, landscape patterns are increasingly disturbed by human activities, leading to increased ecological pressure and risks, causing water shortages, biodiversity degradation, and food scarcity, thereby affecting regional sustainable development. Consequently, ecological evaluation based on landscape pattern changes has become a new research hotspot.

Current domestic and international research in this area mainly focuses on landscape type changes, landscape ecological risk, and landscape ecological security, forming a relatively mature research system. However, research on landscape pattern vulnerability is still in its infancy. Landscape pattern vulnerability originates from ecological vulnerability and studies the relationship between pattern information and ecological vulnerability from a landscape perspective, establishing an indicator system with ecological connotations to provide new ideas for ecological environment vulnerability assessment. It refers to the sensitivity and lack of adaptability of regional landscape patterns when subjected to external disturbances, causing changes in structure, function, and characteristics, and is measured by the landscape vulnerability index.

This index is constructed from landscape sensitivity index and landscape adaptability index, incorporating multiple landscape indices such as landscape type and landscape-level scales, which can accurately reveal regional landscape pattern vulnerability and its dynamic changes. Currently, related research concentrates on vulnerability assessment and spatiotemporal change analysis. Preston et al. explored vulnerability assessment system construction methods. Min et al. analyzed the impact of different landscape patterns on flood vulnerability based on multiple landscape indices, proposing coastal landscape planning guidelines and restoration strategies. Zhang et al. evaluated the spatiotemporal patterns of coastal ecological vulnerability in Qingdao using landscape type vulnerability indices, finding that unused land, grassland, and forestland had the highest vulnerability, while water bodies had the lowest. However, the quantitative vulnerability assessment system still needs improvement, and research on driving factors of landscape pattern vulnerability mainly focuses on landscape types and terrain, with less attention to climate and socioeconomic factors. Moreover, study areas are mostly concentrated in coastal plains or economically developed regions, with few reports on arid areas with complex and diverse landforms, fragile ecology, and underdeveloped economies. Therefore, relevant research is urgently needed to provide scientific support for landscape pattern cognition and management in arid regions.

Liangcheng County is located in central Inner Mongolia, constituting the main body of the Daihai Basin and the location of Daihai Lake, playing an important role in China' s "Two Screens and Three Belts" ecological security strategic pattern. With rapid socioeconomic development, human disturbance of landscape patterns has become increasingly frequent, leading to ecological environment deterioration such as Daihai Lake shrinkage, water level decline, and water quality degradation. Therefore, this study takes Liangcheng County as the research area, constructs a comprehensive landscape vulnerability index based on landscape vulnerability indices, reveals the spatiotemporal changes of landscape patterns and their vulnerability from 1980 to 2020, and explores the influencing mechanisms of different landscape types, terrains, and multiple socioeconomic factors on landscape pattern vulnerability, aiming to provide scientific references for land use and landscape optimization and comprehensive watershed ecological management.

2. Data and Methods

2.1 Study Area Overview

Liangcheng County is located in Ulanqab City, Inner Mongolia Autonomous Region, at the center of the junction of Shanxi, Inner Mongolia, and Hebei provinces (112°02 -113°02 E, 40°10 -40°50 N). The county covers an area of approximately 3452.47 km^2, with hills accounting for 21.1%. The terrain is characterized by mountains on all sides and Daihai Lake in the center, known as "seven parts mountains, one part water, and two parts plains," with elevations ranging from 1138 to 2294 m. The region has a semi-arid continental monsoon climate, cold and dry with little rain and frequent winds; the average annual precipitation is about 392.37 mm, and the average annual temperature is 2–5°C. For many years, Liangcheng has had an economy dominated by agriculture, with forestry, animal husbandry, fishery, and tourism developing together. The county thrives due to water resources, with rivers belonging to the Daihai, Yellow River, and Yongding River systems. Rivers flowing into Daihai account for approximately 70%, making Daihai an important focus for ecological improvement and socioeconomic development. In this study, the 1980 Daihai water area is used as the baseline for analyzing Daihai area changes in different periods.

