



# Spatiotemporal change and driving factors of ecological status in Inner Mongolia based on the modified remote sensing ecological index

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## Abstract

Remote sensing monitoring of regional ecological quality has advanced significantly with the rapid developments of remote sensing technology. At present, remote sensing ecological index (RSEI) has been widely used in ecological status monitoring. However, RSEI was proposed for urban environments, and the rationality and accuracy of its applicability to desert-dominated arid region ecosystems need to be demonstrated. Therefore, in this study, we incorporated desertification monitoring index (DMI) and salinity monitoring index (SMI) to RSEI and developed the modified remote sensing ecological index (MRSEI) for arid regions. Moreover, we analyzed the stability of MRSEI in ecological status monitoring for arid regions. The MRSEI was then used to evaluate the ecological quality of Inner Mongolia from 2000 to 2020 and exploring its causes. The results show that (1) Although the evaluation results of RSEI and MRSEI are more consistent in areas with high ecological status grades, the MRSEI results are more cautious and reliable in extreme conditions (e.g., desertification, salinization) than the RSEI. (2) Approximately 87.66% of ecological quality have improved or remain stable from 2000 to 2020, but the remaining areas (accounting for 12.34% of the whole area) are still under degraded conditions. This demonstrates that although local governments have made some progress in ecological conservation, the areas that are fluctuating or degraded still require protection or management. (3) In Inner Mongolia, the ecological quality which drove by precipitation (P) & temperature (T) accounting for 26.67% of the study area, population density (D) and GDP per capita (G) affected 13.23% of regional ecological quality. Overall, this research is crucial for evaluating spatial and temporal changes in arid region ecology and establishing conservation strategies.

**Keywords** Remote sensing · RSEI · Inner Mongolia · Modis · Ecological status · Spatiotemporal changes

## Introduction

Environmental problems such as desertification, drought, and climate change have negatively affected the sustainable development of socio-economic ecosystems (Wei et al. 2020). At the same time, human activities have generated great pressure on the regional environment, especially in the arid and semi-arid regions, where the environment has

grown vulnerable (Cheng et al. 2022). Therefore, in order to comprehend the characteristics and changes, ecological quality must be monitored and assessed. Inner Mongolia, China, is a typical arid and semi-arid region, which is a case of environmental research in the arid region. In recent years, Inner Mongolia has been affected by both natural and human disturbances (Zhang et al. 2020; Xu et al. 2020); environmental issues such as desertification (Yu et al. 2020), salinization (Zhang et al. 2015), and grassland degradation (Xin et al. 2020) have developed increasingly. In view of this, efficient and accurate monitoring of ecological status, dynamic changes, and its drivers in Inner Mongolia is critical to advancing sustainable development goals.

Remote sensing technology has the advantages of large-scale and macroscopic monitoring, which provides an effective method for monitoring the ecological environment quality in Inner Mongolia (Huang et al. 2021; Wei et al. 2019).

