Postprint: Spatiotemporal Evolution of Ecological Vulnerability and Driving Factors in the Hehuang Region

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Abstract

An evaluation index system was constructed based on the exposure-sensitivity-adaptability ecological vulnerability conceptual model, employing the projection pursuit model and genetic algorithm to determine index weights, calculating the ecological vulnerability index of the Hehuang region, utilizing spatiotemporal scanning to investigate spatial aggregation characteristics and spatiotemporal variation patterns of ecological vulnerability, and applying the geographical detector to examine influencing factors of ecological vulnerability. The results demonstrate that from 2000 to 2020, ecological vulnerability in the Hehuang region was primarily characterized by mild and moderate vulnerability, with pronounced regional disparities in spatial distribution. Ecological vulnerability exhibited significant temporal clustering and local spatial clustering features, wherein high-value and low-value clusters coexisted, and spatial aggregation was predominantly distributed within Gansu Province. During 2000–2020, overall ecological vulnerability demonstrated a decreasing trend, with 53.36% of land area experiencing reduced ecological vulnerability. The most influential factor on ecological vulnerability was vegetation coverage, followed by desertification index, net primary productivity of vegetation, drought index, habitat quality index, altitude, among others.

Full Text

Preamble

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Spatial and Temporal Evolution of Ecological Vulnerability and Its Influencing Factors in the Hehuang Area

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Abstract: Based on the exposure-sensitivity-adaptability conceptual model of ecological vulnerability, an evaluation index system was constructed. The projection pursuit model and genetic algorithm were employed to determine index weights, and the ecological vulnerability index of the Hehuang area was calculated. Spatio-temporal scanning was used to explore the spatial clustering characteristics and spatio-temporal variation patterns of ecological vulnerability, while geographical detectors were applied to investigate the influencing factors. The results indicate that from 2000 to 2020, ecological vulnerability in the Hehuang area was predominantly characterized by light and moderate vulnerability, with significant regional differences in spatial distribution. Ecological vulnerability exhibited obvious temporal clustering and local spatial clustering features, with high-value and low-value clusters coexisting. Spatial clustering was mainly distributed within Gansu Province. From 2000 to 2020, the overall ecological vulnerability showed a decreasing trend, with 53.36% of the land area experiencing reduced ecological vulnerability. The most influential factor on ecological vulnerability was vegetation coverage, followed by desertification index, net primary productivity of vegetation, drought index, habitat quality index, and altitude.

Keywords: ecological vulnerability; ecological protection of the Yellow River basin; spatio-temporal scanning; geographic detector; influencing factors; Hehuang area

The Yellow River basin spans China's three major geographical terraces—eastern, central, and western—and serves as an ecological corridor connecting the Loess Plateau, Qinghai-Tibet Plateau, and North China Plain, as well as a barrier for protecting the ecological environment of northern China. In 2019, ecological protection and high-quality development of the Yellow River basin received national-level attention, providing an opportunity for ecological vulnerability research that focuses on quantitative evaluation of vulnerability and harmonious development strategies between humans and nature. Research indicates that transitional zones exhibit greater potential for ecological vulnerability. The Hehuang area is located in the transitional zone among the Qinghai-Tibet, Loess, and Inner Mongolia plateaus, at the intersection of the eastern monsoon region, northwest arid and semi-arid region, and Qinghai-Tibet region, and represents a complex agro-pastoral 交错 area. With uneven precipitation distribution and low ecological restoration capacity, this region is more likely to demonstrate ecological vulnerability. As an important ecological barrier in the upper reaches of the Yellow River basin, evaluating the ecological vulnerability of the Hehuang area and fully understanding the current status and dynamic trends of its ecological environment can not only provide a basis for ecological restoration and environmental governance but also offer references for regional sustainable development.