2.2 Data Sources and Processing

The study period spans 1980–2020. Landscape type vector data (1:100,000) were obtained from the Resources and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/). According to the national land use classification standard, Liangcheng County was divided into six landscape types: cultivated land, forestland, grassland, water bodies, construction land, and unused land (Kappa coefficients $>$ 0.75, meeting the precision requirements for landscape spatial analysis). Digital Elevation Model (DEM) data with 30 m resolution (ASTER GDEM) were obtained from the Geospatial Data Cloud website (http://www.gscloud.cn/). Meteorological data were obtained from the Liangcheng County Meteorological Bureau. Crop planting area, livestock inventory, total population, and other socioeconomic data were sourced from the "Inner Mongolia Autonomous Region Statistical Yearbook" and "Liangcheng County Statistical Yearbook."

2.3 Methods

2.3.1 Single Landscape Type Dynamic Degree The single landscape type dynamic degree represents the change rate of a particular landscape type within a certain period. The calculation formula is:

$$K_i = \frac{U_{it_2} - U_{it_1}}{U_{it_1}} \times \frac{1}{t} \times 100$$

where K_i is the dynamic degree of landscape type i within period t; U_{it_1} and U_{it_2} are the areas of landscape type i at the beginning and end of the period, respectively; and t is the time interval.

2.3.2 Landscape Vulnerability Index Based on the connotation of landscape pattern vulnerability, landscape sensitivity index and landscape adaptability index were selected to construct the landscape vulnerability index (LVI):

$$\mathrm{LVI} = \mathrm{LSI} \times (1 - \mathrm{LAI})$$

where LSI is the landscape sensitivity index and LAI is the landscape adaptability index.

The landscape sensitivity index is calculated as:

$$\mathrm{LSI} = \sum_{i=1}^{n} \left(\frac{U_i}{S} \times V_i \times \mathrm{DO}_i \right)$$

where U_i is the landscape disturbance index; V_i is the landscape type fragility index; DO_i is the dominance index; i is the landscape type; n is the number of landscape types; and S is the total area.

The landscape adaptability index is calculated as:

$$\mathrm{LAI} = \mathrm{PRD} \times \mathrm{SHDI} \times \mathrm{SHEI}$$

where PRD is the patch richness density index, SHDI is the Shannon diversity index, and SHEI is the Shannon evenness index.

The landscape disturbance index is calculated as:

$$U_i = a \times \mathrm{FN}_i + b \times \mathrm{FD}_i + c \times \mathrm{DO}_i$$

where FNi is the landscape fragmentation index; FDi is the fractal dimension index; DOi is the dominance index; and a, b, c are the weights of each index (0.5, 0.3, and 0.2, respectively), determined by expert scoring.

The landscape type fragility index (V_i) was standardized with values of: cultivated land 0.42, forestland 0.25, grassland 0.21, water bodies 0.09, construction land 0.48, and unused land 0.33.

2.3.3 Semivariogram The landscape vulnerability index is a regionalized variable, and its spatial heterogeneity is caused by random errors and spatial autocorrelation. The fitting parameters of the semivariogram can accurately characterize this heterogeneity. The formula is:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2$$

where $\gamma(h)$ is the semivariance at distance h; h is the sample distance; $N(h)$ is the total number of sample pairs at distance h; and $Z(x_i)$ and $Z(x_i + h)$ are the landscape vulnerability index values at positions x_i and $x_i + h$, respectively. This study uses the 3 km × 3 km grid as the basic unit, with 70 m × 70 m as the sampling unit. Based on semivariogram model parameter fitting, Kriging interpolation was performed using the geostatistical module in ArcGIS to obtain the spatial distribution maps of landscape vulnerability index in Liangcheng County.

2.3.4 Spatial Autocorrelation Analysis Spatial autocorrelation analysis can reflect the spatial dependence of elements. Based on GeoDa software, global and local Moran' s I indices were calculated by constructing a weight matrix to explore the spatial correlation between landscape vulnerability index values of grid cells and their adjacent units in different years.

2.3.5 Grey Correlation Degree Analysis Grey correlation degree analysis originates from grey system theory and characterizes the correlation between reference sequences and 母序列 (mother sequences) based on similarity in development trends. The steps include: (1) dimensionless processing of original data; (2) calculation of correlation coefficients; and (3) calculation of the average value of correlation coefficients as the correlation degree.

To further compare the overall trend and differences of landscape pattern vulnerability in Liangcheng County over the years, this study improved and proposed a landscape vulnerability integrated index (LVII):

$$\mathrm{LVII} = \sum_{i=1}^{5} D_i \times \frac{A_i}{S}$$

where D_i represents the landscape pattern vulnerability grade (i = 1-5 corresponding to low, relatively low, medium, relatively high, and high vulnerability); A_i is the area of grade i; and S is the total regional area.

