Ecological Quality Analysis of Ordos City Based on Baseline Remote Sensing Ecological Index (Postprint)

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Abstract

Ordos City is a critical grassland-desert transition zone and agricultural-pastoral ecotone in the Yellow River Basin. Investigating its ecological quality changes holds significant importance for supporting ecological protection and high-quality development in the Yellow River Basin. Using MODIS remote sensing imagery as the data source, this study calculates the Baseline Remote Sensing Ecological Index (B_{RSEI}) for Ordos City through improved conventional normalization and principal component methods, and analyzes the spatiotemporal variation characteristics of ecological quality in the region from 2001 to 2019. The results indicate: (1) B_{RSEI} exhibits stable directionality and integrity, enabling better reflection of long-term temporal changes in ecological quality. From 2001 to 2019, the B_{RSEI} in Ordos City showed fluctuating growth with spatial heterogeneity characterized by higher values in the east and lower values in the west. (2) The surface water content index is the primary factor promoting B_{RSEI} and the main single factor explaining B_{RSEI} distribution, while land surface temperature is the primary factor inhibiting B_{RSEI}, with their interaction producing the greatest effect. (3) Ecological quality in Ordos is predominantly improving, accounting for 67.13% of the total area, with remarkable ecological restoration effects observed in Jungar Banner, Kangbashi District, and Yijinhuoluo Banner. The study demonstrates that the overall ecological quality of Ordos City has improved, and B_{RSEI} facilitates the analysis of interannual variations in ecological quality, providing a reference basis for ecological governance in Ordos City and high-quality development of the Yellow River Basin.

Full Text

Ecological Quality Analysis of Ordos City Based on the Baseline Remote Sensing Ecological Index

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Abstract

Ordos City is an important grassland-desert transition zone and agro-pastoral ecotone in the Yellow River Basin. Studying its ecological quality changes is significant for supporting ecological protection and high-quality development in the Yellow River Basin. Using MODIS remote sensing imagery as the data source, this study calculates the Baseline Remote Sensing Ecological Index (B_{RSEI}) for Ordos City through improved conventional normalization and principal component methods, and analyzes the spatiotemporal variation characteristics of ecological quality in this region from 2001 to 2019. The results indicate: (1) B_{RSEI} exhibits stable directionality and integrity, better reflecting long-term ecological quality changes. From 2001 to 2019, B_{RSEI} in Ordos City showed a fluctuating increase and spatial differentiation characterized by higher values in the east and lower values in the west. (2) The Surface Water Content Index (SWCI) is the primary factor promoting B_{RSEI} and serves as the main factor explaining the B_{RSEI} distribution. Land Surface Temperature (LST) is the main factor inhibiting B_{RSEI}, with its interaction effect being the most substantial. (3) The ecological quality of Ordos City has improved overall, covering 67.13% of the total area, with notable ecological management effects in the Jungar Banner, Kangbashi District, and Ejin Horo Banner areas. This study demonstrates that B_{RSEI} is useful for analyzing interannual ecological quality changes and provides a reference for ecological governance in Ordos City and high-quality development of the Yellow River Basin.

Keywords: ecological quality; baseline remote sensing ecological index; principal component analysis; Ordos City

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1. Introduction

Ecological quality reflects the condition of the ecological environment and is related to socio-economic development [1]. Good ecological quality is a prerequisite for human survival and development. Remote sensing offers advantages such as wide acquisition range, short cycle, and convenient data access. Traditional remote sensing processing platforms struggle to meet the demands of rapid processing and information mining for big remote sensing data [2]. The Google Earth Engine (GEE) remote sensing cloud platform provides users with rich geospatial data processing and analysis tools [3], improving MODIS image processing efficiency and reducing workload for long-term and large-scale monitoring, making it a hotspot for ecological quality research [4-5].

