Spatiotemporal variations in ecological quality of Otindag Sandy Land based on a new modified remote sensing ecological index Postprint

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Abstract

Otindag Sandy Land in China is an important ecological barrier to Beijing; the changes in its ecological quality are major concerns for sustainable development and planning of this area. Based on principal component analysis and path analysis, we first generated a modified remote sensing ecological index (MRSEI) coupled with satellite and ground observational data during 2001–2020 that integrated four local indicators (greenness, wetness, and heatness that reflect vegetation status, water, and heat conditions, respectively, as well as soil erosion). Then, we assessed the ecological quality in Otindag Sandy Land during 2001–2020 based on the MRSEI at different time scales (i.e., the whole year, growing season, and non-growing season). MRSEI generally increased with an upward rate of 0.006/a during 2001–2020, with clear seasonal and spatial variations. Ecological quality was significantly improved in most regions of Otindag Sandy Land but degraded in the southern part. Regions with ecological degradation expanded to 18.64% of the total area in the non-growing season. The area with the worst grade of MRSEI shrunk by 15.83% of the total area from 2001 to 2020, while the area with the best grade of MRSEI increased by 9.77% of the total area. The temporal heterogeneity of ecological conditions indicated that the improvement process of ecological quality in the growing season may be interrupted or deteriorated in the following non-growing season. The implementation of ecological restoration measures in Otindag Sandy Land should not ignore the seasonal characteristics and spatial heterogeneity of local ecological quality. The results can explore the effectiveness of ecological restoration and provide scientific guides on sustainable development measures for drylands.

Full Text

Preamble

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Spatiotemporal Variations in Ecological Quality of Otindag Sandy Land Based on a New Modified Remote Sensing Ecological Index

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Abstract

Otindag Sandy Land in China serves as a crucial ecological barrier for Beijing, and changes in its ecological quality are major concerns for sustainable development and planning in this region. Using principal component analysis and path analysis, we first generated a modified remote sensing ecological index (MRSEI) coupled with satellite and ground observational data from 2001–2020 that integrated four local indicators: greenness, wetness, and heatness (reflecting vegetation status, water, and heat conditions, respectively), as well as soil erosion. We then assessed ecological quality in Otindag Sandy Land during 2001–2020 based on MRSEI at different time scales (i.e., whole year, growing season, and non-growing season). MRSEI generally increased at a rate of 0.006/a during 2001–2020, with clear seasonal and spatial variations. Ecological quality improved significantly in most regions of Otindag Sandy Land but degraded in the southern part. Regions with ecological degradation expanded to 18.64% of the total area in the non-growing season. The area with the worst MRSEI grade shrank by 15.83% of the total area from 2001 to 2020, while the area with the best MRSEI grade increased by 9.77% of the total area. The temporal heterogeneity of ecological conditions indicated that the improvement process of ecological quality in the growing season may be interrupted or deteriorate in the following non-growing season. Implementation of ecological restoration measures in Otindag Sandy Land should not ignore the seasonal characteristics and spatial heterogeneity of local ecological quality. These results can inform the effectiveness of ecological restoration and provide scientific guidance for sustainable development measures in drylands.

Keywords: ecological quality; modified remote sensing ecological index; principal component analysis; path analysis; Otindag Sandy Land; dryland ecosystem

1 Introduction

Otindag Sandy Land in China constitutes a crucial ecological barrier and represents a typical yet fragile dryland ecosystem adjacent to Beijing (the capital of China) that suffers from structural damage and functional impairment, leading to land degradation and biodiversity loss [?, ?]. To slow land degradation and improve the ecological environment, China has implemented a series of ecological restoration projects, such as the Three-North Shelter Forest Program and the Beijing-Tianjin sand source control project [?, ?, ?]. Nevertheless, debate continues regarding the effectiveness of these ecological restoration projects after 20 years of implementation [?, ?, ?, ?]. Quantitative assessment of spatiotemporal dynamics in ecological quality is essential for sustainable development of Otindag Sandy Land.

With rapid development of remote sensing and GIS technology, several remote sensing-based indices have been proposed to characterize ecological quality [?, ?, ?]. For instance, Wei et al. [?] calculated the environmental vulnerability distance index by considering hydro-meteorological, socio-economic, soil-biological, and topographical factors to assess ecological quality in China' s Shiyang River Basin. Xu et al. [?] developed a remote sensing ecological index (RSEI) based on principal component analysis (PCA) to avoid artificial influences on weights and produce more objective and reasonable results; this index has been widely used in regional ecological quality assessment.

However, researchers have recognized that RSEI may have limitations for ecological quality assessment in areas where urbanization is not the main factor influencing ecological quality [?, ?, ?, ?, ?]. Consequently, the traditional RSEI has been improved and expanded in recent years. For example, Wang et al. [?] developed an arid remote sensing ecological index (ARSEI) by replacing the dryness indicator in RSEI with indicators of salinity and land degradation. Yao et al. [?] modified RSEI with bare soil index and salinity index to reflect macro ecological quality in arid areas. For applications in rocky desertified areas, Ye and Kuang [?] constructed a modified remote sensing ecological index (MRSEI) by incorporating the degree of rocky desertification. An improved composite remote sensing ecological index (CRSEI) was developed by incorporating population density for studying ecological quality in China' s Yellow River Delta [?]. Additionally, to adapt to local conditions, researchers have developed new RSEI variants that can accurately characterize regional ecological quality changes, such as the remote sensing ecological index of local adaptation improvement (RSEILA) [?].

Ecological quality reflects the comprehensive characteristics of ecosystem elements, structures, and functions [?]. Dryland represents a special ecosystem type with sparse precipitation and high evaporation [?]. In dryland ecosystems, vegetation serves as an important guarantee of regional ecosystem stability, and greening constitutes a major measure to mitigate desertification [?, ?]. Meanwhile, water and heat are the principal natural conditions for vegetation growth and ecosystem development [?]. Dryland ecosystems are extremely vulnerable to human activities and climate change [?, ?]. Thus, soil erosion represents a major cause of soil degradation and desertification in drylands that may intensify when soil erosion proceeds faster than pedogenesis [?]. Soil erosion also reduces water and soil conservation capacity, affects regional water reserves, and seriously threatens ecological quality [?]. In this study, focusing on comprehensive ecological quality assessment based on regional dryland characteristics, we combined vegetation status, water and heat conditions, and soil erosion into an integrated index to assess ecological quality in Otindag Sandy Land.