Currently, domestic and international scholars have used different research methods to evaluate regional ecological vulnerability and have achieved numerous results. In terms of research regions and objects, studies have mainly focused on grasslands, forests, wetlands, rivers and lakes, cold and arid regions, karst areas, and loess hilly regions. Regarding research content, studies have covered vulnerability concepts, vulnerability evaluation, index systems, spatio-temporal patterns, dynamic monitoring, impact mechanisms, and driving forces. From a methodological perspective, approaches 主要包括层次分析法、主成分分析法、模糊评价法、多准则评价法、人工神经网络、情景分析法等. To assess ecological vulnerability, researchers have developed a series of evaluation model frameworks based on different principles and objectives, including "Pressure-State-Response (PSR)," "Exposure-Sensitivity-Adaptability (ESA)," "Driving force-Pressure-State-Impact-Response (DPSIR)," and "Vulnerability Scoping Diagram (VSD)." Among these, the ESA framework offers advantages such as clear connotation, distinct evaluation levels, and wide applicability, with good compatibility and extensibility. This study adopts the widely recognized ESA framework, integrating the projection pursuit model with geographical detector analysis to evaluate ecological vulnerability in the Hehuang area, aiming to provide references for regional ecological environment construction and governance.

1. Study Area, Data, and Methods

1.1 Study Area Overview

In the Hehuang area, "He" refers to the Yellow River and "Huang" refers to the Huangshui River. The geographical scope can be defined narrowly or broadly. This study selected the broad definition of the Hehuang area, which constitutes a geographical unit composed of the Yellow River below Longyangxia Gorge and the Huangshui River valley basin along with their surrounding mountains. The geographical location is 34°7 31 ~39°5 7 N, 98°6 49 ~105°38 28 E. Administratively, it includes prefecture-level administrative regions in Gansu Province and Qinghai Province, covering an area of approximately 15.93$\times10^{4}$ km^2. The terrain of the Hehuang area is lower in the northeast and central parts, and higher in the south and west, with elevations ranging from 1200 to 5300 m. Valleys, basins, hills, and mountainous areas are interspersed. Precipitation is scarce with large spatial variations, evapotranspiration is high, sunshine duration is long, temperatures are low with large diurnal temperature ranges.

1.2 Data Sources and Processing

Digital Elevation Model (DEM) data were obtained from the Geospatial Data Cloud Platform (https://www.gscloud.cn/). Land use data were sourced from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (https://www.resdc.cn). This dataset was produced through visual interpretation based on Landsat remote sensing imagery, with a spatial resolution of 30 m and a comprehensive classification accuracy of 95.53% for first-level types. Daily precipitation, temperature, latitude and longitude data were obtained from the China Meteorological Data Network (http://data.cma.cn/) and interpolated to raster format. Population raster data were downloaded from WorldPop (https://www.worldpop.org/geodata/listing?id=74). Nighttime light data, including DMSP/OLS and VIIRS types, were downloaded from the National Oceanic and Atmospheric Administration's National Geophysical Data Center (https://ngdc.noaa.gov/eog). Soil organic carbon data were obtained from the World Soil Database (https://www.fao.org/land-water/en). MODIS data, including MOD09A1 and MOD17A3H products, were acquired from NASA (https://MODIS.gscloud.cn) with a temporal resolution of 8 days and 16 days respectively. To improve matching accuracy among different remote sensing datasets, all data were uniformly processed with projection conversion and resampling using the Albers equal-area secant conic projection, with spatial resolution set to 1 km × 1 km. All calculations were completed in the Matlab software environment.

1.3 Methods

1.3.1 Evaluation Index Selection Ecological vulnerability results from the interaction between natural environmental conditions and human production activities, with different characteristics in different study areas. By analyzing the ecological vulnerability characteristics of the Hehuang area, referencing relevant theories and similar research findings, and combining the widely recognized definition of ecological vulnerability with actual conditions in the Hehuang area, an evaluation index system was established based on the "Exposure-Sensitivity-Adaptability" conceptual model (Table 1).

1.3.2 Projection Pursuit Model To scientifically and accurately determine the importance of each index in ecological vulnerability evaluation, weights must be assigned to indicators. This involves two steps: first, constructing an ecological vulnerability projection index function; second, optimizing the projection index function and determining index weights. The calculation formulas are detailed in the literature. The calculation of optimal projection direction is a nonlinear optimization problem requiring optimization algorithms. This study used a genetic algorithm to find the optimal projection direction and ultimately calculated the weights of each evaluation index for ecological vulnerability for each year (Table 2).

1.3.3 Comprehensive Ecological Vulnerability Evaluation Based on the optimized weights of ecological vulnerability evaluation indices, the exposure index (EI), sensitivity index (SI), and adaptability index (AI) were calculated. The formulas are as follows:

EI = W X
SI = W X

AI = W X

where j is the number of evaluation indicators, X is the standardized value of the indicator, and W is the weight of each indicator.