Many factors influence ecological quality, requiring multiple indicators for evaluation. Among existing remote sensing ecological quality monitoring methods, the Remote Sensing Ecological Index (RSEI) based on greenness, humidity, dryness, and temperature [6] is widely used. With deepening research, scholars have improved RSEI to enhance its application value and universality. For example, Song et al. [7] constructed an improved remote sensing ecological index based on the cumulative contribution rate of principal components to enhance information utilization of ecological indicators. Luo et al. [8] introduced a desertification index to analyze ecological quality impacts from multiple perspectives. Zheng [9] used mean normalization to improve RSEI instability. Zhu et al. [10] proposed a moving window-based remote sensing ecological index to explore gradual ecological environment information. These studies are more suitable for analyzing spatial distribution of ecological quality within a year, neglecting comparisons between multi-year data and the instability of principal component analysis coordinates, which is not conducive to analyzing dynamic changes in ecological quality along the time dimension and does not solve the continuity problem of RSEI in long-term series research.

Cong et al. [11] used pixel-level data extremes within the study period as upper and lower baselines for indicator standardization, evaluating Chinese terrestrial ecosystem ecological quality changes based on a historical baseline ecological quality index. This paper proposes the Baseline Remote Sensing Ecological Index (B_{RSEI}) based on baseline thinking, integrating multi-year remote sensing information data, traversing data time and space dimensions to determine extremes and establish a baseline model. Principal component analysis is used for one-time global information dimensionality reduction, converting long time series information into the same coordinate system so that data analysis has the same reference point. This method can not only intuitively evaluate the spatial distribution of ecological quality but also more accurately analyze regional long-term ecological quality changes.

Ordos City is located at the "几" shaped bend of the Yellow River, connecting the middle and upper reaches of the Yellow River Basin and is one of the main sources of Yellow River sediment. Research on Ordos City's ecological quality contributes to ecological protection and high-quality development of the Yellow River Basin. This study utilizes the GEE cloud platform to process remote sensing data, analyzes Ordos City's ecological quality changes through B_{RSEI}, reveals influencing factors of ecological quality, and provides a clear direction for ecological governance in Ordos City and the Yellow River Basin.

2. Study Area Overview

Ordos City is located in central-western Inner Mongolia Autonomous Region, with elevations ranging from 850 to 2097 m, stretching approximately 400 km east-west and 340 km north-south. The terrain includes plateaus, hills, plains, deserts, and other landforms, with the Mu Us Desert, Kubuqi Desert, and other sandy lands accounting for about 48% of the total area. Ordos City is a typical arid and semi-arid region with a temperate continental climate, concentrated precipitation from June to September decreasing from east to west, and vegetation types dominated by desert steppe, psammophytic vegetation, and meadows [12]. As the second longest prefecture-level city along the Yellow River, Ordos City bears the important responsibility of water conservation and water quality maintenance, demonstrating its important strategic position in the Yellow River Basin (Fig. 1).

Note: This map is produced based on the standard map with review number GS(2019)1822 downloaded from the Standard Map Service website of the National Administration of Surveying, Mapping and Geoinformation, with no modifications to the base map boundaries.

[Figure 1: see original paper]

3. Data and Methods

3.1 Data Sources and Preprocessing Ecological indicator data: MOD13A1 vegetation index product (500 m resolution), MOD09A1 surface reflectance data, and MOD11A2 land surface temperature product (1000 m resolution). Data acquisition time is June-September each year, when vegetation is lush and rainfall is abundant. All data have undergone atmospheric correction and other preprocessing, with mean synthesis performed on the GEE cloud platform.

Other data: Elevation data from the Chinese Academy of Sciences Resource and Environmental Science Data Center (http://www.resdc.cn) with 1000 m spatial resolution; precipitation data from the Spatiotemporal Three Poles Environment Big Data Platform (http://poles.tpdc.ac.cn) with 500 m resolution monthly data generated through spatial downscaling and validated by independent meteorological observation stations, with summation operations used to obtain annual data [13]; Gross Domestic Product (GDP) data from Figshare (https://figshare.com) with 1000 m resolution production data that has undergone relevant corrections [14]; population data from the 100 m resolution WorldPop grid dataset (https://www.worldpop.org), with summation used to obtain 500 m resolution data [15]. All data span 2001-2019, use the WGS-1984 coordinate system, are extracted according to Ordos City boundaries, use equal-area projection, and are resampled to 500 m resolution through interpolation for subsequent analysis.

