Ecological Quality Assessment of Gulang County, Gansu Province Based on Improved Remote Sensing Ecological Index (Postprint)

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Abstract

Arid and semi-arid regions account for approximately 47% of China's total land area, predominantly characterized by desert backgrounds with simple ecological structures and fragile ecosystems. To evaluate the ecological quality of these regions more objectively and accurately, the Remote Sensing Ecological Index (RSEI) was improved, and a Drought Remote Sensing Ecological Index (DRSEI) suitable for arid regions was proposed. This index is constructed by coupling five ecological factors: greenness, humidity, dryness, desertification index, and heat. Compared with RSEI, DRSEI demonstrates greater sensitivity to vegetation and enhanced discriminative capability for impervious surfaces, land, and sandy areas, making it suitable for ecological quality assessment in arid and semi-arid regions. Using DRSEI, the ecological quality of Gulang County from 1994 to 2020 was monitored and evaluated through long-term time series analysis. The results indicate that the overall ecological quality of Gulang County improved during this period, with significantly increased vegetation coverage in the central-western and southeastern regions, exerting a strong ameliorative effect on the ecological environment. Areas with relatively poor ecological quality are mainly concentrated in the Tengger Desert in the north, while regions with excellent, good, and moderate ecological quality are primarily distributed in the eastern branch of the Qilian Mountains in the south. Quantitative evaluation of ecological quality in arid and semi-arid regions based on DRSEI holds important practical significance for guiding ecological environmental remediation and sustainable development in these areas of China.

Full Text

Ecological Quality Evaluation of Gulang County in Gansu Province Based on Improved Remote Sensing Ecological Index

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Abstract: Arid and semi-arid regions account for approximately 47% of China's total land area, with deserts serving as the primary landscape background. These areas feature simple ecological structures and fragile ecosystems. To evaluate ecological quality more objectively and accurately in arid and semi-arid regions, this study improves upon the Remote Sensing Ecological Index (RSEI) and proposes a Drought Remote Sensing Ecological Index (DRSEI) suitable for arid areas. DRSEI integrates five ecological factors: greenness, wetness, dryness, desertification index, and thermal conditions. Compared to RSEI, DRSEI demonstrates greater sensitivity to vegetation and enhanced discriminatory capacity for impervious surfaces, bare land, and sandy areas, making it more appropriate for ecological quality assessment in arid and semi-arid zones. Utilizing Landsat imagery from 1994 to 2020, this research conducts long-term dynamic monitoring and evaluation of ecological quality in Gulang County, Gansu Province. Results indicate that the overall ecological quality of Gulang County improved during the study period, with significant vegetation coverage increases in the central and southeastern regions contributing substantially to environmental enhancement. Areas with poor ecological quality are concentrated primarily in the northern Tengger Desert, while regions with excellent, good, and moderate ecological quality are distributed mainly across the eastern branches of the southern Qilian Mountains. The quantitative evaluation of ecological quality in arid and semi-arid regions based on DRSEI holds important practical significance for guiding ecological restoration and sustainable development in these areas across China.

Keywords: DRSEI; ecological quality evaluation; principal component analysis; coefficient of variation; dynamic monitoring; Gansu Province

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China faces severe desertification challenges, particularly in Northwest China, where desertification processes have impacted regional ecological environments and significantly hindered local socio-economic development. Currently, over 47% of China's terrestrial area consists of arid and semi-arid regions, and 36% of global biodiversity hotspots are located in these zones. Frequent human activities have caused varying degrees of environmental changes, with some areas experiencing gradual ecological degradation or even deterioration. Therefore, monitoring ecological environments in arid and semi-arid regions and accurately obtaining information about ecological changes and their distribution patterns is crucial for scientifically formulating ecological restoration measures.