This study used a spatial vector model to calculate the ecological vulnerability index. A spatial rectangular coordinate system was established, with exposure, sensitivity, and adaptability representing three spatial planes. The modulus of the ecological vulnerability spatial vector was calculated using vector modulus calculation methods, with the modulus size representing the ecological vulnerability value. Specifically, a three-dimensional coordinate system with point O as the origin was established, and the three ecological vulnerability component vectors were projected onto the x, y, and z coordinate axes. The corresponding vector OM represents the ecological vulnerability spatial vector, as shown in Figure 2. The modulus length of vector m was used to represent the ecological vulnerability value, calculated as:

$$|OM| = \sqrt{(EI^2 + SI^2 + AI^2)}$$

where OM is the ecological vulnerability vector, |OM| is the vector modulus, and m is the ecological vulnerability value. This study used the Ecological Vulnerability Index (EVI) to quantitatively describe the degree of ecological vulnerability:

EVI = m

A larger EVI value indicates more obvious ecological vulnerability trends. The ecological vulnerability results obtained through the above steps are continuous values. To comprehensively understand the ecological vulnerability of the study area and facilitate intuitive comparison of ecological vulnerability across different years in the Hehuang area, the EVI needed to be standardized:

SEVI = (EVI - EVI) / (EVI - EVI)

where SEVI is the standardized ecological vulnerability index value for year i, EVI is the actual ecological vulnerability index value for year i, EVI is the minimum ecological vulnerability index value in the study area, and EVI is the maximum value. Referencing relevant research classification standards, ecological vulnerability was divided into five levels: micro-vulnerability, light vulnerability, moderate vulnerability, severe vulnerability, and extreme vulnerability. The classification standards and characteristics of different levels are shown in Table 3.

1.3.4 Spatio-temporal Scanning Analysis This study employed spatio-temporal scanning analysis to conduct spatial clustering analysis of high and low values of ecological vulnerability in the Hehuang area from 2000 to 2020, facilitating understanding of the spatial clustering patterns during the study period. This method calculates the log-likelihood ratio (LLR) for each scanning window to characterize the degree of aggregation of ecological vulnerability, with the maximum LLR value indicating the most aggregated area. The calculation formula is:

LLR = log(C/C)   × ((C - C)/(C - A)) ⁻

where C is the sum of ecological vulnerability grades in the study area, C is the actual sum of ecological vulnerability grades within the scanning window, and A is the expected sum of ecological vulnerability grades within the scanning window. To evaluate whether the scanning results have statistical significance, the Monte Carlo simulation method was used to calculate P-values. Spatio-temporal scanning analysis was implemented using the FleXScan spatial scanning software.

1.3.5 Spatio-temporal Change Analysis Leveraging the advantages of raster data, grids of ecological vulnerability changes from 2000 to 2020 were extracted to describe changes in ecological vulnerability at different spatial locations. The calculation formula is:

$$\text{Codez} = 100 \times \text{Code}_{2000} + 10 \times \text{Code}_{2010} + 1 \times \text{Code}_{2020}$$

where Codez is the ecological vulnerability change code, and Code_{2000}, Code_{2010}, and Code_{2020} represent the ecological vulnerability classification values for 2000, 2010, and 2020 respectively (1-5 representing micro-vulnerability, light vulnerability, moderate vulnerability, severe vulnerability, and extreme vulnerability). Based on the conversion types of Codez, the results were organized into five conversion types, forming the pattern evolution of ecological vulnerability in the Hehuang area. The classification table is shown in Table 4.

1.3.6 Geographic Detector To understand the degree of influence of different indicators on the spatial distribution of ecological vulnerability in the Hehuang area, this study used the factor detector in geographic detectors for analysis. The influence of factors was represented by q-values, with larger q-values indicating greater influence on ecological vulnerability. The calculation formula is:

$$q = 1 - (1/N\sigma^2) \times \quad {}_1 \; N \, \sigma^{\,2}$$

where h is the number of categories or zones for a certain indicator, N is the number of units in the region, N is the number of units in layer h, and σ^2 and $\sigma^{\,2}$ are the variances of ecological vulnerability in layer h and the entire region, respectively.