As noted above, remote sensing image processing technology is flourishing, and ecological indices based on remote sensing technology have been increasingly used in ecological quality assessment. However, adverse atmospheric conditions, sensor failures, and revisit periods still inevitably restrict remote sensing data continuity and hinder wide application of remote sensing-based ecological indices [?, ?]. Multiple data reconstruction methods aiming to improve image quality, such as maximum value composite, local filtering, and function fitting [?, ?, ?, ?], are viable candidates, although these methods are highly dependent on remote sensing data reliability. Therefore, based on PCA and path analysis of four representative indicators (greenness, wetness, heatness, and soil erosion) of ecological quality in Otindag Sandy Land, this study attempted to construct a modified RSEI (i.e., MRSEI) coupled with satellite and ground observational data. Specifically, long-time series MRSEI data (2001–2020) at different time scales (i.e., whole year, growing season, and non-growing season) were calculated and used to assess ecological quality and its spatiotemporal variations in Otindag Sandy Land. The results can inform the effectiveness of ecological restoration and provide scientific guidance for sustainable development measures in Otindag Sandy Land and other similar dryland regions worldwide.

2.1 Study Area

Otindag Sandy Land (41°46 –45°69 N, 111°55 –118°38 E) is located in the central part of Inner Mongolia Autonomous Region, China, and represents one of the world' s major sandy areas [?, ?]. The landform is relatively undulating, with generally higher terrain in the southeast and lower terrain in the northwest, covering an area of approximately 0.17$×10^{6}$ km^2 [?]. Otindag Sandy Land belongs to the arid and semi-arid continental climate zone, with an annual average temperature of 0.9°C–5.5°C. Affected by monsoons, precipitation gradually decreases from southeast to northwest, with annual precipitation ranging from 350–400 mm to 100–200 mm [?].

Grassland is the dominant land cover type across the area, accounting for 81.37% of the total area in 2020. Forests are patchy (5.13%) in the east, while croplands are found in the south and east, occupying 1.92% of the total area (Fig. 1a [Figure 1: see original paper]). From 2001 to 2020, land cover transformation occurred in 17.97% of the total area, of which 11.35% was transformed from grassland to cropland, 27.03% from bare land to grassland, and 11.18% from cropland to grassland, while 6.18% represented afforestation (Fig. 1b).

2.2 Data Sources and Processing

Monthly Normalized Difference Vegetation Index (NDVI) products (MOD13A3) from the Moderate-resolution Imaging Spectroradiometer (MODIS) at 1 km spatial resolution (from January 2001 to December 2020) were collected from the National Aeronautics and Space Administration (NASA) (https://ladsweb.modaps.eosdis.nasa.gov). NDVI data were used to calculate the greenness index (Ig).

Daily meteorological data (2001–2020) from 103 weather stations, including average air temperature (°C), maximum air temperature (°C), minimum air temperature (°C), relative humidity (%), sunshine duration (h), wind speed (m/s), and precipitation (mm), were obtained from the National Meteorological Science Data Center (http://data.cma.cn). These data underwent quality control (e.g., outlier rejection) to ensure authenticity and reasonableness. We interpolated the daily data after quality control using Australian National University Spline (ANUSPLIN) software [**?**] and extracted the final 1-km spatial meteorological datasets for Otindag Sandy Land to calculate wetness index (Iw), heatness index (Ih), and soil erosion index (Is). ANUSPLIN offers advantages of solid thin plate spline function theory and high interpolation accuracy through incorporation of parametric linear sub-models, in addition to independent spline variables; this software has been widely used for meteorological variables [**?**, **?**].

Soil dataset, including soil types, soil organic matter content, soil sand and clay contents, and the percentage of soil organic carbon (SOC), was obtained from the China Soil Characteristics Dataset of the National Cryosphere Desert Data Center (http://www.ncdc.ac.cn), calculated from the 1:1,000,000 soil database of China' s second national soil census. The 30-m digital elevation model (DEM) data were downloaded from the Geospatial Data Cloud (http://www.gscloud.cn). Soil dataset and DEM were used to calculate Is.

All datasets were projected to the UTM-WGS84 coordinate system and resampled to 1 km spatial resolution using nearest neighbor resampling. Moreover, datasets for the whole year and growing season were calculated from monthly average data of January through December and May through September, respectively; while for the non-growing season, datasets were calculated from monthly average data of October through April of the following year.

The 1-km gridded land use cover datasets in 2000 and 2020 were derived from the Resource and Environment Science and Data Center (http://www.resdc.cn). Six land cover types were used in this study: cropland, forestland, grassland, water body, bare land, and built-up land [**?**].

2.3 Construction of Modified Remote Sensing Ecological Index (MRSEI)

Considering the regional characteristics of the dryland ecosystem in Otindag Sandy Land, we selected vegetation status, water and heat conditions, and soil erosion to represent local indicators of ecological quality. The four indicators include Ig, Iw, Ih, and Is. Figure 2 [Figure 2: see original paper] shows the flowchart for spatiotemporal analysis of ecological quality in Otindag Sandy Land using MRSEI in this study.

Vegetation cover is not only an important environmental element but also an indicator of the sensitive state of terrestrial ecosystems, playing a crucial role in analyzing and evaluating regional ecological and environmental factors [?, ?]. Ig reflects the growth status and distribution characteristics of green vegetation in the study area and is expressed by Equation 1:

$$I_g = \frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{soil}}}{\mathrm{NDVI}_{\mathrm{veg}} - \mathrm{NDVI}_{\mathrm{soil}}}$$

where NDVI and NDVI g are the NDVI values for areas covered with bare soil and complete vegetation, respectively.

Iw is expressed by the ratio of regional total precipitation to total potential evapotranspiration, which can effectively characterize regional wet and dry conditions to determine ecosystem water requirements [?]. It was calculated using the following equation:

$$I_w = \frac{\mathrm{PRE}}{\mathrm{ET}_0}$$

where PRE is total precipitation (mm) and ET_0 is total potential evapotranspiration (mm), calculated based on the Penman-Monteith model using interpolated climate datasets [?, ?].