3. Results

3.1 Landscape Type Spatiotemporal Changes

3.1.1 Spatial Distribution of Landscape Types The spatial distribution of landscape types in Liangcheng County is shown in [Figure 2: see original paper]. Cultivated land is mainly distributed around Daihai Lake, forestland is primarily located in the northwest (Manhan Mountain) and southeast (Matou Mountain), grassland is scattered, water bodies are dominated by Daihai Lake, and construction land is relatively evenly distributed but mostly in the Daihai Basin. Overall, the spatial pattern shows a zonal distribution: northwestern agro-forestry-pastoral 交错带 (ecotone), Daihai Basin economic core area, and southeastern hilly agro-pastoral belt.

From 1980 to 2020, landscape type changes in Liangcheng County were significant. The main landscape types were cultivated land and grassland, with cultivated land area continuously decreasing and grassland area first decreasing and then slowly recovering since 2010. Forestland is the third dominant landscape type, with area change trends similar to grassland but with larger change rates. Water body area rapidly increased during 1980-1995, slowly increased during 1995-2010, and continuously decreased during 2010-2020, with the most significant decrease in 2020. Construction land area continuously increased, with the largest increase during 2010-2020. Unused land had the smallest area proportion and the largest change rate.

3.1.2 Landscape Dynamic Degree Changes The dynamic degree changes of single landscape types in Liangcheng County from 1980 to 2020 were complex ([Figure 4: see original paper]). Cultivated land area continuously decreased, with the largest increase rate during 1980-1995 and the largest decrease rate during 1995-2010. Forestland area decreased during 1980-1995 (converted to cultivated land), recovered during 1995-2010 (with 0.40% dynamic degree increase), and decreased again during 2010-2020. Grassland area change trend was similar to forestland but with a 0.16% dynamic degree increase overall. Water body and construction land dynamic degrees were largest during 2010-2020, as large-scale construction and mining industries developed while Daihai water resources were heavily exploited. Since 2015, urbanization accelerated but awareness of Daihai environmental protection increased, allowing water area to slowly recover.

3.2 Spatiotemporal Evolution of Landscape Pattern Vulnerability

Based on the actual situation of Liangcheng County and previous research results, using a 3 km × 3 km grid as the basic unit and 70 m × 70 m sampling units, Kriging interpolation was performed based on semivariogram model parameters to obtain the spatial distribution maps of landscape vulnerability index ([Figure 5: see original paper]). The spatial distribution of landscape pattern vulnerability in Liangcheng County from 1980 to 2020 was similar, indicating strong dependence on geographical patterns. High-value zones were concentrated in southeastern and central Liangcheng because the southeast is dominated by cultivated land and grassland with high dominance and severe fragmentation, leading to high landscape sensitivity. The central area is dominated by cultivated land with scattered construction land, low landscape richness, poor evenness, and frequent external disturbances, resulting in high vulnerability. Low-value zones were mainly located in Daihai Lake and southern-central Maihutu Town.

The landscape vulnerability integrated index (LVII) in Liangcheng County showed a trend of first decreasing, then increasing, and finally decreasing ([Figure 6: see original paper]). The maximum and minimum values were relatively stable, but the maximum value significantly decreased in 2020. During 1980–1995, LVII decreased as appropriate landscape type adjustments positively impacted the ecological environment. During 1995–2010, LVII continuously increased due to rapid urbanization, increased land resource development intensity, intensified landscape fragmentation, and reduced ecosystem adaptability. During 2010–2020, LVII decreased again as ecological problem governance advanced, people began integrating land resources and optimizing landscape patterns (such as Daihai environmental remediation), and regional ecological environment vulnerability decreased.

This study divided landscape vulnerability into five grades: low vulnerability (LVI $<$ 0.20), relatively low vulnerability (0.20–0.30), medium vulnerability (0.30–0.40), relatively high vulnerability (0.40–0.50), and high vulnerability (LVI $>$ 0.50). The results show that landscape pattern vulnerability in the study area was dominated by medium and relatively high grades, accounting for over 70% of the total area. Each vulnerability grade showed different changes across periods. Low vulnerability area first decreased then increased, corresponding to water area changes. Relatively low vulnerability area showed fluctuating increases. Medium vulnerability area first increased, then decreased, and then increased again. Relatively high vulnerability area showed opposite changes. High vulnerability area showed a fluctuating pattern of first decreasing, then increasing, and then decreasing, with the most significant decrease during 2010–2020 due to simplified patch shapes of forestland and grassland in Caonianmanzu Township, reducing landscape sensitivity.

