Spatiotemporal Evolution of Ecological Environment Quality and Its Drivers in the Helan Mountains, China Postprint

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Abstract

Understanding the ecological evolution is of great significance in addressing the impacts of climate change and human activities. However, the ecological evolution and its drivers remain inadequately explored in arid and semi-arid areas. This study took the Helan Mountain, a typical arid and semi-arid area in China, as the study area. By adopting an Enhanced Remote Sensing Ecological Index (ERSEI) that integrates the habitat quality (HQ) index with the Remote Sensing Ecological Index (RSEI), we quantified the ecological environment quality of the Helan Mountain during 2010–2022 and analyzed the driving factors behind the changes. Principal Component Analysis (PCA) was used to validate the composite ERSEI, enabling the extraction of key features and the reduction of redundant information. The results showed that the contributions of first principal component (PC1) for ERSEI and RSEI were 80.23% and 78.72%, respectively, indicating that the ERSEI can provide higher precision and more details than the RSEI in assessing ecological environment quality. Temporally, the ERSEI in the Helan Mountain exhibited an initial decline followed by an increase from 2010 to 2022, with the average value of ERSEI ranging between 0.298 and 0.346. Spatially, the ERSEI showed a trend of being higher in the southwest and lower in the northeast, with high-quality ecological environments mainly concentrated in the western foothills at higher altitudes. The centroid of ERSEI shifted northeastward toward Helan County from 2010 to 2022. Temperature and digital elevation model (DEM) emerged as the primary drivers of ERSEI changes. This study highlights the necessity of using comprehensive monitoring tools to guide policy-making and conservation strategies, ensuring the resilience of fragile ecosystems in the face of ongoing climatic and anthropogenic pressures. The findings offer valuable insights for the sustainable management and conservation in arid and semi-arid ecosystems.

Full Text

Preamble

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Spatiotemporal Evolution of Ecological Environment Quality and Its Drivers in the Helan Mountain, China

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Abstract: Understanding ecological evolution is of great significance for addressing the impacts of climate change and human activities. However, ecological evolution and its drivers remain inadequately explored in arid and semi-arid regions. This study examined the Helan Mountain, a typical arid and semi-arid area in China, and quantified its ecological environment quality from 2010 to 2022 using an Enhanced Remote Sensing Ecological Index (ERSEI) that integrates habitat quality (HQ) with the Remote Sensing Ecological Index (RSEI). Principal Component Analysis (PCA) was employed to validate the composite ERSEI, enabling extraction of key features and reduction of redundant information. The results showed that the first principal component (PC1) contributions for ERSEI and RSEI were 80.23% and 78.72%, respectively, indicating that ERSEI can provide higher precision and more detail than RSEI in assessing ecological environment quality. Temporally, ERSEI in the Helan Mountain exhibited an initial decline followed by an increase from 2010 to 2022, with average values ranging between 0.298 and 0.346. Spatially, ERSEI showed a pattern of higher values in the southwest and lower values in the northeast, with high-quality ecological environments concentrated mainly in the western foothills at higher altitudes. The centroid of ERSEI shifted northeastward toward Helan County from 2010 to 2022. Temperature and digital elevation model (DEM) emerged as the primary drivers of ERSEI changes. This study highlights the necessity of using comprehensive monitoring tools to guide policy-making and conservation strategies, ensuring the resilience of fragile ecosystems in the face of ongoing climatic and anthropogenic pressures. The findings offer valuable insights for sustainable management and conservation in arid and semi-arid ecosystems.

Keywords: ecological environment quality; Enhanced Remote Sensing Ecological Index (ERSEI); Principal Component Analysis (PCA); Moran’ s I; centroid migration analysis; geographic detector (Geodetector); Helan Mountain

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1 Introduction

Arid areas occupy approximately 40.60% of the global land surface and hold significant importance for global ecosystems and human society (Tariq et al., 2024). Northwest China represents a typical arid and semi-arid region characterized by high evapotranspiration, severe wind erosion, and water scarcity, which contribute to ecological fragility in the region (Zhang et al., 2023). Monitoring and assessing ecological environment quality in this region is imperative for scientifically evaluating its ecological status. Identifying the spatiotemporal dynamics of ecological environment quality and the main influencing factors serves as a critical foundation for ecosystem management and constitutes a crucial indicator of the effectiveness of regional ecological civilization construction.

Numerous studies have explored ecological changes in arid and semi-arid areas, though often focusing on specific aspects. For instance, Li et al. (2021) examined the theoretical framework of water resource allocation, mathematical model construction, and optimized allocation schemes based on an ecological priority model in arid areas of central and southern Ningxia Hui Autonomous Region, China. Lu et al. (2023) focused on trends, driving mechanisms, and spatial non-stationarity of ecological risks, constructing a research framework for the ecological risk index based on land use and socio-economic data. Xu et al. (2024) conducted a case study in arid areas of Northwest China, investigating the relationship between vegetation cover and soil erosion. However, these studies often rely on panel data and lack further quantification and detailed analysis of entire ecosystems.