3.2 Construction of the Baseline Remote Sensing Ecological Index

3.2.1 Ecological Indicators Ecological indicators determine B_{RSEI}. The model uses greenness, humidity, dryness, and temperature indicators, which are not only closely related to human survival but also the most intuitive indicators reflecting ecological quality changes [6]. This study selects the Enhanced Vegetation Index (EVI) suitable for monitoring lush vegetation periods as the greenness indicator [16]; the Surface Water Content Index (SWCI) suitable for arid regions as the humidity indicator [17]; the Normalized Difference Built-up and Soil Index (NDBSI) as the dryness indicator [6]; and the thermodynamic land surface temperature from the MOD11A2 product as the temperature indicator (LST). To reduce the impact of surface water systems on greenness and humidity indicators [18], the Modified Normalized Difference Water Index (MNDWI) is used for large-scale water body masking in the study area [19].

The calculation formulas for NDBSI, MNDWI, etc. are as follows:

$SWCI = ({}_5 - {}_6) / ({}_5 + {}_6)$

$NDBSI = (NDBI + SI) / 2$

where represents surface reflectance from MOD09A1 bands.

3.2.2 Overall Normalization of Indicators Since the four ecological indicators used to construct B_{RSEI} have different units and ranges, normalization is required. This study selects data from 2001-2019 for traversal, screens out extremes that can serve as upper and lower baselines, and performs overall normalization of indicator data under the same standard. This method retains more inter-data information, solves the indicator dimension problem while preserving original data attribute characteristics, and is suitable for long time series research. The overall normalization formula is:

$DNa = (DNb - DNmin) / (DNmax - DNmin)$

where DNb is the original indicator data for year n, DNa is the overall normalized data for year n, and DNmin and DNmax are the minimum and maximum values of the original indicator data across all years.

3.2.3 Construction of B_{RSEI} Using the four normalized ecological indicators as the basis, B_{RSEI} is constructed through principal component analysis (PCA) algorithm, which excludes subjective factor interference and models multi-dimensional data while maximizing retention of original information to comprehensively reflect regional ecological quality. To accurately analyze regional ecological quality changes, overall normalized indicator data from 2001-2019 undergo global principal component analysis (converting data from time dimension to space dimension for calculation), eigenvectors are calculated, and annual B_{RSEI} values are obtained. The integration process can be implemented through programming. The principal component analysis formula is:

B_{RSEI} = PCA(EVI, SWCI, NDBSI, LST)

B_{RSEI} = VPC_{11} × EVI + VPC_{12} × SWCI + VPC_{13} × NDBSI + VPC_{14} × LST

where EVI, SWCI, NDBSI, and LST are the normalized greenness, humidity, dryness, and temperature indicators, respectively, and VPC_{11}-VPC_{14} are the eigenvectors of each indicator in the first principal component.

Principal component analysis components are uncorrelated. Typically, the component containing more information is selected as the weight for calculating B_{RSEI}. However, PCA direction is related to data variance and cannot guarantee consistency with actual conditions (i.e., areas with high vegetation coverage have a restorative effect on ecological quality). When performing PCA, the direction must be kept consistent with B_{RSEI}, similar to Xu Hanqiu' s [6] "1-PC1" principle. The formula is:

VPC1 = { vpc1, if EVI ≥ 0 (-1) × vpc1, if EVI < 0 }

where VEVI is the eigenvector corresponding to EVI in the first principal component, vpc1 is the original first principal component eigenvector, and VPC1 is the modified first principal component eigenvector.