Current domestic and international research on arid and semi-arid region ecology has primarily focused on climate change, water resources, ecological risk assessment, and other specific directions, while comprehensive, long-term temporal evaluations of overall regional ecological quality remain relatively scarce. Remote sensing-based regional ecological quality assessment methods mainly fall into two categories. The first employs single indicators, such as using Normalized Difference Vegetation Index (NDVI) to evaluate ecosystem service values in China's island counties, or calculating heat island proportion indices to analyze diurnal surface temperature variations and heat island effect temporal changes in the Yellow River urban belt of Ningxia. However, ecosystems are complex, and using single ecological factors for evaluation has significant limitations that make it difficult to effectively characterize regional ecological quality. The second approach integrates multiple ecological factors for comprehensive assessment, most notably the Remote Sensing Ecological Index (RSEI) proposed by Xu Hanqiu, which couples four ecological factors—greenness, wetness, dryness, and thermal conditions—to effectively evaluate urban ecological quality. RSEI has been widely applied in urban and natural ecological area assessments. Many scholars have improved RSEI for different study areas, such as Zhang Qinrui et al., who constructed a normalized impervious surface and bare soil index to replace the original building index as the dryness indicator, establishing an improved RSEI for urban ecological environment quality assessment. Results showed that compared with RSEI, the improved version more accurately reflected the negative ecological impacts of dryness indicators and was more suitable for urban ecological environment quality evaluation. Wu et al. evaluated ecological quality in Africa's Sahel region using dryness, wetness, greenness, and reversed desert difference index. Nong Lanping et al. used MODIS data to construct an improved RSEI model to investigate ecological environment quality changes in central Yunnan, finding that interactions between natural factors and newly introduced socio-economic factors significantly impacted ecological quality. However, research specifically targeting arid and semi-arid regions is scarce, and RSEI was primarily developed for urban ecological environments. In arid and semi-arid regions, sandy and desertified land constitute the main landscape components, making the dryness indicator alone insufficiently representative. Due to these substantial regional ecological differences, RSEI must be adapted to better reflect local ecological conditions.

Given the severe land desertification characteristic of arid and semi-arid regions, this study improves RSEI and proposes a Drought Remote Sensing Ecological Index (DRSEI), applying it to evaluate ecological quality in Gulang County, Gansu Province. By analyzing the spatiotemporal characteristics of ecological changes in Gulang County using DRSEI, this research provides methodological support for ecological environment monitoring and management in China's arid and semi-arid regions.

1. Study Area Overview

Gulang County is located in the southwestern part of Wuwei City, Gansu Province, covering a total area of 5,046 km^2 between 37°09 –37°54 N and 102°35 –103°54 E. The county extends approximately 102 km from east to west and 88 km from north to south. Situated at the eastern end of the Hexi Corridor, it borders the Tengger Desert to the north and Tianzhu Tibetan Autonomous County to the south, forming a striking "south mountain, north desert" geographical pattern [Figure 1: see original paper]. The terrain slopes from high in the south to low in the north, with elevations ranging from 1,577 to 3,536 m and an average of 1,810 m. The county comprises three climatic zones: a cool arid zone in the north, a cold arid zone in the center, and a cold semi-arid zone in the south, where precipitation is inversely proportional to altitude. Annual average precipitation is 306.7 mm, while annual average evaporation reaches 1,903.8 mm. Due to complex topography and climatic conditions, vegetation shows distinct vertical distribution patterns, with arboreal shrubs and meadow plants in southern mountainous areas, protective and economic forests in central regions, and xerophytic shrubs and semi-shrubs in northern desert zones.

2.1 Data Sources and Preprocessing

This study utilized Landsat imagery data from the "Geospatial Data Cloud" website (http://www.gscloud.cn), including Landsat 5 and Landsat 8 images. Considering seasonal impacts on indicator retrieval, we selected images from July and August with cloud cover less than 10% for the years 1994, 2000, 2006, 2010, 2015, and 2020. During this period, vegetation growth states were essentially consistent, ensuring good comparability of results. ENVI software was used for necessary preprocessing including radiometric calibration and atmospheric correction. Finally, the study area images were extracted using Gulang County administrative vectors.