Advancements in remote sensing technology have revolutionized ecosystem monitoring by providing substantial remote sensing data and reliable assessments of ecological conditions across different scales (Willis, 2015). Xu (2013) proposed the Remote Sensing Ecological Index (RSEI), an ecological index capable of rapidly monitoring and assessing the quality of complex ecological environments within a region. This index uses Principal Component Analysis (PCA) to couple four evaluation indicators: Normalized Difference Vegetation Index (NDVI), Wetness Component (WET), Normalized Difference Built-up and Soil Index (NDBSI), and Land Surface Temperature (LST). The PCA approach mitigates the subjectivity of manually assigned weights and overcomes limitations inherent in using single remote sensing indices, making RSEI a widely adopted tool for ecological assessments in diverse environments, including urban areas, river basins, deserts, nature reserves, and mining areas (Shi et al., 2021; Wang et al., 2021; Bai et al., 2023; Wang et al., 2023a).

Given the unique ecological environment characteristics across different regions (Shi et al., 2023), scholars have proposed various improved RSEI models tailored to surface features in regions such as mining areas, wetlands, farms, and coastal cities, demonstrating their efficacy (Jiang et al., 2021; Ma et al., 2024). For example, a desertification index was integrated into RSEI to generate the Drought Remote Sensing Ecological Index (DRSEI) for analyzing ecological environment quality in the arid area of Northwest China from 1994 to 2020 (Luo et al., 2023). Similarly, the Arid Remote Sensing Ecological Index (ARSEI) was constructed by integrating vegetation coverage, humidity, salinity, and land degradation degree to assess ecological environment quality in the Aral Sea Basin in Central Asia (Jie et al., 2021).

While these studies have expanded the application of RSEI, they often overlook the impacts of land use and land cover (LULC) types. Different LULC types offer distinct ecosystem service functions (Liu et al., 2020; Wang et al., 2023b). For example, croplands provide basic food production functions, forests provide ecological functions such as soil and water conservation, climate regulation, and biodiversity maintenance, while water bodies and wetlands play critical roles in hydrology regulation and wastewater treatment (Li et al., 2020; Li et al., 2022). The primary determinant of the habitat quality (HQ) index discussed in this paper is LULC type. Therefore, combining RSEI with the HQ index can better mitigate biases caused by different LULC types.

Helan Mountain, located in Northwest China, experiences extreme climatic conditions and has a fragile ecosystem that is highly sensitive to climate change and human activities. This study utilized Google Earth Engine (GEE) and Landsat remote sensing imagery to dynamically monitor ecological environment changes in the Helan Mountain from 2010 to 2022 based on an Enhanced Remote Sensing Ecological Index (ERSEI) that includes five ecological indicators: NDVI, WET, NDBSI, LST, and HQ. Additionally, the geographic detector (Geodetector) was used to explore the driving factors behind these changes. This study can help reveal ecological response mechanisms and provide a theoretical basis for ecological environment protection and restoration in the region.

2.1 Study Area

Helan Mountain (105°17 -106°32 E, 37°38 -39°30 N; Fig. 1 [Figure 1: see original paper]) acts as a natural divide separating the arid and semi-arid areas of Northwest China (Yang and Dong, 2020), possessing a unique natural geographical environment. The annual average temperature at the foothills is around 8°C, while at the summit it is about -1°C. Annual precipitation increases from 200 mm at the foothills to over 400 mm at the summit, with precipitation concentrated mainly from July to September, accounting for 60.00% of the total annual precipitation. Topographically, the mountain features steep slopes, deeply incised valleys, and an elevation range of 1070 to 3492 m. It shields against the eastward progression of the Tengger Desert and the westward advance of the southeastern monsoon, while weakening the influence of Siberian high-pressure cold air, contributing to significant differences in climate, water sources, and vegetation on either side of the mountain. The ecological security of the region directly impacts the survival of endangered species and the ecological balance of the Ningxia section of the northern arid desert belt. Due to its unique geographic location and fragile ecosystem, Helan Mountain was designated as a national ecological reserve in May 1988. However, despite its protected status, the region faces ecological threats caused by unregulated mining activities.

[Figure 1: see original paper]

2.2 Data Sources

The study selected the years 2010, 2014, 2018, and 2022 as key time points. Since 2010, Helan Mountain has been gradually incorporated into the primary monitoring framework of national ecological governance. Consequently, the data gathered in 2010 served as a baseline, reflecting environmental conditions prior to the implementation of extensive ecological restoration efforts. In 2014 and 2018, the Chinese government initiated several regional restoration projects to address ecological vulnerability in Northwest China. After years of ecological protection measures, the ecological conditions of Helan Mountain in 2022 were evaluated to assess the effectiveness of these conservation efforts.