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Generally, numerous assessment models use a single-remote sensing spectral inversion index, such as vegetation coverage (Liu et al. 2021), normalized difference vegetation index (NDVI) (Chen et al. 2022), normalized difference building index (NDBSI) (Kim et al. 2020), or land surface temperature (LST) (Li et al. 2022a). Although the indices mentioned above can describe changes in a single-ecosystem component, in fact, the interactions between each environmental component in an ecosystem have the potential to affect the whole ecosystem and they are interdependent (Suter et al. 2010). Consequently, integrating multiple indicators can more comprehensively describe the ecological status (Pariha et al. 2021), and the inversion models that combine multiple environment elements are applied to numerous studies. For example, the ecological index (EI) integrates multiple factors such as biological abundance, vegetation cover, water network density, land degradation, and environmental quality (Jing et al. 2020). However, there are significant limitations to EI, such as the weight of each indicator being set by the researcher's personal experience. In addition, the indicators used for EI calculation are difficult to obtain, making EI evaluation more complex. Based on this, Xu (2013) developed the remote sensing ecological index (RSEI) by integrating four indicators: NDVI, Wet, LST, and NDBSI. In recent years, RSEI has been widely used in monitoring ecological quality because it is easy to obtain from remote sensing data and is unaffected by subjective intervention. At the local scale, Hang et al. (2020) used Nan Jing, Jiang Su Province, as the study area to monitor the ecological quality based on the RSEI. Liu et al. (2020) calculated the RSEI of Pingtan County, Fujian Province, which was used to evaluate the trend of the ecological environment in the study area. At the regional scale, Xu et al. (2019) calculated the RSEI from 2002 to 2017 using Moderate Resolution Imaging Spectroradiometer (MODIS) data to analyze ecological changes in Fujian Province, China. Yang et al. (2021) calculated the RSEI of the Yangtze River basin based on the MODIS product image set and analyzed the ecological quality of the study area as well as the driving forces. Overall, RSEI expands ecological quality evaluation through remote sensing technology, which benefits regional ecological quality monitoring and protection.

However, RSEI is not without flaws, and it is still being discovered to have disadvantages in its application. The RSEI is proposed for urban environments, with application scenarios focusing on human gathering locations or river and lake basin areas with generally "excellent" ecological conditions. Therefore, the RSEI's rationality and accuracy for arid region ecosystems need to be further proved (Firozjahi et al. 2021). Based on this, Wang et al. (2020a) took the Ulan Buh Desert as the study area and proposed the arid remote sensing ecological index (ARSEI) by replacing the dryness index with the salinization index and land degradation index.

In this study, the land degradation index was obtained by assigning values on various land types and then calculated the ARSEI; however, when the study area is large, assigning values to land types is insufficient to meet the pixel-level monitoring accuracy. In order to make the indicators suitable for the arid region, and meet pixel-level monitoring requirements, it is required to adapt the indicators to the real condition of the study area when utilizing RSEI to evaluate the ecological quality of the arid region. The current study, however, lacks a comparative analysis of the applicability of different indicators and methodologies.