2. Results

2.1 Spatial Pattern of Ecological Vulnerability

Based on the ecological vulnerability classification standards, the ecological vulnerability from 2000 to 2020 was classified into different levels. The results show (Figure 3) that the spatial distribution of ecological vulnerability in different research years has certain regional differences. Ecological vulnerability in the study area mainly manifests as light vulnerability, moderate vulnerability, and severe vulnerability. Among them, moderate vulnerability, severe vulnerability, and extreme vulnerability areas are primarily distributed in an east-west orientation, while micro-vulnerability and light vulnerability areas are mainly distributed in a north-south orientation, forming a large intersecting spatial distribution pattern with Haidong City as the intersection. The ecological vulnerability in Haibei Prefecture and Gannan Prefecture is mainly characterized by light vulnerability, interspersed with some micro-vulnerability areas. The ecological vulnerability in Hainan Prefecture, Lanzhou City, Baiyin City, and Dingxi City is mainly characterized by moderate vulnerability and severe vulnerability.

From the perspective of specific area changes of different vulnerability types (Figure 4), the area of micro-vulnerability first increased, then gradually decreased from 2010, and increased again by 2020. The area of moderate vulnerability first decreased, then increased, and finally decreased again, indicating that the ecological conditions in micro-vulnerability and moderate vulnerability areas were unstable with relatively large fluctuations. The area of light vulnerability continued to increase, while the area of severe vulnerability continued to decrease, indicating that ecological vulnerability in the study area was gradually improving. The area proportion of extreme vulnerability was very small, only 0.08%.

2.2 Spatio-temporal Scanning Results

The spatio-temporal scanning results are shown in Figure 5. The Hehuang area exhibited not only temporal clustering but also strong spatial clustering characteristics during the study period. Temporally, the study area showed clustering phenomena in three time periods. Spatially, clustering was mainly manifested as high-value clustering (high-high areas) and low-value clustering (low-low areas), with a small portion of sub-high-value clustering areas. Both high-value and low-value spatial clustering phenomena were mainly distributed within Gansu Province, indicating that ecological vulnerability in Gansu Province within the Hehuang area consistently showed more extreme performance and was prone to clustering, while areas within Qinghai Province showed more balanced performance with insignificant spatial clustering.

Low-value clustering areas were mainly distributed in the southern part of Gansu Province, with counties (districts) consistently showing low-value clustering including Xiahe County, Hezuo City, Hezheng County, Zhuoni County, Lintan County, Min County, and Zhang County. These counties (districts) have good vegetation conditions, sufficient water conservation, low population density, and lower levels of human disturbance, resulting in lower ecological vulnerability and good ecological environmental conditions.

High-value clustering areas were mainly distributed in the northern part of Gansu Province, with counties (districts) consistently showing high-value clustering including Yongdeng County, Gaolan County, Baiyin District, and Jingtai County. Most of these areas belong to Lanzhou City and Baiyin City, where vegetation conditions are poor and sparse due to high evapotranspiration and scarce precipitation, directly affecting ecological restoration capacity. Additionally, Lanzhou and Baiyin have large populations and high densities, creating correspondingly greater pressure and disturbance on the ecosystem, thus exhibiting higher ecological vulnerability. Some high-value clustering also appeared in the southern part of Gonghe County. Although rivers pass through these high-altitude valleys, severe soil erosion problems result in fragile ecological environments, showing sub-high-value clustering states. Other counties (districts) in the Hehuang area showed insignificant temporal and local spatial clustering characteristics without statistical significance.

2.3 Pattern Evolution of Ecological Vulnerability

Using 2000, 2010, and 2020 as time nodes, the overall conversion pattern of ecological vulnerability was calculated and divided into five types according to different conversion codes (Figure 6). From the perspective of area proportion of each type, the combined area of continuous stable type and fluctuating stable type was 42.79%, indicating that more than 40% of the land in the study area had relatively stable ecological vulnerability conditions that did not change during the study period. These areas are mainly located in the northwestern and southeastern parts of the study area, concentrated at the north and south ends of Qilian County, the central part of Haiyan County, the eastern part of Menyuan County, the border areas between Yongdeng County, Huzhu County, and Ledu District, the northeastern part of Jingtai County, and parts of Gannan Prefecture and Dingxi City.