3.3 Spatial Autocorrelation Analysis of Landscape Pattern Vulnerability

The global Moran' s I values for landscape vulnerability index from 1980 to 2020 were all positive and generally increased, indicating that landscape pattern vulnerability in Liangcheng County had positive spatial correlation and enhanced spatial aggregation over the past 40 years. However, Moran' s I decreased during 1995–2010, suggesting a dispersion trend in vulnerability spatial distribution and emergence of a multi-center pattern.

The high-high value clusters were mainly distributed in central Caonianmanzu Township and northwestern Liusumu Town ([Figure 7: see original paper]). The high-high value area shrank during 2010–2020, while the low-low value area around Daihai expanded after 2015, related to the implementation of Daihai environmental governance policies. Additionally, after 2010, scattered cultivated land in Caonianmanzu Township was converted to forestland and grassland, improving landscape connectivity and reducing high vulnerability areas. Since 2015, accelerated urbanization led to rapid construction land expansion, especially in northwestern Liusumu Town, intensifying landscape fragmentation and expanding high vulnerability areas. Low-low value clusters were concentrated in Daihai Lake and southern-central Maihutu Town, with a banded distribution recently appearing in central Manhan Town, possibly related to landscape type conversions.

3.4 Vulnerability Characteristics by Landscape Type and Terrain

3.4.1 Vulnerability Changes by Landscape Type To clarify the evolution characteristics of regional landscape pattern vulnerability, statistical analysis of LVI minimum, maximum, range, and LVII values for each landscape type was conducted (). The results show significant differences in landscape pattern vulnerability among different landscape types. Cultivated land showed the largest LVI fluctuation range across periods, with the largest variation range (mean 0.52), indicating unstable vulnerability across multiple grades. Water bodies showed the smallest LVI fluctuation, followed by unused land, while unused land had the smallest variation range (mean 0.21), indicating stable vulnerability grades for water bodies and unused land. However, over the past 40 years, forestland and grassland had the highest LVII values because only some forestland in Manhan Town and grassland in Tiancheng Township were concentrated and contiguous with stable ecosystems and low vulnerability. Most forestland and grassland were interspersed with other landscape types, resulting in severe patch fragmentation and high vulnerability. Water bodies had the lowest LVII due to high aggregation around Daihai Lake and strong resistance to interference.

3.4.2 Vulnerability Changes by Terrain To further explore the vertical spatial variation of landscape pattern vulnerability, elevation and slope were used as terrain indicators. Elevation and slope were divided into five grades

(), and LVII values were calculated for each grade. The results show that with increasing elevation and slope, LVII first increased and then decreased. From the multi-year average perspective, areas below 1300 m elevation had the lowest LVII because the Daihai Basin has flat terrain, pleasant climate, and contains Daihai Lake. Although population density is high, the landscape pattern is relatively reasonable, resulting in lowest vulnerability. Areas at 1700–1900 m elevation had the highest LVII due to high altitude, steep terrain, susceptibility to natural disasters like soil erosion, plus unreasonable slope cultivation and construction land expansion, leading to poor ecological environment stability. Similarly, slopes of 25°–40° showed the highest vulnerability.

3.5 Influencing Factors of Landscape Pattern Vulnerability

To explore the influencing factors of landscape pattern vulnerability, grey correlation analysis was introduced. Based on vulnerability characteristics and regional development patterns, seven factors were selected: total population, water area, crop planting area, temperature, precipitation, livestock inventory, and construction land area. The grey correlation degrees ranged from 0.435 to 0.952, with an average of 0.752. Except for precipitation, all other factors showed high correlation with LVII. Total population had the highest correlation degree (0.952), as population growth accelerates urbanization, leading to rapid expansion of residential and industrial areas, frequent landscape pattern changes, and altered regional ecological environments. Water area and crop planting area ranked second and third, indicating that human disturbance affects the ecological environment more than climate factors. LVII was negatively correlated with temperature, precipitation, and water area, and positively correlated with other factors. Therefore, reducing excessive human interference and rationally utilizing natural resources are crucial for protecting the county' s ecological environment.