2.2 Drought Remote Sensing Ecological Index Model Construction

This study selected Gulang County as the research area, where sandy land accounts for a large proportion and land desertification is severe. Ecological restoration of desertified land and sandy areas primarily employs 1 m × 1 m straw checkerboard sand barriers with xerophytic shrubs and semi-shrubs planted inside. Issues such as planting density and survival rates result in sparse vegetation, causing the greenness indicator (NDVI) in RSEI to be susceptible to background effects and reduced extraction accuracy. Moreover, the dryness indicator in RSEI is synthesized from the bare soil index and building index, but in arid and semi-arid regions, the proportion of built-up area is relatively small compared to other land use types, weakening the representativeness of the dryness indicator. Therefore, this study introduces the Desertification Index (DI) and Soil-Adjusted Vegetation Index (SAVI) to make the index more suitable for arid and semi-arid region research and correctly reflect ecological quality conditions in these areas. Considering these factors, this study calculated five ecological factors—greenness (SAVI), wetness (Wet), dryness (NDBSI), desertification index (DI), and thermal conditions (LST)—to construct DRSEI for objective and rapid assessment of ecological quality in arid regions.

2.2.1 Ecological Factor Indicator Calculations **(1) Greenness Indicator.** This study uses the Soil-Adjusted Vegetation Index (SAVI) to calculate the greenness indicator. SAVI demonstrates 2%–7% higher overall extraction accuracy than NDVI in low-to-medium vegetation coverage areas and has been widely applied to grassland, arid and semi-arid region, and ecological restoration area vegetation extraction. Its calculation formula is:

$$SAVI = \frac{(\rho_{nir} - \rho_{red})(1 + L)}{\rho_{nir} + \rho_{red} + L}$$

where SAVI is the soil-adjusted vegetation index; L is the soil adjustment parameter with an empirical value of 0.5; ρ_{red} is the reflectance of the red band after image preprocessing; and ρ_{nir} is the reflectance of the near-infrared band after image preprocessing.

(2) Wetness Indicator. The wetness component obtained through tasseled cap transformation is closely related to vegetation and soil moisture, so the wetness indicator is represented by the wetness component [26]. Its calculation formula is:

$$Wet_{TM} = 0.0315\rho_1 + 0.2021\rho_2 + 0.3102\rho_3 + 0.1594\rho_4 - 0.6806\rho_5 - 0.6109\rho_6 - 0.056\rho_7$$

$$Wet_{OLI} = 0.1511\rho_1 + 0.1973\rho_2 + 0.3283\rho_3 + 0.3407\rho_4 - 0.7117\rho_5 - 0.4559\rho_6 - 0.071\rho_7$$

where Wet_{TM} is the wetness component from tasseled cap transformation of Landsat 5 TM data; Wet_{OLI} is the wetness component from tasseled cap transformation of Landsat 8 OLI data; and ρ_i (i = 1, 2, …, 7) represents the reflectance values of blue, green, red, near-infrared, SWIR1, SWIR2, and thermal infrared bands after image preprocessing.

(3) Dryness Indicator. The dryness indicator is composed of the Building Index (IBI) and Soil Index (SI) [9]. Its calculation formula is:

$$IBI = \frac{2\rho_{swir1}}{\rho_{swir1} + \rho_{nir}} - \frac{\rho_{nir}}{\rho_{nir} + \rho_{red}} - \frac{\rho_{green}}{\rho_{green} + \rho_{swir1}}$$

$$SI = \frac{(\rho_{swir1} + \rho_{red}) - (\rho_{blue} + \rho_{nir})}{(\rho_{swir1} + \rho_{red}) + (\rho_{blue} + \rho_{nir})}$$

$$NDBSI = \frac{IBI + SI}{2}$$

where IBI is the building index; SI is the soil index; and NDBSI is the normalized difference built-up and soil index.