Ih is closely related to energy exchange processes within the ecosystem and reveals the potential amount of vegetation cover, expressed by land surface temperature–an important indicator of the surface environment [?]. In this study, we replaced the land surface temperature in RSEI derived from remote sensing data [?] with air temperature from the National Meteorological Science Data Center (http://data.cma.cn).

Is was calculated using the Revised Universal Soil Loss Equation (RUSLE) model, which synthetically considers the effects of precipitation and runoff on near-surface soil; this model has been widely used for water and soil erosion assessment [?, ?]. The indicator Is was calculated as follows:

$$I_s = \frac{A_p - A_r}{A_p} \times 100\%$$

where:

$$A_p = R \times K \times L \times S \times C \times P$$

$$A_r = \sum_{i=1}^{n} \sum_{k=1}^{24} \sum_{j=1}^{N} \left[0.1317 \times P_{i,j,k} \times \left(0.2 + 0.3e^{-0.25\times \mathrm{SOC}}\right)\right]$$

$$K = \left(0.0034 + 0.0405e^{-\frac{(\mathrm{SOC}-3.72)^2}{2.95}}\right) \times \left(\frac{\mathrm{msilt}}{\mathrm{ms}+\mathrm{msilt}}\right)^{0.3} \times \left(1 - \frac{0.25 \times \mathrm{SOC}}{\mathrm{SOC} + e^{3.72-2.95\times \mathrm{SOC}}}\right)$$

$$L = \left(\frac{\lambda}{22.13}\right)^m$$

$$S = 10.8 \sin\theta + 16.8 \sin^2\theta - 21.9$$

where A and A are potential and actual soil erosion (t/(km^2 · a)), respectively; R is the precipitation erosion factor (MJ · mm/(km^2 · h · a)); K is the soil erodibility factor (t · h/(MJ · mm)); L and S are slope length and angle factors, respectively (dimensionless); C is vegetation cover and management factor; and P is soil and water conservation measures factor.

P , , represents the jth daily precipitation with erosiveness on the kth half-month of the ith year, where k is the serial number of half-month in a year (k=1, 2, ···, 24) and i is the serial number of years (i=1, 2, ···, n). j and N are the serial number and cumulative frequency of daily precipitation with erosiveness on the kth half-month of the ith year, respectively. K c is the soil erodibility factor in pre-revision. mc, msilt, and ms represent percentage contents of clay (<0.002 mm), silt (0.002-0.050 mm), and sand (0.050-2.000 mm), respectively, in units of %. SOC is the percentage of soil organic carbon (%). λ is horizontal slope length (m), m is slope length index, and is slope degree (°). Detailed calculation methods for model factors refer to Masroor et al. [**?**].

The above four indicators (Ig, Iw, Ih, and Is) were projected to the UTM-WGS84 coordinate system at 1 km spatial resolution and 1 month temporal resolution during 2001-2020, then normalized to dimensionless form in the range of 0-1.

The weight for initial MRSEI (denoted as MRSEI$_0$) based on the four normalized indicators from 2001 to 2020 was calculated through PCA. This approach effectively avoids bias caused by artificially defined weights, making results more objective and reliable [?]. During 2001-2020, contribution rates of the first component (PC1) were all greater than 73.00%, indicating that PC1 integrated most characteristics of the four indicators (Fig. 3 [Figure 3: see original paper]); therefore, PC1 was selected to calculate MRSEI_0.

The MRSEI_0 formula is expressed as:

$$\mathrm{MRSEI}_0 = 0.35I_g + 0.63I_w - 0.68I_h + 0.06I_s$$

where MRSEI_0 is the initial MRSEI value (from -1.000 to 1.000) at different time scales (i.e., whole year, growing season, and non-growing season) for a given year.

To facilitate comparison among different time periods, we normalized MRSEI_0 values to obtain final MRSEI values based on Equation 13:

$$\mathrm{MRSEI} = \frac{\mathrm{MRSEI}_0 - \mathrm{MRSEI}_{0\mathrm{min}}}{\mathrm{MRSEI}_{0\mathrm{max}} - \mathrm{MRSEI}_{0\mathrm{min}}}$$

where MRSEI_0 and MRSEI_0 are the maximum and minimum MRSEI_0 values, respectively.

Higher MRSEI values indicate better ecological quality, while lower values represent poorer quality. According to the Technical Criterion for Ecosystem Status Evaluation issued by China' s Ministry of Environmental Protection [?], we divided MRSEI (0.000-1.000) into five grades: worst (0.000-0.200), poor (0.200-0.400), general (0.400-0.600), good (0.600-0.800), and best (0.800-1.000) for further analysis.

2.4.1 Path Analysis

Path analysis is widely used to explore causal structure patterns between dependent and independent variables based on factor analysis and multiple linear regression [?, ?]. In this study, we regarded MRSEI as the dependent variable and Ig, Iw, Ih, and Is as independent variables to clarify correlations between them and initially verify MRSEI reliability and effectiveness. The larger the absolute path coefficient value, the stronger the effect of the independent variable on MRSEI. Positive or negative path coefficients indicate promotion or inhibition of MRSEI, respectively.

2.4.2 Trend Analysis

Theil-Sen' s slope method is a robust nonparametric method for estimating linear trends [?, ?]. Therefore, it was used to calculate the slope of each variable in each pixel and analyze change trend distribution patterns [?]. The slope (β) represents the variable change rate. A negative slope (β<0) indicates decreasing variables; otherwise, variables are increasing (β>0). Additionally, the non-parametric Mann-Kendall test [?] evaluated variable change trend significance. MRSEI trends in Otindag Sandy Land were categorized as: significant increase (β>0 and P<0.05), increase (β>0 and P>0.05), significant decrease (β<0 and P<0.05), and decrease (β<0 and P>0.05).