This study selected Landsat 5 TM and Landsat 8 OLI images, each with a spatial resolution of 30 m. To minimize seasonal variability in remote sensing parameters, image acquisition was confined to the months of June–September, selected for optimal vegetation growth and minimal snow cover. To ensure consistency and accuracy of data across varying resolutions, this study employed the geostatistical interpolation method of Kriging during data processing (Srivastava et al., 2019). This method utilizes spatial autocorrelation to generate high-precision interpolation results, ensuring spatial consistency among different data sources after resolution unification. Additionally, we compared the spatial distribution characteristics of the interpolated data with the original high-resolution data to assess the effectiveness of the resampling method, ensuring that the interpolated data could accurately reflect real ecological environment changes.

The GEE platform was employed to perform cloud removal, create mosaics, mask water bodies, and synthesize mean values to construct interannual images of the study area (Akhoondzadeh, 2022; Zhao et al., 2022). Considering the local environment and related studies (Zhao et al., 2022), we selected a total of seven driving factors influencing ecological environment quality, including six natural factors and one human factor (Table 1). Natural factors included temperature, precipitation, digital elevation model (DEM), slope, aspect, and net primary production (NPP). Population density was selected as the human factor.

A suite of software tools was utilized to enhance the precision and reliability of data processing and analysis. ENVI 5.6 was employed for radiometric correction, atmospheric correction, and image cropping of remote sensing data; ArcMap 10.5 was used for spatial data processing and regional statistical analysis; InVEST 3.14.1 was used to assess HQ; and GEE facilitated large-scale remote sensing data acquisition, time-series analysis, and extraction of ecological indicators such as NDVI, NDBSI, and LST. The integrated use of these tools significantly enhanced the efficiency of data processing, the precision of analysis, and the reliability of results.

2.3 Methods

To characterize the spatiotemporal dynamics of ecological environment quality and its driving factors in Helan Mountain, we designed a comprehensive characterization framework (Fig. 2 [Figure 2: see original paper]). This research can be summarized into four stages: data acquisition and preprocessing, ERSEI model establishment, ERSEI trend analysis, and driving factor analysis.

[Figure 2: see original paper]

2.3.1 Construction of ERSEI

The ERSEI was constructed using the PCA method (Yulianti et al., 2024), incorporating five ecological indicators: NDVI, WET, NDBSI, LST, and HQ. NDVI is the most widely used vegetation index, accurately reflecting vegetation growth and seasonal variations. It is highly sensitive to environmental changes caused by climate change and human activities, making it suitable for large-scale ecological monitoring. WET addresses NDVI’ s limitations in monitoring soil moisture, thereby enhancing ERSEI’ s ability to monitor ecological changes in arid areas. NDBSI reflects soil exposure and land degradation, particularly in unused and construction land areas, thus enabling improved comprehensive evaluation of regional ecological environments. LST represents thermal changes in the environment, capturing the direct impact of land use and climate change on ecosystems and elucidating how temperature influences vegetation and ecological environment quality. HQ assesses changes in habitat fragmentation and quality, emphasizing biodiversity and ecosystem services that may be overlooked by other indicators. These indicators complement each other, forming a multi-dimensional ecological quality evaluation system that comprehensively reflects the characteristics of arid and semi-arid areas, overcoming limitations inherent in single indicators and providing robust scientific support for model construction.

The indicators and corresponding calculations are described below. NDVI has been extensively utilized to monitor vegetation growth and health and is closely associated with ecosystem resilience and vitality. The specific calculation formula is as follows:

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}, \quad (1)$$

where ρ_{nir} and ρ_{red} represent the reflectance of near-infrared and red bands of Landsat TM (or OLI) images, respectively.

WET can be calculated using remote sensing Kirchhoff Transform, which accurately reflects surface vegetation and soil moisture. As an important indicator of ecological environment quality, its calculation is outlined in Equation 2:

$$WET = 0.1511\rho_{blue} + 0.1973\rho_{green} + 0.3283\rho_{swir1} + 0.3407\rho_{swir2}, \quad (2)$$

where ρ_{blue}, ρ_{green}, ρ_{swir1}, and ρ_{swir2} represent the reflectance of the blue, green, short-wave infrared 1, and short-wave infrared 2 bands of the Landsat TM (or OLI) image, respectively. The coefficients for each band are sensor-specific, with values tailored to each individual sensor.

NDBSI is comprised of the building index (BI) and the bare soil index (SI) (Peng et al., 2023). However, given the sparse population and negligible presence of buildings and man-made surfaces, BI was excluded from the dryness index in this study, leaving only SI for evaluation and reflecting the degree of land surface desertification. The calculation formula is as follows:

$$NDBSI = SI = \frac{\rho_{swir1} + \rho_{red}}{\rho_{swir1} + \rho_{red} + \rho_{nir} + \rho_{green}}, \quad (3)$$