For better comparison and classification of multi-year B_{RSEI}, the original B_{RSEI} is overall normalized. Higher regional B_{RSEI} values indicate better ecological quality. The formula is:

B_{RSEI} = (B_{RSEI}$_0$ - B_{RSEImin}) / (B_{RSEImax} - B_{RSEImin})

where B_{RSEI}$_0$ is the original B_{RSEI} for year n, and B_{RSEImin} and B_{RSEImax} are the minimum and maximum B_{RSEI} values across all years.

To intuitively express spatiotemporal evolution of ecological quality, referencing previous studies [7-8,11-12] and retaining interannual changes, the normalized B_{RSEI} is divided into five grades using equal interval classification based on the same standard: 0.0-0.2 (poor), 0.2-0.4 (low), 0.4-0.6 (moderate), 0.6-0.8 (good), and 0.8-1.0 (excellent), with different years analyzed accordingly.

[Figure 2: see original paper]

3.2.4 Geographical Detector Geographical Detector is a statistical method for detecting spatial heterogeneity and revealing its driving mechanisms [20], widely used for feature analysis of numerical variables and qualitative data [4,29-30]. In Geographical Detector, factor detection is used to detect the explanatory power of different factors on the spatial distribution of variable (Y), with intensity measured by q value:

q = 1 - (Σ 1 N σ 2) / (Nσ^2)

where h is the stratum of factor or variable (Y), L is the number of strata, N and N are the number of units in stratum h and the entire region, respectively, σ 2 and σ^2 are the variances of variable (Y) in stratum h and the entire region, respectively. The q value represents explanatory power, with larger q values indicating stronger explanatory power of the factor on variable (Y) [20].

Interaction detection in Geographical Detector identifies the impact of interactions between different factors on the dependent variable [20], mainly by comparing the relationship between independent and interactive effects of two factors.

3.2.5 Trend Analysis The Theil-Sen Median trend analysis is a robust non-parametric statistical trend calculation method that can avoid the influence of time series data missing and data distribution morphology [13,30]. This method uses median slope to analyze multi-year data changes and is suitable for long time series trend analysis [31]. When Sen > 0.0005, B_{RSEI} increases; when Sen < 0.0005, B_{RSEI} decreases; otherwise, it remains stable.

The Mann-Kendall test allows for the existence of null values and outliers, does not require data to follow normal distribution or linear trends, and is widely adapted for significance testing of long time series information trends [4,29-30]. When the absolute value of Z is greater than 1.96, the trend passes the significance test at the 95% confidence level.

4. Results

4.1 Analysis of Factors Influencing B_{RSEI} Global modeling of the 2001-2019 ecological indices yields principal components (Table 1). Results show that the first principal component (PC1) contribution rate exceeds 70%, indicating that PC1 explains the vast majority of information in the four ecological indicators and can be used to calculate B_{RSEI}.

Table 1 Principal component analysis of four factors

In PC1, the eigenvalues for greenness indicator EVI and humidity indicator SWCI are positive, indicating they promote B_{RSEI}, while the eigenvalues for dryness indicator NDBSI and temperature indicator LST are negative, indicating they inhibit B_{RSEI}, which matches reality. The absolute eigenvalue sum for LST is 0.621, with regional indicator influence degree 依次为: temperature (0.621) > dryness (0.421) > humidity (0.355) > greenness (0.254). The possible reason is that Ordos City is located in an arid/semi-arid region with fragile ecosystems sensitive to climate anomalies [21]. High temperatures enhance potential evapotranspiration, reduce soil water content, and make humidity' s promoting effect on B_{RSEI} less than NDBSI' s inhibiting effect.