2.4.3 Barycenter Model

Because dynamic barycenter variation can reflect contrast and shift in regional element distribution [?], it was used for spatial analysis of barycenter changes in this study. The MRSEI barycenter was calculated using:

$$X = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J} x_i \cdot \mathrm{CRR}_i}{\sum_{i=1}^{I}\sum_{j=1}^{J} \mathrm{CRR}_i}$$

$$Y = \frac{\sum_{i=1}^{I}\sum_{j=1}^{J} y_j \cdot \mathrm{CRR}_j}{\sum_{i=1}^{I}\sum_{j=1}^{J} \mathrm{CRR}_j}$$

where X and Y are latitude and longitude coordinates of the barycenter, respectively; x and y are latitude and longitude coordinates corresponding to the ith and jth pixels, respectively; I and J are numbers of latitude and longitude pixels, respectively; CRR and CRR are MRSEI values corresponding to the ith and jth pixels, respectively.

All data processing and analysis were executed in Python 3.7 (Anaconda Inc., Austin, USA), and visualization was conducted in OriginPro 2023 (OriginLab Inc., Northampton, USA) and ArcMap 10.2 (Esri Inc., Redlands, USA).

2.5 Validation

To further assess MRSEI feasibility, we compared MRSEI with traditional RSEI [?] and ARSEI for arid areas [?] based on 1-km MODIS datasets. RSEI was constructed with four indicators: greenness, wetness, dryness, and heatness, whereas ARSEI considered five indicators: greenness, wetness, heatness, salinity, and land degradation. In this study, we calculated RSEI and ARSEI in the growing seasons of 2001, 2005, 2010, 2015, and 2020 using PCA via Google Earth Engine. Detailed principles of RSEI and ARSEI can be found in Xu [?] and Wang et al. [?], respectively.

3.1 Feasibility Analysis of MRSEI

The four MRSEI indicators (Ig, Iw, Ih, and Is) were calculated by PCA based on their contribution rates. Because PC1 of the four indicators from 2001 to 2020 could integrate most indicator characteristics, we selected 2001 and 2020 as typical years for more detailed analysis. Subsequent path analysis further verified significant correlations between the four indicators and MRSEI.

As shown in Table 1 , PC1 loads for Ig, Iw, and Is were positive, with average PC1 load for Iw (0.63) larger than those for Is (0.06) and Ig (0.35). This indicated that all three indicators positively affected MRSEI, with Iw contribution rate higher than Is and Ig, consistent with path analysis results. This confirmed the actual situation that precipitation is the key environmental factor in this area. Conversely, PC1 loads for Ih were negative, with absolute average load value (0.68) greater than those for Ig, Iw, and Is. This indicated that Ih negatively affected MRSEI, with its contribution higher than Ig, Iw, and Is, also consistent with path analysis results. Additionally, the absolute PC1 load value for Ih was highest in 2001, but for Iw was highest in 2020, indicating that the main influencing indicator of MRSEI changed from Ih in 2001 to Iw in 2020. PC1 load values for the whole year were roughly similar to those in the growing season, implying that ecological quality was affected more across the whole year than just the growing season. Therefore, MRSEI based on PC1 is feasible for ecological quality assessment of Otindag Sandy Land.

As shown in Figure 4 [Figure 4: see original paper] based on path analysis, Iw was the most important indicator affecting MRSEI with highly significant correlation in all time periods from 2001 to 2020, followed by Ig, Ih, and Is in sequence. Ih and MRSEI were negatively correlated, with stronger correlation in the non-growing season. Ig was positively and significantly correlated with MRSEI, with correlation coefficients of 0.80 in the growing season and 0.66 in the non-growing season, indicating that vegetation status (greenness) influence weakened in the non-growing season. Path analysis results also verified MRSEI feasibility from another perspective.

3.2 Spatial Changes of Ecological Quality

Average MRSEI values in Otindag Sandy Land from 2001 to 2020 at different time scales are shown in Figures 5 and 6. Regions with worst and poor MRSEI grades at the whole-year scale were scattered in western Otindag Sandy Land (Fig. 5a1 [Figure 5: see original paper]), accounting for 10.55% and 17.29% of total area on average, respectively. As shown in Figure 5b1 and c1, regions with these grades (worst and poor) shrank in the growing season (8.92% and 15.96% of total area, respectively) but expanded to the east side of Otindag Sandy Land in the non-growing season (15.40% and 21.67% of total area, respectively). Additionally, increased areas with the worst MRSEI grade in the non-growing season expanded to most regions in Sonid Right Banner (Fig. 5c1). Conversely, regions with good and best MRSEI grades were mostly found in southeastern Otindag Sandy Land, accounting for 31.19% and 19.41% of total area, respectively (Fig. 5b1), but regions with the best MRSEI grade transformed to good and general grades in the non-growing season (Fig. 5c1). This resulted in regions with the best MRSEI grade decreasing to 8.58% of total area in the non-growing season.

Correspondingly, MRSEI variations across Otindag Sandy Land varied considerably in space over the past 20 years. At the whole-year scale, MRSEI increased in

96.56% of total area, with 75.62% showing significant increasing trends ($P<0.05$; Fig. 5a2). MRSEI increases in western and southern Otindag Sandy Land mainly occurred in the growing season (Fig. 5b2), while increases in northern and eastern parts mostly occurred in the non-growing season (Fig. 5c2). In contrast, MRSEI at the whole-year scale decreased in remaining regions (3.44% of total area), mostly distributed in Taibus Banner in southern Otindag Sandy Land, primarily due to ecological degradation in the non-growing season. Additionally, regions with decreased MRSEI reached 18.64% of total area in the non-growing season, scattered across southern, western, and northern parts of Otindag Sandy Land; however, only 0.27% showed significant MRSEI decrease ($P<0.05$). Comparison of MRSEI in 2001, 2005, 2010, 2015, and 2020 further indicated that ecological quality in the growing season was stably improved across Otindag Sandy Land, while MRSEI in the non-growing season showed stronger inter-annual fluctuation (Fig. S1). Severe ecological quality degradation occurred in the non-growing season of 2010, mainly in southern and northern parts of Otindag Sandy Land (Fig. S1). Overall, ecological quality improved across most regions of Otindag Sandy Land from 2001 to 2020, though some small patches showed degradation.