LST correlates with vegetation, water resources, and human activity intensity. In this study, we employed the atmospheric correction method to derive LST to characterize the heat index (Thompson et al., 2019). The specific calculation formulas are as follows:

$$LST = \frac{k_2}{\ln\left(\frac{k_1}{B(T_s)} + 1\right)}, \quad (4)$$

$$B(T_s) = \frac{L_\lambda - L_\uparrow - \tau(1-\varepsilon)L_\downarrow}{\tau\varepsilon}, \quad (5)$$

$$L_\lambda = \frac{DN_{thermal} - 1}{\Delta\lambda}, \quad (6)$$

where L_λ is the thermal infrared radiation brightness value (W/(m$^2\cdot$sr$\cdot$ m)), obtained by correcting the atmospheric delay in the thermal infrared image; ε is the surface specific emissivity; T_s is the surface temperature (°C); $B(T_s)$ is the brightness of blackbody radiation (W/(m$^2\cdot$sr$\cdot$ m)); τ is the transmittance rate of the atmosphere in the thermal infrared wavelengths; $L_\uparrow$ and $L_\downarrow$ represent the atmospheric upward and downward radiation to the ground, respectively (W/(m$^2\cdot$sr$\cdot$ m)); and k_1 and k_2 are calibration constants specific to the sensor.

HQ is derived from LULC data using the InVEST model (Liu et al., 2024a). This metric assesses the degree of regional habitat fragmentation and resilience to habitat degradation. The calculation is specified in Equation 7:

$$HQ_{ij} = H_j \left(1 - \frac{D_{ij}^Z}{D_{ij}^Z + k^Z}\right), \quad (7)$$

where HQ_{ij} denotes the habitat quality of grid i in LULC type j; H_j denotes the habitat suitability of LULC type j; D_{ij} denotes the stress level of grid i in LULC type j; Z denotes the normalization constant; and k is a scaling constant.

The values of HQ_{ij} range from 0.000 to 1.000. Larger values indicate higher habitat quality, greater suitability for biological survival, and higher biodiversity. Lower values indicate poorer habitat quality, making it less favorable for maintaining regional biodiversity. This study referred to the user manual of the InVEST model and considered the actual conditions of the study area. Farmland and construction land were taken as threat sources. Different maximum impact distances and weights for threat factors were set based on actual conditions, as detailed in Tables 2 and 3. Additionally, data calibration and validation were conducted to reduce model biases and ensure that the parameters used align with the specific characteristics of the study area.

The study utilized PCA to integrate the five indicators (NDVI, WET, NDBSI, LST, and HQ). The weights of these indicators were determined by the load values generated through PCA. To address potential imbalance in indicator weights, normalization was performed prior to analysis, ensuring that the weights of the indicators were uniformly set in the range of 0.000–1.000 (Liu et al., 2024b). NDVI, WET, and HQ were positively normalized using Equation 8, and NDBSI and LST were negatively normalized using Equation 9:

$$y_{pos} = \frac{y_0 - y_{min}}{y_{max} - y_{min}}, \quad (8)$$

$$y_{neg} = \frac{y_{max} - y_0}{y_{max} - y_{min}}, \quad (9)$$

where y denotes the normalized value of an indicator; y_0 denotes the value of an indicator before normalization; and y_{max} and y_{min} denote the minimum and maximum values of an indicator before normalization, respectively.

The ERSEI is expressed in Equation 10:

$$ERSEI = F_{PCA}(NDVI, WET, LST, NDBSI, HQ), \quad (10)$$

where F_{PCA} refers to the use of PCA to perform dimensionality reduction on input variables; and NDVI, WET, LST, NDBSI, and HQ are normalized values for each indicator. The normalization process aimed to derive the ERSEI, with values ranging between 0.000 and 1.000. A larger value indicates a better ecological environment, while lower values signify poorer conditions. The ERSEI, which incorporates HQ, places greater emphasis on changes in ecological threats and ecosystem services compared to traditional RSEI. By considering HQ, ERSEI enhances its sensitivity in identifying threats to biodiversity, particularly in areas with complex LULC types.

The specific technical route is shown in Figure 2. Natural Breaks is a data classification technique that maximizes homogeneity within each class and minimizes differences between classes, thus scientifically reflecting the inherent distribution characteristics of the data. Using the Natural Breaks method, ecological environment quality was divided into five categories based on ERSEI values: very poor (0.000-0.200), poor (0.200-0.400), medium (0.400-0.600), good (0.600-0.800), and excellent (0.800-1.000).

2.3.2 ERSEI Trend Analysis

The study used linear regression analysis to calculate the trend of ERSEI and then classified the trend of change with the following definitions: increase (0.150≤Slope<0.230), slight increase (0.050≤Slope<0.150), unchanged (-0.050≤Slope<0.050), slight decline (-0.150≤Slope<-0.050), and decline (-0.250≤Slope<-0.150).

Moran’ s I is a commonly used spatial autocorrelation analysis method that can effectively evaluate spatial clustering or dispersion in ERSEI. In this study, Moran’ s I was used to reveal the spatial distribution characteristics of ERSEI over different time periods, providing a quantitative measure of spatial heterogeneity in ERSEI. Additionally, it serves as a crucial basis for understanding the spatiotemporal dynamics of ERSEI (Tillé et al., 2018; Chen, 2023). The specific calculation formula is as follows:

$$I = \frac{n \sum_{k=1}^{n} \sum_{l=1}^{n} w_{kl}(x_k - \bar{x})(x_l - \bar{x})}{\sum_{k=1}^{n} \sum_{l=1}^{n} w_{kl} \sum_{k=1}^{n}(x_k - \bar{x})^2}, \quad (11)$$

where I is the Moran’ s I index; n is the number of samples; W is the geographic neighborhood weight; w_{kl} is the spatial weight between location k and location l; x_k is the value of the kth sample; x_l is the value of the lth sample; and $\bar{x}$ is the average of all samples.