The combined area of fluctuating decreasing type and continuous decreasing type was 53.36%, accounting for more than half of the entire Hehuang area. This indicates that ecological vulnerability decreased in the vast majority of land in the study area, with these regions showing improvement. The combined area of continuous increasing type and fluctuating increasing type was smallest, only 3.85%, mainly located around the built-up areas of Lanzhou City, Lanzhou New Area, and Xining City, and sporadically distributed in Qilian County, Menyuan County, Datong County, and Huzhu County, indicating that urban expansion and development have obvious impacts on ecological vulnerability.

2.4 Influencing Factors of Ecological Vulnerability

The results obtained through geographic detectors are shown in Table 5. The P-values of detection indicators for each year from 2000 to 2020 were all 0.001, indicating that the explanatory power of the detection indicators for ecological vulnerability was sufficient, and the detection results were statistically significant at the 0.001 significance level. The q-values of each detection indicator were sorted and organized. Overall, the ranking order of q-values did not change significantly across research years. The top six detection indicators were: vegetation coverage, desertification index, net primary productivity of vegetation, drought index, habitat quality index, and altitude. These factors had strong explanatory power for ecological vulnerability, with q-values all exceeding 0.1. Among them, vegetation coverage was the most important factor affecting the overall distribution of ecological vulnerability in the Hehuang area, with the average q-value of the three-period data reaching 0.25, indicating that ecological vulnerability was most influenced by vegetation coverage.

2.5 Ecological Vulnerability Zoning

Considering the specific conversion paths of each ecological vulnerability level and the transformation patterns of ecological vulnerability types, the study area was divided into five ecological vulnerability zones (Figure 7). The basis for division, area size, and conversion codes for different ecological vulnerability zones are shown in Table 6.

Ecological Core Protection Zone: This zone is mainly distributed in the northwestern and southern parts of the study area, accounting for 20.79% of the study area. It is primarily located in Qilian County, Haiyan County, Menyuan County, Datong County, and Huzhu County within Qinghai Province. The average altitude of the core protection zone is above 3000 m, with good vegetation coverage and minimal human impact. The scientific concept of "protection first, ecological priority" should be firmly established, ecological red lines should be strictly observed, and further ecological environment deterioration should be prevented.

Ecological Comprehensive Management Zone: This zone is mainly characterized by consistently moderate, severe, or extreme vulnerability, accounting for 20.79% of the area. It is mainly distributed in the northernmost high-altitude area of Qilian County in Qinghai Province, the border area between northeastern Jingtai County and Jingyuan County in Gansu Province, and the northern part of Pingchuan District in Baiyin City. The distribution is relatively concentrated, with stable but significant vulnerability over the years. Targeted measures should be implemented for special management in this region, such as returning farmland to forest and grassland for low-yield cultivated land, and implementing grazing bans and rest periods in mountainous areas to reduce human disturbance. Ecological migration policies could also be encouraged in extremely vulnerable areas to relieve ecological pressure.

Ecological Restoration Attention Zone: This zone is mainly distributed on the eastern and western sides of the study area, with a relatively large overall area, particularly in Gansu Province. It is characterized by transformation from high ecological vulnerability to low ecological vulnerability, with continuous ecological restoration throughout the region. This zone should strengthen ecological protection policies, continue to adhere to protection-first and nature-based restoration strategies, further improve the ecological security barrier system, and maintain the positive trend of natural ecological restoration.

Ecological Priority Management Zone: This zone shows ecological status transitioning from low vulnerability to high vulnerability, with ecological deterioration and intensification trends. It is concentrated around the rapidly developing urban built-up areas of Xining City, Lanzhou City, and Lanzhou New Area. Due to significant human impact and interference, and rapid development and construction, the ecological environment is inevitably shifting toward vulnerability. Therefore, priority management should be implemented to curb and reverse the trend toward greater vulnerability. During development and construction, reasonable and specific assessments of environmental interference should be made, and corresponding effective ecological compensation measures should be proposed. Efforts should be made to improve land conservation and intensive use levels, introduce advanced technologies to vigorously promote green industrial development, and improve the living environment.

Ecological Key Monitoring Zone: This zone shows fluctuating changes in ecological vulnerability, sporadically distributed throughout the study area, with relatively concentrated areas in small northern parts of Yongdeng County and southern parts of Min County. Reasonable ecological monitoring should be conducted, using multiple geographic information and remote sensing methods for continuous prediction and early warning of ecological vulnerability to prevent regional ecological environments from developing toward high ecological vulnerability during fluctuating changes.