Table 2 shows the MRSEI grade area transfer matrix at the whole-year scale from 2001 to 2020. Relative to 2001, areas with best, good, and general MRSEI grades increased in 2020, while areas with worst and poor grades decreased. Areas with best and good grades increased by 20,493.89 km^2 (from 30,214.83 km^2 in 2001 to 47,105.73 km^2 in 2020 for the best grade, and from 42,136.76 km^2 in 2001 to 45,739.75 km^2 in 2020 for the good grade), accounting for 9.77% and 2.09% of total area, respectively, with most converted from general-grade areas (19,351.89 km^2) and 1,142.00 km^2 from worse and poor-grade areas. Meanwhile, area degrading from good to general grade was 2,254.99 km^2. General-grade area in 2020 increased by 10,668.94 km^2, accounting for 6.17% of total area. Worst-grade area significantly decreased by 27,357.84 km^2 (from 35,832.79 km^2 in 2001 to 8,474.95 km^2 in 2020), indicating that only 4.90% of Otindag Sandy Land had the worst MRSEI grade in 2020.

3.3 Temporal Evolution of Ecological Quality

Figure 7a [Figure 7: see original paper] shows temporal variations in ecological quality of Otindag Sandy Land from 2001 to 2020. MRSEI in the growing season exhibited a significant increasing trend with a change rate of 0.004/a ($P<0.05$) from 2001 to 2020. The corresponding trend in the non-growing season slowed after 2010 with insignificant change rate ($P>0.05$). Additionally, inter-annual fluctuation was high in the non-growing season, such as the dramatic decline from 2015 to 2018. Due to growing season MRSEI dominance, whole-year MRSEI change followed the growing season trend, increasing significantly at 0.006/a ($P<0.05$) from 2001 to 2020.

Figures 7b–d depict MRSEI barycenter movements from 2001 to 2020. The longitudinal barycenter of whole-year MRSEI declined ($P<0.05$) and tended to move 0.2° westward. However, the latitudinal barycenter barely changed and did not pass significance testing (P>0.05). Longitudinal and latitudinal barycenter changes at the whole-year scale were basically determined by growing season shifts. Non-growing season longitudinal and latitudinal barycenters showed insignificant increasing trends (P>0.05), with the longitudinal barycenter inclining back eastward and the latitudinal barycenter at higher latitude. Longitudinal barycenter movement direction in the non-growing season was opposite to that in the growing season in some years (e.g., 2005 and 2015). Overall, the MRSEI barycenter in Otindag Sandy Land tended to move westward, indicating that ecological quality in western Otindag Sandy Land improved significantly over the past 20 years.

3.4 Impact of Climate and Land Cover on Ecological Quality

Figures 8a1 and a2 depict relationships between MRSEI changes and precipitation and air temperature variations. Precipitation was positively related to MRSEI; specifically, precipitation increased by 1.5 mm/a, corresponding to MRSEI increase of 0.002 ($±0.002)$per year (Fig. 8a1). In contrast, air temperature was negatively related to MRSEI (Fig.$
per year. However, precipitation and air temperature were not linearly related to MRSEI changes. MRSEI change magnitude became more apparent when precipitation increase exceeded 4.5 mm/a and air temperature decrease exceeded 0.02°C/a. As seen in Figure 8a2, precipitation showed increasing trends across Otindag Sandy Land, with change rates of 1.5–4.5 mm/a in over 76.49% of total area, whereas precipitation increases exceeding 4.5 mm/a occurred only in central Sonid Right Banner and Sonid Left Banner in western Otindag Sandy Land. Correspondingly, air temperature decreased in the same regions where precipitation increase exceeded 4.5 mm/a (Fig. 8b2). This synergistic effect directly increased MRSEI, significantly improving ecological quality from worst to poor or general grades (Figs. 5 and S1).

Land cover types had different effects on MRSEI. For the four major land cover types in Otindag Sandy Land (forestland, cropland, grassland, and bare land), multi-year average MRSEI values were 0.805, 0.779, 0.544, and 0.433, respectively (Fig. 8c1). For land cover changes (Fig. 8c2), MRSEI increased by 0.004 ($±0.004)$per year for both cropland-to-grassland conversion and grassland-to-cropland inversion. Bare land to grassland transformation increased MRSEI by 0.006 (±0.004) per year. Affo$
per year.

4.1 Validation of MRSEI Effectiveness

We examined MRSEI' s ability to capture local texture information of water bodies and topography (Fig. 9 [Figure 9: see original paper]). Figure 9a showed that MRSEI could accurately capture Dalai Nur Lake' s shape and presence of small lakes, as well as higher vegetation coverage in eastern Otindag Sandy Land where MRSEI values were also higher. Meanwhile, MRSEI accurately captured annular vegetation coverage zones with topographic changes, and buildings in the southeastern part of the annular zone corresponded to lower MRSEI values (Fig. 9b). Clearly, MRSEI could well reflect actual land surface conditions in Otindag Sandy Land.

Comparisons of PC1 contribution rates for RSEI, MRSEI, and ARSEI indicators in growing seasons of 2001, 2005, 2010, 2015, and 2020 are shown in Figure 10a [Figure 10: see original paper]. PC1 contribution rates for MRSEI indicators were highest in all years, followed by RSEI and ARSEI indicators. Furthermore, spatiotemporal variations were compared among these three indices (Fig. 10b). RSEI, ARSEI, and MRSEI depicted similar low-high zonal changes, with values increasing from west to east and culminating at nearly 117°–118°E, but showed different spatial heterogeneity, with MRSEI highest and RSEI lowest. Interestingly, all three indices exhibited increasing temporal trends, but their change rates differed slightly. Overall, all three indices reflected ecological quality improvement in Otindag Sandy Land over the past 20 years. However, RSEI did not consider local Otindag Sandy Land characteristics (e.g., soil erosion) in drylands even though PC1 contribution rates for RSEI indicators exceeded 70.00%. PC1 contribution rates for ARSEI indicators ranged between 56.50%–68.38%. In such cases, considering only PC1 may omit much information [?]. Therefore, MRSEI can be considered an effective alternative index for ecological quality assessment in Otindag Sandy Land. Our results also showed that indicator selection should ideally be adapted to local conditions to accurately characterize regional ecological quality changes.

4.2 Impact of Climate and Land Cover on MRSEI

Based on PCA and path analysis results, the wetness indicator played a major role in improving ecological quality, confirming the pivotal status of water resources in arid and semi-arid areas [?]. In Otindag Sandy Land, precipitation is higher in eastern and northeastern parts [?], consistent with MRSEI spatial distribution. The western part with less precipitation and sparser vegetation [?] was rated as the region with worst MRSEI grade. Fragile ecosystems in Otindag Sandy Land are sensitive to water resources, and spatial water resource differences can lead to ecological quality heterogeneity.