Centroid migration analysis was used to assess the direction and magnitude of spatiotemporal variations in ERSEI in this study. Helan Mountain features complex terrain, and its ecological environment quality is influenced by both natural and human factors, showing significant spatial heterogeneity. Through centroid migration analysis, the centroid migration trajectory of ERSEI within the study area can be clearly displayed, helping to intuitively understand the direction and magnitude of variations in ERSEI over different time periods (Tillé et al., 2018; Chen, 2023). The spatial transfer characteristics of ERSEI in different periods can be calculated using the centroid migration model, and the migration distance can be determined as follows:

$$D_{t(t+m)} = \sqrt{(X_{t+m} - X_t)^2 + (Y_{t+m} - Y_t)^2}, \quad (12)$$

where $D_{t(t+m)}$ is the migration distance of the centroids of ERSEI in the study area from year t to year $t+m$; X_t and Y_t denote the horizontal and vertical coordinates of the centroid in year t, respectively; and X_{t+m} and Y_{t+m} denote the horizontal and vertical coordinates of the centroids in year $t+m$, respectively.

When analyzing the migration direction of the ecological centroid, it is crucial to consider the angle of the centroid relative to the north direction. Assuming the initial angle starts from the north and rotates clockwise, the angle will increase. The rotation angle is the deviation from true north. The arctangent function for the angle of centroid migration is expressed in Equation 13:

$$\alpha = \arctan\left(\frac{Y_{t+m} - Y_t}{X_{t+m} - X_t}\right) \times \frac{180}{\pi}, \quad (13)$$

where α is the clockwise angle between the north direction and the shift direction of the centroid.

2.3.3 Geodetector

Geodetector is a statistical method designed to identify spatial heterogeneity and reveal the driving factors behind it (Yu et al., 2021). It has been widely used in socio-economic research (Liang et al., 2022) and ecological studies (Hu and Zhang, 2021). The model consists of four detectors: factor detector, interaction detector, risk detector, and ecological detector. In this study, the factor detector and interaction detector were used to analyze the main factors affecting the ecological environment quality of the study area.

The factor detector identifies the distribution of ERSEI and gauges the impact of a single factor on this distribution, which is measured using Equation 14:

$$q = 1 - \frac{\sum_{h=1}^{Z} N_h \sigma_h^2}{N\sigma^2}, \quad (14)$$

where q represents the explanatory power of each driving factor on ERSEI changes, and greater values indicate stronger explanatory power; N and N_h are the number of units in layer h ($h = 1, 2, ..., Z$) and the whole region, respectively; Z is the stratification of ERSEI (or its driving factors), that is, classification or partitioning; and σ^2 and σ_h^2 are the variances of ERSEI in layer h and the whole region, respectively.

The interaction detector was utilized to assess whether the explanatory power of driving factors on ERSEI changes is enhanced or diminished when considering the synergistic effects of driving factors. The evaluation method involves obtaining the q-values of two factors individually through factor detection, denoted as $q(F1)$ and $q(F2)$. Subsequently, the q-value of the two factors when acting synergistically can be calculated as $q(F1 \cap F2)$. The comparison of these q-values results in categorizing the outcomes into five distinct types (Table 4).

In this study, by maximizing the q-value, we divided different grid variables using various partitioning methods and breakpoints. This approach optimized the discretization of independent variables and mitigated the impact of manual divisions on the q-value.

3.1 Comparison of ERSEI with RSEI

We selected three regions within Helan Mountain—region A in the western part, region B in the central region, and region C in the southeastern part—to compare the results of ERSEI and RSEI in 2010 and 2022 (Fig. 3 [Figure 3: see original paper]). These regions encompass grassland, woodland, unused land, and construction land. The spatial distributions of ERSEI and RSEI showed significant similarities, indicating that ecological environment quality indicated by ERSEI and RSEI was similar in most areas. However, differences existed in some areas. For example, in region A, a mixed area of unused land, grassland, and woodland (Fig. 3a and b), the RSEI values were higher in unused land (bare land with bare rock texture) than in woodland (Fig. 3g and h), which is unreliable. This error stemmed from over-reliance of RSEI on image inversion techniques, neglecting the potential ecological threats posed by different LULC types. In contrast, ERSEI considered the impact of LULC types on ecological environment quality, providing more accurate and meaningful results (Fig. 3m and n). In unused land, ERSEI showed greater sensitivity to processes like desertification or land degradation.