(4) Thermal Indicator. The thermal indicator is represented by land surface temperature corrected by emissivity. The thermal infrared band of Landsat is inverted to brightness temperature, then corrected by emissivity to obtain this indicator [27]. Its calculation formula is:

$$LST = \frac{T_B}{1 + (\lambda \times T_B/\rho)\ln\varepsilon}$$

where LST is land surface temperature (K); T_B is brightness temperature (K); λ is the central wavelength of the thermal infrared band; ρ is a constant valued at 1.438×10^{-2} m · K; and ε is emissivity.

(5) Desertification Index. Based on Fractional Vegetation Cover (FVC), the desertification index is calculated according to the principle that land desertification degree is negatively correlated with vegetation coverage—as vegetation coverage decreases, desertification degree increases [28]. Its calculation formula is:

$$FVC = \frac{SAVI - SAVI_{soil}}{SAVI_{veg} - SAVI_{soil}}$$

$$DI = 1 - FVC$$

where FVC is fractional vegetation coverage; SAVI is the soil-adjusted vegetation index; $SAVI_{soil}$ is the SAVI value for bare soil without vegetation; $SAVI_{veg}$ is the SAVI value for high vegetation coverage areas; and DI is the desertification index.

General Normalization Formula for All Indicators:

$$N_i = \frac{I_i - I_{min}}{I_{max} - I_{min}}$$

where N_i is the normalized indicator value; I_i is the pre-normalization indicator value; and I_{min} and I_{max} are the minimum and maximum pre-normalization indicator values, respectively.

This study employs principal component analysis to couple the five ecological indicators. Indicator weights are objectively determined by loadings generated from principal component transformation without subjective human intervention, giving the model strong robustness [20]. To avoid weight imbalance during principal component analysis due to different measurement units, all indicators were normalized to a uniform range of [0, 1] before transformation. The first principal component (PC1) from the transformation was selected as the initial drought remote sensing ecological index ($DRSEI_0$), which was then normalized to obtain DRSEI with values between [0, 1]. Note that higher DRSEI values indicate better ecology, and vice versa. When the PC1 loading for NDBSI is negative while others are positive, a "1-" reversal operation is required; otherwise, this step is unnecessary [9].

$$DRSEI_0 = 1 - \{PC1[SAVI, Wet, NDBSI, DI, LST]\}$$

$$DRSEI = \frac{DRSEI_0 - DRSEI_{0_{min}}}{DRSEI_{0_{max}} - DRSEI_{0_{min}}}$$

where $DRSEI_0$ is the initial drought remote sensing ecological index; $DRSEI$ is the final drought remote sensing ecological index; and $DRSEI_{0_{max}}$ and $DRSEI_{0_{min}}$ are the maximum and minimum values of the initial index.

2.3 DRSEI Fluctuation Analysis

Coefficient of variation analysis effectively reveals data fluctuation degrees through the relationship between standard deviation and mean values [30]. This study uses this method to analyze DRSEI fluctuations and overall ecological environment changes in Gulang County. The specific formula is:

$$C_v = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(DRSEI_i - \overline{DRSEI})^2}}{\overline{DRSEI}}$$

where C_v is the coefficient of variation; n is the total number of years; $DRSEI_i$ is the DRSEI value for year i; and $\overline{DRSEI}$ is the mean DRSEI value.

3.1 DRSEI Effectiveness Analysis

Table 1 shows the principal component analysis results, where the first eigenvalue contribution rate exceeds 80%, indicating that PC1 integrates most features of the five indicators. Examining each indicator's contribution to DRSEI reveals that SAVI and Wet contribute positively, demonstrating that green plants and soil moisture have positive effects on Gulang County's ecological quality. Conversely, NDBSI and LST contribute negatively, indicating that dryness and thermal conditions negatively impact ecological quality, which aligns with reality and validates DRSEI's rationality.