Overall ecological quality in Otindag Sandy Land improved from 2001 to 2020, but showed large inter-annual variations. Improved regions accounted for approximately 96.56% of total area. The main reason is that climate in Otindag Sandy Land is becoming more humid [?, ?], as shown in Figure 8, which helps alleviate local water resource shortages. Increased precipitation tends to improve vegetation coverage, especially in western Otindag Sandy Land with grasslands and bare lands [?], where MRSEI increased significantly and ecological quality improved (Fig. 5). However, reported warming in the non-growing season might increase evapotranspiration and dry out soils [?, ?]. Vegetation and soil condition improvements in the growing season were interrupted or deteriorated in the following non-growing season (Fig. 5). These results indicate that ecological quality has seasonal changes, and attention should be paid to seasonal degradation. Given that future climate will become more humid in this region, there remains room for sustainable ecological improvement from a water supply perspective.

In addition to climate change impacts, implementation of ecological restoration measures in Otindag Sandy Land—such as maintaining grass-livestock balance, returning farmland to forests, and implementing enclosures and grazing prohibitions [?, ?]—can improve ecological quality. Due to these measures' effectiveness, regional vegetation has been restored, alleviating ecological deterioration, especially for grasslands and bare lands. Combined with precipitation increases, many regions with poorer ecological quality (worst and poor grades) transformed into regions with better quality (general, good, and best grades). Afforestation in forest regions of eastern Otindag Sandy Land with richer precipitation directly increased NDVI, thereby enhancing ecological quality. However, afforestation may lower groundwater levels in arid areas [?, ?]. We therefore recommend that local climate change and water resources be fully considered when implementing ecological restoration measures.

Regarding land cover and land use change, grassland is the dominant land cover type in Otindag Sandy Land; grassland quality has improved over the last 20 years due to increased precipitation and ecological restoration measures. Land cover types with denser vegetation had higher MRSEI values. However, this does not mean that higher MRSEI changes in regions with denser vegetation are always positive. For example, higher MRSEI in southern Otindag Sandy Land decreased, especially in the non-growing season. As shown in Figure 1, transformation of grasslands to croplands and cropland expansion in southern Otindag Sandy Land may lead to soil salinization and natural habitat degradation [?, ?], explaining degradation in southern Otindag Sandy Land with good ecological quality, especially in Taibus Banner. In sum, ecological restoration is important for sustainable development, but local economic benefits from agriculture and husbandry expansion must not be ignored. Thus, balancing local economic benefits and ecological revitalization is the most crucial factor for regional ecological sustainability.

Although MRSEI changes showed gradually improving ecological quality in Otindag Sandy Land, uncertainties remain for future ecological quality restoration. According to previous studies [?], these highly precipitation-sensitive regions are ecologically fragile and vulnerable to droughts due to rain-fed vegetation properties, so both significant inter-annual and seasonal precipitation fluctuations and increased water consumption from rapid warming can increase short-term drought threats to local ecosystems [?]. Thus, seasonal evaluation of ecological conditions and corresponding conservation measures are very important. How to reasonably and scientifically formulate measures to improve Otindag' s ecological quality according to local characteristics and environmental conditions requires further evaluation. Based on this study, priority should be given to maintaining natural landscapes and avoiding overgrazing in western

Otindag Sandy Land with scarce water resources. In regions with severe ecological degradation, graded governance implementation and encouraging local tourism are essential to satisfy harmonious economic and natural development. On the other hand, since MRSEI development aims to explore ecological quality in Otindag Sandy Land with typical dryland ecosystems, its practicality is temporarily limited to dryland ecosystems, and whether it can be extended to broader areas needs further research.

5 Conclusions

In this study, we constructed MRSEI integrating greenness, wetness, heatness, and soil erosion indicators coupled with local characteristics and environmental conditions based on PCA and path analysis to evaluate ecological quality in Otindag Sandy Land from 2001 to 2020. All PC1 contribution rates exceeded 73.00% during 2001–2020. MRSEI based on PC1 appeared promising for Otindag Sandy Land. PCA and path analysis results showed that greenness, wetness, and soil erosion indicators had positive effects on MRSEI, whereas heatness had a negative effect. PC1 contribution rate for wetness was highest, followed by heatness, greenness, and soil erosion.

Over the past 20 years (2001–2020), ecological quality changes in Otindag Sandy Land showed seasonal and regional differences. Ecological quality improved significantly in the growing season but fluctuated with an insignificant increasing trend in the non-growing season. Spatially, regions with good and best MRSEI grades were mostly distributed in eastern Otindag Sandy Land, while regions with worst and poor grades concentrated in western Otindag Sandy Land. However, regions with worst and poor MRSEI grades accounted for 8.92% and 15.96% of total area in the growing season but 15.40% and 21.67% in the non-growing season. Ecological quality improved in most regions during the growing season but degraded in western, northern, and southern parts during the non-growing season (18.64% of total area). Altogether, worst-grade MRSEI area shrank by 15.83% of total area during the study period, from 35,832.79 km^2 in 2001 to 8,474.95 km^2 in 2020, while best-grade MRSEI area in the east increased by 9.77% of total area from 30,214.83 km^2 in 2001 to 47,105.73 km^2 in 2020. Over time, spatiotemporal ecological quality variations differed by season. Such seasonal differences should be considered to better reflect ecological quality assessment results. For multi-year analysis, we suggest selecting indicators to represent seasonal ecological conditions according to local study area characteristics.

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References

[?] Allen R G, Pereira L S, Raes D, et al. 1998. Crop evapotranspiration: Guidelines for computing crop requirements. In: FAO Irrigation and Drainage Paper 56. Rome: FAO, 17–25.

[?] Chen J Q, John R, Sun G, et al. 2018. Prospects for the sustainability of social-ecological systems (SES) on the Mongolian Plateau: five critical issues. Environmental Research Letters, 13(12): 123004, doi: 10.1088/1748-9326/aaf27b.

[?] Chen J Q. 2021. Biophysical Models and Applications in Ecosystem Analysis. East Lansing: Michigan State University Press.