In region B (Fig. 3c and d), ERSEI (Fig. 3o and p) showed a larger high-value area on the right side of the region compared to RSEI (Fig. 3i and j), which aligns more closely with actual ecological characteristics. In region C (Fig. 3e and f), ERSEI demonstrated higher contrast and clarity in LULC delineation (Fig. 3q and r) compared to RSEI (Fig. 3k and l). ERSEI clearly depicted boundaries between different LULC types, such as between grassland and unused land, whereas RSEI appeared blurry in these areas. Such contrast indicated that ERSEI can be more effective in identifying and displaying ecological environment quality changes among different LULC types within complex ecosystems.

[Figure 3: see original paper]

The PCA results of RSEI and ERSEI are presented in Table 5 . The PC1 contributions for ERSEI and RSEI were 80.23% and 78.72%, respectively. Specifically, the feature vector coefficient values of NDVI, WET, and HQ in PC1 were positive, indicating a positive impact on ecological environment quality. In contrast, the feature vector coefficient values of LST and NDBSI were negative, suggesting a negative impact on ecological environment quality. This aligns with the actual situation and suggests that ERSEI may serve as a reliable reference for ecological environment quality.

3.2 Spatiotemporal Variation in the Five Ecological Indicators Integrating ERSEI

Figure 4 [Figure 4: see original paper] shows the spatial distributions of the five ecological indicators integrating ERSEI. Under the influence of altitude on vegetation and climate, NDVI showed a distribution pattern of being higher in the southwest and lower in the northeast, while LST displayed an opposite trend, with lower values in the southwest and higher values in the northeast and southeast. Areas with high WET values were primarily concentrated in the central part of Helan Mountain. Due to the impact of land desertification, NDBSI values were higher in the northeastern and eastern foothill regions. Meanwhile, the distribution of HQ was mainly influenced by LULC types, with significantly lower values observed in the mining areas of the central and northern regions.

[Figure 4: see original paper]

Figure 5 [Figure 5: see original paper] shows that NDBSI and WET exhibit a pattern of initial increase followed by stabilization during 2010-2022. NDVI and HQ declined before rising steadily since 2014. Moreover, the trend of LST was relatively stable during 2010-2022. Higher NDBSI indicated prevalent arid landscapes such as deserts, mountains, and bare rocky terrain in the study area. Lower NDVI suggested relatively sparse vegetation cover, mainly concentrated in the southwest.

[Figure 5: see original paper]

3.3 Spatiotemporal Variation in ERSEI

From 2010 to 2022, the mean ERSEI value in Helan Mountain fluctuated between 0.298 and 0.346 (Fig. 6 [Figure 6: see original paper]). The index initially decreased and then increased, with an overall rise of 0.034. High-ERSEI areas were located in the southwest of Helan Mountain with dense vegetation cover that supports a complete forest ecosystem. The main LULC types consist of forestland, shrubland, and a few medium-coverage grassland areas. Low-ERSEI areas were in the northeast of Helan Mountain, where the main LULC types are unused land (bare land and bare rocky land), with bare rocky land being predominant.

[Figure 6: see original paper]

From 2010 to 2022, the overall trend of ERSEI showed little change, with areas of slight increase mainly concentrated in the high-altitude regions of the central and southwestern areas (Fig. 6e). Considering the high altitude of these regions, changes in ERSEI may be related to topography and climate, especially in the central area where relatively little human activity allows vegetation to naturally recover. In contrast, areas with declining ERSEI were more scattered, primarily located on the outer sides of the mountains near human activity zones, especially in mining areas.

In summary, the ecological environment quality of Helan Mountain exhibited notable improvement over the past decade. This improvement was most pronounced in the central and southwestern high-altitude regions, while the northeastern arid areas exhibited a slight decline. Compared with 2010, 2022 saw a decrease of 9.19% from 54.61% to 45.42% in the proportion of very poor grade areas (Fig. 7 [Figure 7: see original paper]). The proportion of excellent grade areas increased from 7.61% to 9.35%. These results demonstrated an overall improvement in the ecological situation.

[Figure 7: see original paper]

3.4 Spatial Stratified Heterogeneity of ERSEI

The global Moran' s I index values for ERSEI in Helan Mountain were 0.904, 0.988, 0.881, and 0.881 in 2010, 2014, 2018, and 2022, respectively ($P<0.001$; Fig. 8 [Figure 8: see original paper]). Most data points in the scatter plots were concentrated in the first and third quadrants, with an aggregation pattern predominantly characterized by "high-high" and "low-low" clusters, indicating a discernible spatial correlation. The Moran' s I index declined significantly from 2014 to 2018, followed by stabilization at approximately 0.881. This trend indicated that the spatial aggregation of ERSEI in the study area has weakened and approached a stable state.

[Figure 8: see original paper]

This study analyzed the centroid migration trajectory of ERSEI in the study area during 2010-2022 (Table 6 ; Fig. 9 [Figure 9: see original paper]). During this period, ERSEI was higher in the southwest and lower in the northeast. The centroid consistently remained in the northern part of Huinong District, with only slight variations in latitude and longitude, and gradually shifted from the southwest to the northeast. The overall fluctuation in the direction angle was minimal, shifting from 40°00 00 to 41°03 00 . The oblateness remained stable at approximately 0.66.