Table 2 presents DRSEI and indicator means from 1994 to 2020. Overall, positively contributing indicators (SAVI, Wet) show a trend of first decreasing, then increasing, then decreasing again, while negatively contributing indicators (NDBSI, LST) show the opposite trend. These individual indicator trends closely match the ecological change trends obtained from the integrated DRSEI index, confirming that DRSEI can represent the five indicators for ecological quality assessment.

DRSEI's comprehensive representativeness can also be analyzed through its correlation with each indicator. Table 3 shows DRSEI has extremely strong positive correlations with SAVI and Wet, and extremely strong negative correlations with NDBSI, DI, and LST. The average correlation with all five indicators exceeds 0.83, indicating DRSEI integrates main information from each component and has stronger correlations with individual indicators than any single indicator alone, making it more capable of reflecting the study area's ecological quality status.

3.2 DRSEI Applicability Analysis

Compared to the other four indicators, SAVI shows the largest contribution degree, indicating vegetation and temperature significantly influence the region's ecological quality. Figure 2 compares local details between RSEI and DRSEI in 2020, demonstrating DRSEI's clear advantages. In typical regions, DRSEI shows significantly improved precision. The circled area in Region A shows central residential land where DRSEI more completely displays the outline and distribution patterns of ecological restoration zones and sandy land. Region B shows southern mountainous residential areas where DRSEI reveals deeper colors for residential areas, presenting more realistic ecological quality conditions. Region C, near the Tengger Desert with low vegetation coverage, suffers from background effects in vegetation extraction using NDVI. By replacing the greenness indicator with SAVI, DRSEI shows more complete ecological restoration area and sandy land contour features with prominent image texture details and improved vegetation extraction accuracy.

Ideally, impervious surfaces should have high NDBSI values and low DRSEI values. Table 4 shows the mean ecological index values for circled impervious surfaces in Figure 2: RSEI values are 0.51 and 0.48, while DRSEI values are 0.38 and 0.35. Combined with actual conditions, DRSEI results are more reasonable.

In summary, the improvements to RSEI have practical value. DRSEI effectively integrates positive and negative ecological factors, enhancing its applicability breadth, particularly for arid and semi-arid regions.

3.3 Spatial Pattern Distribution and Analysis of Ecological Quality in Gulang County

To analyze the study area's ecological quality more intuitively and quantitatively from a spatial perspective, DRSEI values were classified into five ecological levels using equal interval classification: excellent (0.8–1.0), good (0.6–0.8), moderate (0.4–0.6), poor (0.2–0.4), and very poor (0.0–0.2). The proportion and area of each level were statistically analyzed (Table 5). Water bodies were masked using the Modified Normalized Difference Water Index (MNDWI) to prevent interference with DRSEI construction.

The mean DRSEI values from 1994 to 2020 were 0.31, 0.29, 0.32, 0.34, 0.36, and 0.34, respectively, showing an overall trend of slight increase, decrease, continuous increase, and final decrease. Figure 3 visually demonstrates that northern Gulang County has low DRSEI values, indicating poor ecological quality; the desert edge in central areas shows gradually increasing DRSEI; while southern areas have higher DRSEI values, particularly in the southwest where DRSEI exceeds 0.6, indicating good ecological quality. Gulang County borders the Tengger Desert to the north with poor ecological conditions, while its southwestern region lies near Qilian Mountain branches with abundant forest resources and better ecological conditions, which matches actual conditions and further confirms DRSEI's applicability for regional ecological evaluation.

3.4 Spatiotemporal Change Analysis of Ecological Quality

To further analyze spatiotemporal changes in ecological quality, difference analysis was used to classify ecological change into three types: improvement (ΔDRSEI > 0.1), no change ($-0.1 \leq \Delta$DRSEI ≤ 0.1), and degradation (ΔDRSEI < -0.1). Overall, ecological quality in Gulang County showed obvious improvement trends from 1994 to 2020. The southwestern mountainous area experienced slight improvement, the southeastern mountainous area slight degradation, and the central-northern region obvious improvement (Figure 4).