[?] Chen J Q, John R, Yuan J, et al. 2022. Sustainability challenges for the social-environmental systems across the Asian Drylands Belt. Environmental Research Letters, 17(2): 023001, doi: 10.1088/1748-9326/ac472f.

[?] Chen Z F, Wang W G, Fu J Y. 2020. Vegetation response to precipitation anomalies under different climatic and biogeographical conditions in China. Scientific Reports, 10(1): 830, doi: 10.1038/s41598-020-57910-1.

[?] Cong W W, Li X Y, Pan X B, et al. 2022. A new scientific framework of dryland ecological quality assessment based on 1OAO principle. Ecological Indicators, 136: 108595, doi: 10.1016/j.ecolind.2022.108595.

[?] Coutts A M, Harris R J, Phan T, et al. 2016. Thermal infrared remote sensing of urban heat: Hotspots, vegetation, and an assessment of techniques for use in urban planning. Remote Sensing of Environment, 186: 637–651.

[?] Fan Y, Chen J Q, Shirkey G, et al. 2016. Applications of structural equation modeling (SEM) in ecological studies: an updated review. Ecological Processes, 5: 19, doi: 10.1186/s13717-016-0063-3.

[?] Fernandes T J G, del Campo A D, Herrera R, et al. 2016. Simultaneous assessment, through sap flow and stable isotopes, of water use efficiency (WUE) in thinned pines shows improvement in growth, tree-climate sensitivity and WUE, but not in WUEi. Forest Ecology and Management, 361: 298–308.

[?] Fick S E, Hijmans R J. 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology, 37(12): 4302–4315.

[?] Guo B B, Zhang J, Meng X Y, et al. 2020. Long-term spatio-temporal precipitation variations in China with precipitation surface interpolated by ANUSPLIN. Scientific Reports, 10(1): 81, doi: 10.1038/s41598-019-57078-3.

[?] Hang X, Li Y C, Luo X C, et al. 2020. Assessing the ecological quality of Nanjing during its urbanization process by using satellite, meteorological, and socioeconomic data. Journal of Meteorological Research, 34(2): 280–293.

[?] Huang J, Chen J H, Zhang F M. 2021. Spatio-temporal evolution of climate-induced reduction risk for winter wheat in Anhui Province based on principal component analysis. Chinese Journal of Applied Ecology, 32(9): 3185–3194. (in Chinese)

[?] Hutchinson M F, Xu T. 2013. Anusplin version 4.4 user guide. [2022-03-30]. http://fennerschool.anu.edu.au/files/anusplin44.pdf.

[?] IPCC. 2019. Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. In: Climate Change and Land. Shukla P R, Skea J, Calvo Buendia E, et al. Geneva: IPCC.

[?] Jiang F, Zhang Y Q, Li J Y, et al. 2021. Research on remote sensing ecological environmental assessment method optimized by regional scale. Environmental Science and Pollution Research, 28(48): 68174–68187.

[?] John R, Chen J Q, Ou-Yang Z T, et al. 2013. Vegetation response to extreme climate events on the Mongolian Plateau from 2000 to 2010. Environmental Research Letters, 8(3): 035033, doi: 10.1088/1748-9326/8/3/035033.

[?] John R, Chen J, Lu N, et al. 2009. Land cover/land use change in semi-arid Inner Mongolia: 1992–2004. Environmental Research Letters, 4(4): 045010, doi: 10.1088/1748-9326/4/4/045010.

[?] Liu S L, Wang T. 2010. Regionalization for aeolian desertification control and countermeasures in the Otindag Sandy Land Region, China. Journal of Desert Research, 30(5): 999–1005. (in Chinese)

[?] Lou J P, Wang X M, Cai D W. 2019. Spatial and temporal variation of wind erosion climatic erosivity and its response to ENSO in the Otindag Desert, China. Atmosphere, 10: 614, doi: 10.3390/atmos10100614.

[?] Lu C X, Zhao T Y, Shi X L, et al. 2018. Ecological restoration by afforestation may increase groundwater depth and create potentially large ecological and water opportunity costs in arid and semiarid China. Journal of Cleaner Production, 176: 1–11.

[?] Ma W Y, Wang X M, Zhou N, et al. 2017. Relative importance of climate factors and human activities in impacting vegetation dynamics during 2000–

2015 in the Otindag Sandy Land, northern China. Journal of Arid Land, 9(4): 558-567.

[?] Mamat Z, Halik Ü, Keyimu M, et al. 2018. Variation of the floodplain forest ecosystem service value in the lower reaches of Tarim River, China. Land Degradation & Development, 29(1): 47-57.

[?] Masroor M, Sajjad H, Rehman S, et al. 2022. Analysing the relationship between drought and soil erosion using vegetation health index and RUSLE models in Godavari middle sub-basin, India. Geoscience Frontiers, 13(2): 101312, doi: 10.1016/j.gsf.2021.101312.

[?] Niu L N, Shao Q Q, Ning J, et al. 2023. The assessment of ecological restoration effects on Beijing-Tianjin Sandstorm Source Control Project area during 2000-2019. Ecological Engineering, 186: 106831, doi: 10.1016/j.ecoleng.2022.106831.

[?] Priyadarshi N, Chowdary V M, Srivastava Y K, et al. 2018. Reconstruction of time series MODIS EVI data using de-noising algorithms. Geocarto International, 33(10): 1095-1113.

[?] Qureshi S, Alavipanah S K, Konyushkova M, et al. 2020. A remotely sensed assessment of surface ecological change over the Gomishan Wetland, Iran. Remote Sensing, 12(18): 2989, doi: 10.3390/rs12182989.

[?] Shao W Y, Wang Q Z, Guan Q Y, et al. 2022. Distribution of soil available nutrients and their response to environmental factors based on path analysis model in arid and semi-arid area of northwest China. Science of The Total Environment, 827: 154254, doi: 10.1016/j.scitotenv.2022.154254.

[?] Shi L, Zhang Z J, Zhang C Y, et al. 2004. Effects of sand burial on survival, growth, gas exchange and biomass allocation of Ulmus pumila seedlings in the Hunshandak Sandland, China. Annals of Botany, 94(4): 553-560.