[Figure 9: see original paper]

3.5 Driving Mechanism of ERSEI Changes

NPP reflects vegetation health and ecosystem productivity, while temperature and precipitation, as climate factors, directly influence plant growth and ecosystem stability. Population density measures the impact of human activities on the ecological environment, revealing the relationship between human development and ecological stress. Topographic factors such as DEM, slope, and aspect determine vegetation distribution, soil and water conservation, and climatic conditions within the study area. By comprehensively analyzing these factors, the driving mechanism behind ecological changes in the study area can be fully understood, providing a scientific basis for ecological protection and restoration.

As shown in Table 7 , temperature had the greatest impact on ERSEI throughout the study period (average q-value of 0.603 and $P<0.01$), followed by DEM (average q-value of 0.590 and $P<0.01$), while population density had minimal impact (average q-value of 0.043 and $P>0.05$), primarily because population density in the study area is relatively low. During the study period, the influence of these driving factors fluctuated significantly, but the main factors remained largely consistent. In 2010, 2014, 2018, and 2022, temperature and DEM were the primary influencing factors, while the impact of precipitation gradually increased (average q-value of 0.588 and $P<0.01$).

In addition, this study used the interaction detector to understand interactions between variables, and the results are shown in Figure 10 [Figure 10: see original paper]. In 2010, the interaction between DEM and aspect had the highest q-value of 0.718, indicating that their interaction had the greatest impact on ERSEI changes. In the years 2014, 2018, and 2022, the q-values for this interaction were 0.675, 0.668, and 0.656, respectively. The interaction between precipitation and aspect also maintained high q-values across the years, with values of 0.717 in 2010, 0.690 in 2014, 0.656 in 2018, and 0.659 in 2022. Overall, the ecological environment in the study area was shaped by the interaction of multiple factors. Among these, the interaction between DEM and aspect was the primary factor affecting ERSEI changes.

[Figure 10: see original paper]

4.1 Advantages and Applicability of ERSEI

Some scholars have proposed models for assessing ecological environment quality in the study area, including the RSEI (Xu, 2013) and the Improved Remote Sensing Ecological Index (IRSEI) (Feng et al., 2024). The RSEI model is mainly applicable to urban areas, while Helan Mountain has little construction land and serious soil erosion, which results in overall low NDBSI, reducing its representativeness. To address this, the ERSEI established in this study substituted NDBSI with SI, which can improve the accuracy of ERSEI in this context.

Feng et al. (2024) integrated Particulate Matter 10 (PM10) into RSEI to create an atmospheric environment quality model, the IRSEI, which has been employed to study spatiotemporal changes of ecological environment quality throughout Ningxia, including Helan Mountain. The IRSEI findings align with ERSEI findings in terms of macroscopic spatial distribution, both presenting high values in the southwestern region and low values in the northeastern region. However, some discrepancies were still observed in localized areas. We conducted a detailed comparison between ERSEI and IRSEI (Table 8), using 169 key ecological restoration site data provided by the Department of Natural Resources of Ningxia Hui Autonomous Region. When using IRSEI, 87 sites were in the range of very poor ecology, while the number reached 101 when using ERSEI. Optical satellite images showed that the 14 different sites were all located in waste mine construction sites. ERSEI can better reflect the actual situation of Helan Mountain, as it considers the impact of key factors such as LULC types and human activities on the ecological environment. The ERSEI values were lower in ecologically poor areas such as construction sites and unused land.

The study selected five ecological indicators closely related to the ecological environment to develop the ecological environment quality assessment index, ERSEI, which integrated comprehensive evaluations of ecological threats such as habitat fragmentation and land degradation. In contrast, RSEI primarily relies on physical properties like surface temperature and humidity and fails to address functional differences in LULC types. ERSEI can identify and quantify potential threats within different ecosystems, enhancing its overall ecological quality assessment capability. However, the ecological environment in arid and semi-arid areas is extremely complex and comprehensive, shaped by a variety of factors such as climate change and human activities. The interactions among these factors are complex and difficult to fully capture. In addition, local environmental characteristics such as microclimate and topography within the nature reserve also impact the calculation results of the ecological index (Wang et al., 2021), which increases the complexity of the assessment. Therefore, accurately selecting environmental impact factors is key to comprehensive quantitative evaluation of local ecological environment quality. In arid and semi-arid areas, where soil is impoverished and wind erosion is severe, future research can consider disaster factors and salinity factors as ecological indices in predicting ecological environment changes.

4.2 Recommendations for Future Ecological Restoration

The ERSEI in the study area decreased from 0.312 in 2010 to 0.298 in 2014, before gradually increasing. This trend aligns with the decrease in NDVI, as NDVI was the most significant contributing factor in the PCA results. The most notable growth of ERSEI occurred between 2018 and 2022, closely related to the ecological protection project implemented by the local government in 2017. This project restored 169 sites within the reserve, leading to significant improvements in ERSEI during this period (Fig. 11a [Figure 11: see original paper]). Areas with improved ecological environment quality were mainly distributed in grassland and desert vegetation-covered regions, as well as in human activity zones in the central part of the study area, covering 1606.52 km^2 and accounting for 32.45% of the total study area.