4.2 Spatiotemporal Evolution Analysis of B_{RSEI}

4.2.1 Temporal Evolution Analysis of B_{RSEI} Based on the grade classification results, B_{RSEI} grade changes from 2001-2019 were calculated (Fig. 3). The results show that the area of poor ecological quality grades in Ordos City gradually decreased, with a few low-grade areas converting to poor grade. Most poor-grade ecological quality areas shifted to low grade, with very few shifting to moderate and good grades. The area of excellent ecological quality grades first decreased then increased, with a few good-grade and individual moderate-grade areas converting to excellent in 2019. Most excellent-grade ecological quality areas flowed to good grade, with a few flowing to moderate grade. This indicates that Ordos City' s ecological quality showed an overall upward trend from 2001-2019, with ecological quality improvement.

Ordos City has large areas of grassland ecosystems [32], and ecological quality changes are consistent with vegetation growth, while precipitation and temperature have direct and indirect effects on vegetation growth status and spatial distribution [33]. The ecological indicators composing B_{RSEI} are closely related to precipitation. Increased precipitation raises greenness and humidity while reducing dryness and regulating temperature. Analysis of ecological quality using overall normalized precipitation and temperature (Fig. 5) shows that compared to 2001, precipitation in Ordos City increased while temperature decreased in 2019.

[Figure 3: see original paper]

4.2.2 Spatial Evolution Analysis of B_{RSEI} Analysis of B_{RSEI} grade change trends (Fig. 4) shows that from 2001-2019, Ordos City' s ecological quality was generally at a moderate-to-low level, presenting a spatial differentiation characteristic of high in the east and low in the west.

Areas with poor ecological quality are mainly distributed in the northwest, where the Kubuqi Desert is located, making ecological quality improvement difficult. Most western and central areas are desert steppes with low vegetation coverage. Areas with excellent ecological quality are more distributed in the Yellow River alluvial plain about 10 km north of the region, where water is sufficient, land is fertile, and agricultural conditions are good. The northeastern region is dominated by shrub forests with higher B_{RSEI} values. Over time, B_{RSEI} shows an expansion trend, with ecological quality grades improving from low to moderate and ecosystems remaining relatively stable.

[Figure 4: see original paper]

Point-line and scatter plots of precipitation, temperature, and B_{RSEI} (Fig. 5) show that precipitation is positively correlated with B_{RSEI}, with a correlation coefficient of 0.85. Precipitation was generally low before 2010 and high after 2010. Temperature is negatively correlated with B_{RSEI}, with a correlation coefficient of -0.89. Temperature was generally high before 2010 and low after 2010. This indicates that rising temperatures and decreasing precipitation are causes of B_{RSEI} reduction.

[Figure 5: see original paper]

4.3 Driving Analysis of B_{RSEI} Spatial Distribution To explore influencing factors of ecological quality spatial heterogeneity in Ordos City, considering both natural and human factors, five factors were selected as independent variables: EVI, precipitation, population, elevation, and NDBSI. Geographical Detector was used for factor detection and interaction detection analysis (Fig. 6).

Factor detection results show that ecological indicators have different explanatory powers for B_{RSEI} but are generally similar. The q value for humidity is largest, indicating humidity is an important factor affecting B_{RSEI} spatial distribution. Precipitation' s explanatory power shows a significant increasing trend, indicating its increasing influence on B_{RSEI} spatial distribution, consistent with arid/semi-arid region characteristics [21]. Comparative analysis shows natural factors have greater influence on B_{RSEI} than human factors.

Interaction detection results show that except for the interaction between precipitation and population in 2019 showing non-linear enhancement, all other interactions show dual-factor enhancement, with no independent factors. Single-factor indicators show enhanced explanatory power after interacting with other factors, indicating dual-factor interactions have stronger effects on Ordos City ecological quality spatial distribution than single factors. Among them, EVI LST and SWCI LST show relatively high interaction explanatory power, followed by NDBSI LST. These results further indicate that temperature largely influences regional ecological quality.