4. Discussion

Landscape pattern changes are closely related to ecological processes. Research on ecological vulnerability based on landscape pattern methods is beneficial for evaluating regional ecological environmental quality. Drawing on international comprehensive ecological vulnerability index research methods, this study proposed a landscape vulnerability integrated index (LVII), which facilitates multi-level vulnerability analysis and provides new ideas for driver analysis through grey correlation degree analysis. This study combined LVII and grey correlation degree analysis to reveal landscape pattern vulnerability trends and quantitatively and intuitively show relationships between various factors and regional vulnerability. The study provides research methods and case studies for lake basin landscape pattern vulnerability and its influencing factors, with a reproducible assessment system that can provide references for similar regions.

The results show that from 1980 to 2020, landscape pattern vulnerability in Liangcheng County generally decreased, with low vulnerability areas mainly located in Daihai Lake and its surroundings. This is consistent with findings from Feng et al., Xu et al., and Lai, demonstrating that LVII can effectively reveal regional vulnerability. The relationship between landscape pattern vulnerability and landscape types shows that cultivated land changed most significantly, while forestland and grassland had higher vulnerability. This is because cultivated land is the main landscape type with wide distribution, while forestland and grassland patches are fragmented and complex, interspersed with other types. Additionally, the study area is a semi-arid hilly basin with steep terrain, severe soil erosion, and poor vegetation growth, leading to high vulnerability.

Total population and water area are the two main factors affecting county landscape pattern vulnerability. More population means greater human activity intensity, frequently disturbing and shaping regional landscape patterns. Daihai water area changed dramatically, continuously shrinking from 1980 to 2015 due to large industrial and agricultural water consumption, industrial sewage discharge, and groundwater environment deterioration. Since 2015, Daihai protection policies have allowed water area to slowly recover. Human activities significantly impact regional vulnerability, while national and regional policies are also important factors affecting vulnerability changes. Therefore, future efforts should rationally utilize land and water resources, reduce unreasonable human activities, cultivate land where suitable, plant forests where suitable, and develop construction where suitable, to improve forestland and grassland connectivity and stability; implement comprehensive Daihai Basin management to reduce watershed ecological vulnerability and achieve coordinated development among humans, nature, and economy.

When constructing the landscape vulnerability integrated index at medium and small scales (county level), terrain and climate factors were not considered because landscape types can reflect geographical location and climate characteristics to some extent, and climate 要素空间分异 (spatial differentiation) is small at medium and small scales. However, this may affect result accuracy and scientificity to some degree, and terrain and climate 要素分异 (differentiation) should be fully considered in large-scale studies. On the other hand, understanding of the intrinsic ecological mechanisms of landscape indices is limited, making it difficult to ensure assessment system objectivity. Therefore, research on landscape indices based on ecological connotations is a future priority. Additionally, investigation of spatial mechanisms of driving factors should be strengthened to provide scientific references for developing operable, effective, and precise ecological management and restoration plans.

5. Conclusion

Based on six periods of landscape type data from 1980 to 2020, this study analyzed landscape type change processes in Liangcheng County on a 3 km × 3 km grid basis, and explored spatiotemporal variation patterns and influencing factors of regional landscape pattern vulnerability. The main conclusions are:

(1) The dynamic degrees of landscape types showed different characteristics across periods. Except for unused land, forestland, grassland, and cultivated land changed frequently before 1995; all landscape types had large dynamic degrees during 1995–2010; and water bodies and construction land had the largest dynamic degrees during 2010–2020.

(2) The global Moran' s I of landscape pattern vulnerability was positive and generally increased from 1980 to 2020, indicating positive spatial correlation and enhanced spatial aggregation. High-high value clusters were located in Caonianmanzu Township and Liusumu Town, while low-low value clusters were located in Daihai Lake and southern Maihutu Town. The ecological environment quality gradually improved, with LVII showing a decrease-increase-decrease trend.

(3) Cultivated land LVII showed large variation, while forestland and grassland had relatively high LVII. The vulnerability ranking was: forestland > grassland > cultivated land > construction land > unused land > water bodies. In vertical space, areas at 1700–1900 m elevation and slopes of 25°–40° had the highest landscape vulnerability, while the flat, resource-rich Daihai Basin had better ecological conditions but showed deterioration trends. Grey correlation analysis revealed that the ecological conditions were more susceptible to human activities.

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