[Figure 11: see original paper]

Our trend analysis of ERSEI revealed a two-phase ecological change in Helan Mountain over the past 12 years, with 2017 representing a significant turning point. Prior to 2017, issues such as coal seam spontaneous combustion and uncontrolled resource exploitation caused great disturbance and damage to the ecological environment. After 2017, ecological environment quality gradually improved due to the implementation of ecological restoration projects, including afforestation and artificial sowing of grass seeds. The closure of all open-pit coal mines also led to a significant increase in ERSEI from 2018 to 2022, which is consistent with the findings of Lin et al. (2022). This study also confirmed the importance of NDVI in ecological environmental improvement (Lin et al., 2022). The continuous increase in vegetation coverage may be a key factor in changing local ecological environment quality. However, different LULC types and ecological issues should be treated differently. For instance, in construction areas and abandoned mining sites, the focus should be on soil restoration, vegetation reconstruction, and ecological closure to reduce surface exposure and prevent soil erosion. A combination of trees, shrubs, and grasses can enhance ecosystem stability and resilience. In grasslands and areas severely affected by desertification, priority should be given to planting shrubs and herbaceous plants to increase vegetation coverage and reduce wind and water erosion. For wetlands and water conservation areas, it is crucial to implement ecological hydraulic engineering measures to maintain water supply, enhance wetland vegetation diversity, and sustain regional ecological balance (Wang et al., 2024).

The analysis of Moran' s I index revealed that the spatial aggregation of ERSEI in the study area gradually weakened and stabilized over recent years. The stabilization of aggregation means that the spatial distribution pattern of ERSEI has reached a relatively balanced state, offering important reference and support for ecological protection, policy formulation, resource allocation, assessment of restoration measures, and scientific research. Furthermore, it indicates that these measures may be effective and can continue to be promoted and applied.

There is a deteriorating trend concentrated in the Ruqigou mining area (the largest mining area in the study area) and the southeastern part of the mountain. According to the spatial pattern of LULC in Ningxia, these deteriorating areas were basically concentrated on development land within the reserve, which was the focal point of coal mining activities. Since the 1950s, mining enterprises in Helan Mountain expanded rapidly. The accompanying pollution and tailings became the main reason for the relative deterioration of the ecological environment in these areas. Long et al. (2022) analyzed the impact of tailings ponds on soil, which aligns with the findings of this study. However, following the implementation of a series of ecological governance policies by the Ningxia government, the environment of the mining area underwent significant changes from 2013 to 2021 (Fig. 11b and c). More damaged surfaces have gradually recovered, improving local ecological environment quality to a certain extent, which also confirms the increasing trend of ERSEI in this region.

The application results of the Geodetector model showed that temperature, precipitation, and DEM remained the main driving factors affecting ecological environment quality in the study area. The explanatory power of other factors was relatively low, consistent with the conclusions of Fu et al. (2024). In their study, they employed Soil-Adjusted Vegetation Index (SAVI) instead of NDVI and added the Normalized Difference Salinity Index (NDSI), concluding that precipitation and temperature were the main controlling factors influencing the ecological environment quality of Hami City, Xinjiang Uygur Autonomous Region. The ecological environment quality of Hami City and Helan Mountain was influenced by different factors, reflecting distinct characteristics of the natural environment and human activities in the two regions. In Hami City, temperature and precipitation are the primary determinants of ecosystem health due to the region’ s arid climate and scarce water resources (Fei et al., 2022). However, Helan Mountain has complex topography, and DEM and slope directly affect vegetation type, coverage, soil conservation, and light conditions. DEM changes lead to variations in temperature, humidity, vegetation types, and vegetation coverage, while aspect determines differences between sunny slopes (which receive more solar radiation, resulting in higher temperatures and faster evaporation) and shady slopes (which are relatively more humid). This can explain why the combined effect of DEM and aspect showed significance in the interaction detection for ERSEI.

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5 Conclusions

This study developed the ERSEI based on multiple ecological indicators to evaluate spatiotemporal variations of ecological environment quality in Helan Mountain and identified its main driving factors during 2010-2022. The results showed that the ERSEI model, by incorporating multi-dimensional ecological indicators such as HQ and NDBSI, can more accurately capture ecological changes in complex surface environments. Geodetector analysis indicated that temperature, DEM, and precipitation were the primary factors affecting the ecological environment quality of the region. Additionally, validation data from 169 key ecological restoration sites further confirmed the precision of ERSEI in assessing local ecological environment quality. The findings of this study provide important theoretical support for the assessment and conservation of ecological environments in arid and semi-arid areas. By identifying key driving factors, the study offers essential guidance for policymakers in formulating regional ecological restoration and protection strategies, particularly in the context of increasing pressures from climate change and human activities. Future research could further integrate more detailed ecological data and optimize the model to expand the application scope of ERSEI, providing support for broader ecological environment monitoring.

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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