Literature review reveals that since reform and opening up, Gulang County has controlled 132 km of wind-sand lines and initially treated 12 key inland dunes and major wind-sand outlets. Forest coverage has increased from 12.2% to 18.86%, and vegetation coverage has risen from 28% to 42%, resulting in overall ecological quality improvement.

From 1994–2000, the unchanged area was 3,839 km^2, improvement area 461 km^2, and degradation area 745 km^2, with improvement area smaller than degradation area, indicating slight overall ecological degradation. From 2000–2006, unchanged area was 3,571 km^2, improvement area 1,166 km^2, and degradation area 309 km^2, with improvement area far exceeding degradation area, showing gradual overall improvement. From 2006–2010, unchanged area was 3,583 km^2, improvement area 456 km^2, and degradation area 1,003 km^2, with improvement area smaller than degradation area, indicating more serious ecological degradation. From 2010–2015, unchanged area was 3,203 km^2, improvement area 1,387 km^2, and degradation area 456 km^2, with improvement area exceeding degradation area, showing certain ecological quality improvement. From 2015–2020, unchanged area was 3,772 km^2, improvement area 892 km^2, and degradation area 383 km^2, with improvement area exceeding degradation area, indicating ecological quality improvement. These results align with the "2020 Wuwei City Ecological Environment Status Bulletin," which reported slight ecological quality improvement in Gulang County, demonstrating DRSEI model reliability.

3.5 Ecological Quality Volatility Analysis

Figure 6 shows the spatial distribution of DRSEI coefficient of variation (C_v) and its statistical results. In 2020, Gulang County exhibited large C_v value fluctuations with obvious spatial heterogeneity. The southwestern region had lower C_v values, the southeastern region had higher values, and the southern mountainous area showed smaller overall fluctuations. This is because southern mountainous areas experienced farmland-to-forest conversion and ecological migration, reducing cultivated land while residential construction land had not yet been reclaimed. The southeastern mountainous area, affected later by ecological migration, saw reduced forest area due to lack of maintenance and natural drought, causing local ecological degradation. Central and northern regions showed higher C_v values, as central areas are major ecological migration resettlement zones where new residential construction, wasteland reclamation, and strengthened sand control efforts at the northern desert edge caused significant land use changes—the main reason for greater fluctuations in these areas. Therefore, enhanced ecological management and supervision should be implemented in southern mountainous and desert areas to prevent forest/grassland degradation and sand expansion.

4. Conclusions

This study developed DRSEI based on Gulang County's ecological characteristics, effectively integrating greenness, wetness, dryness, desertification index, and thermal indicators. With average correlation exceeding 0.83, DRSEI demonstrates clearer comprehensive information, more distinct local texture features, and improved extraction accuracy, particularly in sparsely vegetated sandy areas and residential zones. The improvements optimize ecological factors and enhance applicability, especially for arid and semi-arid regions.

DRSEI evaluation results for Gulang County show the overall mean increased from 0.31 (1994) to 0.34 (2020). Ecological improvement area totaled 849 km^2, while degradation area was 614 km^2, indicating obvious overall ecological quality improvement. Spatially, DRSEI shows large fluctuations in areas near Tianzhu Tibetan Autonomous County in the southwest and toward Baiyin City in the southeast, primarily due to six ecological migration relocations since 2012 that prevented regular forest/grassland maintenance. These areas should be prioritized for enhanced supervision and improved management mechanisms.

This study's limitation is that DRSEI calculation does not consider land salinization, which may cause evaluation bias in areas with large saline-alkali lands. Additionally, interactions between different land use types and driving effects of population and regional development on overall ecological quality require further exploration. Future work will address these issues.

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