[?] Sun B, Wang Y, Li Z Y, et al. 2019. Estimating soil organic carbon density in the Otindag Sandy Land, Inner Mongolia, China, for modelling spatiotemporal variations and evaluating the influences of human activities. CATENA, 179: 85-97.

[?] Tang L P, Ke X L, Chen Y Y, et al. 2021. Which impacts more seriously on natural habitat loss and degradation? Cropland expansion or urban expansion? Land Degradation & Development, 32(2): 946-964.

[?] Tian Q J, Min X J. 1998. Advances in study on vegetation indices. Advances in Earth Science, 13(4): 327-333. (in Chinese)

[?] Toy T J, Osterkamp W R. 1995. The applicability of RUSLE to geomorphic studies. Journal of Soil and Water Conservation, 50(5): 498-503.

[?] Wang J, Ma J L, Xie F F, et al. 2020. Improvement of remote sensing ecological index in arid regions: Taking Ulan Buh Desert as an example. Chinese Journal of Applied Ecology, 31(11): 3795-3804. (in Chinese)

[?] Wang J, Liu D X, Ma J L, et al. 2021. Development of a large-scale remote sensing ecological index in arid areas and its application in the Aral Sea Basin. Journal of Arid Land, 13(1): 40-55.

[?] Wang X M, Lou J P, Ma W Y, et al. 2017. The impact of reclamation on aeolian desertification of four species in the Otindag Desert, China. CATENA, 157: 189-194.

[?] Wei W, Shi S N, Zhang X Y, et al. 2020. Regional-scale assessment of environmental vulnerability in an arid inland basin. Ecological Indicators, 109: 105792, doi: 10.1016/j.ecolind.2019.105792.

[?] Wen H, Chen J Q, Wang Z F. 2020. Disproportioned performances of protected areas in the Beijing-Tianjin-Hebei Region. Sustainability, 12(16), 6404, doi: 10.3390/su12166404.

[?] Wu R N, Cong W W, Li Y H, et al. 2019. The scientific conceptual framework for ecological quality of the dryland ecosystem: Concepts, indicators, monitoring and assessment. Journal of Resources and Ecology, 10(2): 196-201.

[?] Wu S P, Gao X, Lei J Q, et al. 2022. Ecological environment quality evaluation of the Sahel region in Africa based on remote sensing ecological index. Journal of Arid Land, 14(1): 14-33.

[?] Wu Z T, Wu J J, Liu J H, et al. 2013. Increasing terrestrial vegetation activity of ecological restoration program in the Beijing-Tianjin Sand Source Region of China. Ecological Engineering, 52: 37-50.

[?] Xu H Q. 2013. A remote sensing index for assessment of regional ecological changes. China Environmental Science, 33(5): 889-897. (in Chinese)

[?] Xu H Q, Wang M Y, Shi T T, et al. 2018. Prediction of ecological effects of potential population and impervious surface increases using a remote sensing based ecological index (RSEI). Ecological Indicators, 93: 730-740.

[?] Xu H Q, Wang Y F, Guan H D, et al. 2019. Detecting ecological changes with a remote sensing based ecological index (RSEI) produced time series and change vector analysis. Remote Sensing, 11(20): 2345, doi: 10.3390/rs11202345.

[?] Xu L L, Yu G M, Zhang W J, et al. 2020. Change features of time-series climate variables from 1962 to 2016 in Inner Mongolia, China. Journal of Arid Land, 12(1): 58-72.

[?] Yang X Y, Meng F, Fu P J, et al. 2022a. Time-frequency optimization of RSEI: A case study of Yangtze River Basin. Ecological Indicators, 141: 109080, doi: 10.1016/j.ecolind.2022.109080.

[?] Yang X Y, Meng F, Fu P J, et al. 2022b. Instability of remote sensing ecological index and its optimisation for time frequency and scale. Ecological Informatics, 72: 101870, doi: 10.1016/j.ecoinf.2022.101870.

[?] Yao K X, Halike A, Chen L M, et al. 2022. Spatiotemporal changes of eco-environmental quality based on remote sensing-based ecological index in the Hotan Oasis, Xinjiang. Journal of Arid Land, 14(3): 262–283.

[?] Ye X, Kuang H H. 2022. Evaluation of ecological quality in southeast Chongqing based on modified remote sensing ecological index. Scientific Reports, 12(1): 15694, doi: 10.1038/s41598-022-19851-9.

[?] Yuan Z H, Bao G, Yin S, et al. 2016. Vegetation changes in Otindag sand country during 2000–2014. Acta Prataculturae Sinica, 25(1): 33–46. (in Chinese)

[?] Zhang Q, Yang Z S, Hao X C, et al. 2019. Conversion features of evapotranspiration responding to climate warming in transitional climate regions in northern China. Climate Dynamics, 52(7): 3891–3903.

[?] Zhao X, Wang P, Yasir M, et al. 2022. Decision support system based on spatial and temporal pattern evolution of ecological environmental quality in the Yellow River Delta from 2000 to 2020. Soft Computing, 26(20): 11033–11044.

[?] Zhao X H, Zhang F M, Han D C, et al. 2021. Evapotranspiration changes and its attribution in semi-arid regions of Inner Mongolia. Arid Zone Research, 38(6): 1614–1623. (in Chinese)

[?] Zheng Z H, Wu Z F, Chen Y B, et al. 2022. Instability of remote sensing based ecological index (RSEI) and its improvement for time series analysis. Science of The Total Environment, 814: 152595, doi: 10.1016/j.scitotenv.2021.152595.

[?] Zhu D Y, Chen T, Wang Z W, et al. 2021. Detecting ecological spatial-temporal changes by Remote Sensing Ecological Index with local adaptability. Journal of Environmental Management, 299: 113655, doi: 10.1016/j.jenvman.2021.113655.

[?] Zhuang Q W, Shao Z F, Huang X, et al. 2021. Evolution of soil salinization under the background of landscape patterns in the irrigated northern slopes of Tianshan Mountains, Xinjiang, China. CATENA, 105561, 10.1016/j.catena.2021.105561.

Appendix

Fig. S1 [FIGURE:S1] Spatial distributions of MRSEI at whole year (a1–a5), growing season (b1–b5), and non-growing season (c1–c5) scales in 2001, 2005, 2010, 2015, and 2020 in Otindag Sandy Land

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