[Figure 6: see original paper]

Table 2 Analysis results of interactive detectors from 2001 to 2019

4.4 Change Trend Analysis of B_{RSEI} Theil-Sen Median trend analysis and Mann-Kendall test divide ecological quality change trends into five categories: significant improvement, slight improvement, stable, slight degradation, and severe degradation (Fig. 7). Results show that from 2001-2019, B_{RSEI} in Ordos City showed obvious improvement, with improved areas accounting for 67.13% of the total area. Stable areas account for 19.69%, while degraded areas account for 13.18%, with severely degraded areas 仅占 0.49%. The improvement area in Ordos City is far greater than the degradation area, indicating gradual ecological quality improvement with obvious effects.

Degraded areas are concentrated in southwestern Ordos City, mainly in Otog Banner and Otog Front Banner, which are typical semi-desert steppe areas with widely distributed wild plants. Unscientific planning of traditional production methods such as free-range grazing and land reclamation has led to overgrazing, indiscriminate cultivation, and deforestation, which are important causes of ecological quality degradation in this region [17,33]. On the other hand, after the implementation of the Grain for Green Project, local herders planned grain plots with low yields on steep slopes and sandy cultivated land, established sandy land protection areas, planted forage grass in forest gaps, developed diversified economies, implemented grazing bans and rotational grazing, and improved vegetation coverage [32].

Significantly improved areas are concentrated in eastern Ordos City, dominated by mountain meadows with high vegetation coverage, stable ecosystem structure, and strong anti-interference capability. The improvement in ecological quality in Uxin Banner demonstrates positive results from Mu Us Desert management. Jungar Banner and Ejin Horo Banner have higher terrain and rich energy mineral resources, with extensive underground and open-pit mining sites. The government has explored green mine development by adjusting resource development projects, closing unreasonable open-pit mines, and timely conducting greening restoration in subsidence areas, achieving significant improvement trends and demonstrating excellent results in mining area ecological environment management, making positive contributions to Ordos City' s ecological quality improvement.

[Figure 7: see original paper]

4.5 Applicability of B_{RSEI} The B_{RSEI} model still uses principal component analysis, performing one-time global modeling on overall normalized data based on the same coordinate concept (Fig. 8). The figure shows that global modeling and year-by-year modeling have relatively consistent distribution trends each year, with the former being more stable in long-term series distribution. The B_{RSEI} model places indicator data from time and space dimensions in the same coordinate system, obtains eigenvectors to calculate B_{RSEI}, retains PCA advantages, eliminates coordinate uncertainty of principal component analysis to some extent, maintains continuity of multi-year data after overall normalization, and makes long-term series remote sensing ecological indices comparable and referential. This study transforms Ordos City data from time dimension to space dimension for calculation, performs global modeling through principal component analysis, and then calculates annual B_{RSEI} to analyze temporal evolution.

[Figure 8: see original paper]

5. Conclusion

Ordos City is located in an arid/semi-arid region with large desert and grassland areas. With the implementation of national policies such as Grain for Green and the Three-North Shelter Forest Program, vegetation coverage in Ordos City has been substantially improved. This study uses MODIS data, determines baselines through extremes, performs global modeling using principal component analysis, and analyzes spatiotemporal changes in ecological quality in Ordos City, Inner Mongolia from 2001-2019. The conclusions are:

1) B_{RSEI} better reflects long-term ecological quality changes. Spatiotemporal analysis shows B_{RSEI} has stable directionality. From 2001-2019, B_{RSEI} in Ordos City showed fluctuating growth, ecological quality improved, and presented spatial differentiation of high in the east and low in the west.
2) Humidity is the main factor promoting B_{RSEI}, while temperature is the main factor inhibiting B_{RSEI}. Using Geographical Detector to analyze each factor’ s contribution to B_{RSEI} spatial distribution shows humidity is the main single factor, and temperature has the largest interaction with other detection factors.
3) Ordos City’ s ecological quality is dominated by improvement, accounting for 67.13% of the total area, with significant ecological management effects in Jungar Banner, Kangbashi District, and Ejin Horo Banner. Hanggin Banner and Otog Banner have the worst overall ecological quality, while Otog Front Banner has weak ecological quality stability and requires strengthened ecological management.

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