3. Discussion

The spatial distribution characteristics, trends, and calculation results of ecological vulnerability in this study maintain high consistency with those of Zhang Liangxia et al. and Li Zhenzhen et al. for the overlapping regions of their study areas in northwestern China. This is mainly because these regions belong to arid and semi-arid climates with many similarities in vegetation and climate conditions, thus showing similar macro-level ecological vulnerability characteristics. From 2000 to 2020, whether considering area changes of each ecological vulnerability type or conversions between different vulnerability levels, the regional ecological vulnerability showed an improving trend. The reasons include: on one hand, global warming has become increasingly significant, with rising temperatures in the region and improved precipitation conditions, creating favorable conditions for vegetation growth; on the other hand, government efforts such as expanding ecological protection red lines and increasing ecological protection areas during the study period have also played a promotional role.

This study conducted spatial analysis based on multi-source raster data, using image spatial overlay and model operations to achieve quantitative expression of ecological vulnerability across the entire spatial region. The projection pursuit model was used to determine index weights, greatly reducing human intervention, with its robustness and accuracy being superior to traditional weighting methods such as the analytic hierarchy process, entropy weight method, and principal component analysis. The spatio-temporal scanning model incorporates temporal dimensions compared to spatial autocorrelation analysis, facilitating research on clustering patterns of ecological vulnerability results in both time and space. Spatio-temporal change analysis facilitates tracking changes in the same grid cell across different research periods, helping to grasp the dynamic change process of ecological vulnerability in the Hehuang area. Since ecological vulnerability has obvious spatial heterogeneity in its distribution, the factor detector in geographic detectors can better analyze and understand the main influencing factors of ecological vulnerability.

Regarding the calculation results of ecological vulnerability, Zhang Liangxia et al. and Li Zhenzhen et al. calculated ecological vulnerability for northwestern China, and the overlapping regions with the Hehuang area showed consistent characteristics. However, due to different research purposes and principles, the weights of indicators should differ accordingly. This study used an integrated projection pursuit model and genetic algorithm to obtain weights for each evaluation indicator for each year. Since each year's set of indicators was calculated as an independent sample to obtain the maximum value of each component vector (i.e., indicator weights), the indicator weights differed between years. Although there were differences in weight values between years, the differences were not substantial, and no 颠覆性的 changes occurred. Regarding data acquisition, due to limitations in data availability, the indicator selection process inevitably had imperfections. Some indicators, particularly socio-economic indicators, had to be abandoned due to difficulties in spatialization. Additionally, for calculation consistency, the spatial resolution of remote sensing data was set to 1 km × 1 km, and the available time period of remote sensing data was limited, restricting more refined research over longer time series. Due to the lack of unified classification standards, equal interval method was used for vulnerability classification in this study. These deficiencies and limitations should be addressed in future work.

4. Conclusions

1) The spatial distribution of vulnerability in the Hehuang area shows significant differences. Micro-vulnerability and light vulnerability areas are mainly distributed in the northwest and southeast, moderate and severe vulnerability areas are mainly distributed in the east and west sides, and extreme vulnerability areas are sporadically distributed within severe vulnerability areas. Each year is dominated by light vulnerability and moderate vulnerability, with extreme vulnerability areas accounting for the smallest proportion. High-value and low-value clustering patterns coexist, showing obvious spatio-temporal clustering characteristics. "High-high" clustering is mainly distributed in some counties (districts) under Lanzhou City and Baiyin City, while "low-low" clustering is mainly distributed in

some counties (districts) under Linxia Prefecture, Gannan Prefecture, and Dingxi City.

2) From 2000 to 2020, the overall ecological vulnerability in the Hehuang area showed a decreasing trend. 42.79% of the land area maintained stable ecological vulnerability without change, while 53.36% of the land area showed decreased ecological vulnerability.

3) Vegetation coverage is the main factor affecting ecological vulnerability in the Hehuang area, followed by desertification index, net primary productivity of vegetation, drought index, habitat quality index, altitude, and other factors that have varying degrees of influence on ecological vulnerability.

4) Based on the transformation patterns of ecological vulnerability types, the Hehuang area was divided into five ecological vulnerability zones: ecological core protection zone, ecological comprehensive management zone, ecological restoration attention zone, ecological priority management zone, and ecological key monitoring zone.

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