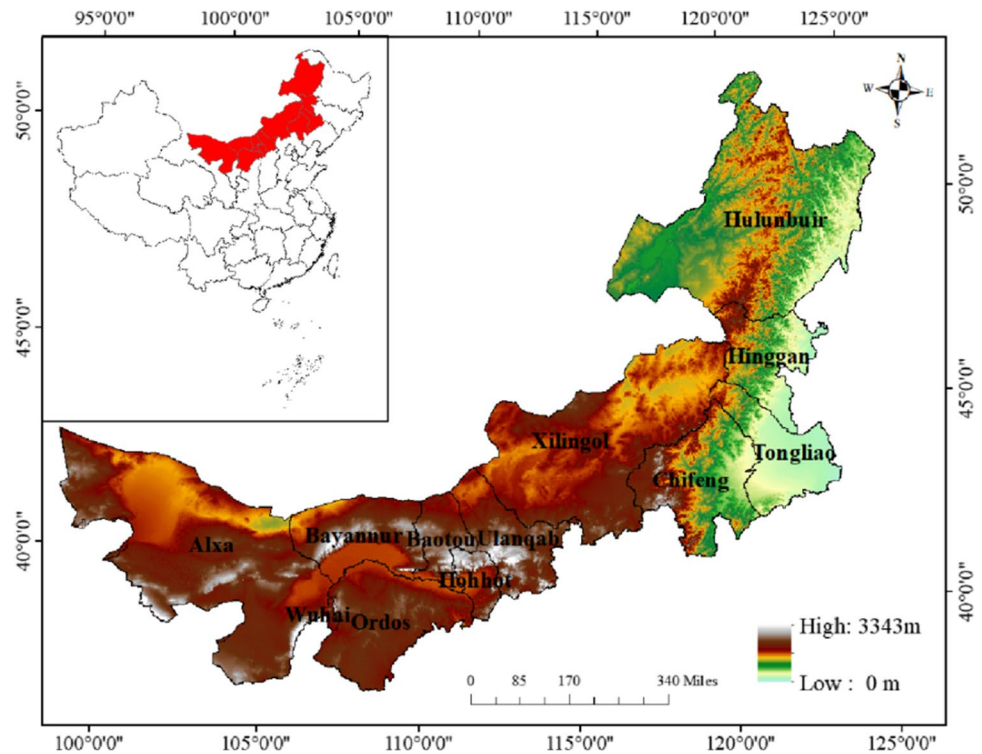
In Inner Mongolia, China, there are 1.057 million hectares of salinized cultivated (Zhang et al. 2018) and 40.79 million hectares of desertification (Zhao et al. 2020), which have a significant impact on the region's ecological stability. Therefore, when assessing the ecological quality in Inner Mongolia, the ecological effects of salinization and desertification should be fully considered as well. Bai et al. (2022) suggested a desertification monitoring index (DMI) that can identify potentially the status of desertification in the study area. Guo et al. (2019b) proposed a salinity monitoring index (SMI) that can accurately monitor land salinity. In addition, SMI and DMI can meet pixel-level monitoring requirements. In view of this, our study took Inner Mongolia as an example and developed the modified remote sensing ecological index (MRSEI) for arid regions by adding two indicators of SMI and DMI on the basis of the original RSEI in order to expand the applicability of RSEI in arid regions. Then, the applicability of MRSEI and RSEI was compared and analyzed. Finally, the trends in ecological quality in Inner Mongolia from 2000 to 2020 were determined, and the degree of ecological quality response to the drivers in the study area was analyzed.

## Study area and data sources

### Study area

Inner Mongolia is located in the northern part of China (37°24'N ~ 53°23'N, 97°12'E ~ 126°04'E) (Fig. 1), and comprises 1.18 million km<sup>2</sup> of land, which accounts for more than 12.3% of China. Inner Mongolia has a typical temperate continental climate; the average annual temperature is around 0–8°C, and between 50 and 450 mm of precipitation on average from west to east (Tian et al. 2018). The terrain of Inner Mongolia is dominated by plateaus, and the average altitude of the whole region is greater than 1000 m. The vegetation types vary and include both coniferous and broad-leaved forests, forested prairies, temperate prairies, desert steppes, and deserts intergrading (Wang et al. 2020b). Inner Mongolia has the largest grasslands in China and is

**Fig. 1** Research region overview



one of the most important bases for agriculture and livestock production, both of which are extremely sensitive to drought.

**Data sources**

We used the Moderate Resolution Imaging Spectroradiometer (MODIS) provided by the US Geological Survey (USGS, <https://earthexplorer.usgs.gov>) as the primary data source for our study. There are numerous standardized products in the MODIS dataset, including surface reflectance, vegetation index, land surface temperature (LST), and land use classification products. Therefore, the standard products for each ecological component needed to construct MRSEI and RSEI were selected from the MODIS product library. MODIS products from 2000, 2005, 2010, 2015, and 2020 were selected as the primary data source for our study. The description of these products is shown in Table 1, and to maintain a consistent spatial resolution, all standard products were resampled to 1 km in this paper. Additionally, we obtained precipitation data of stations from

the China Meteorological Data Network (<http://data.cma.cn>), and we interpolated the station data using the inverse distance weight method to obtain 1 km × 1 km precipitation raster data. The population density and GDP per capita in Inner Mongolia come from the Inner Mongolia Statistical Yearbook.

**Methods**

**Methods of previous RSEI**

**Standardization of indexes**

According to the scheme proposed by Xu (2013), RSEI integrates four ecological elements including greenness (NDVI), wetness (WET), heat (LST), and dryness (NDBSI), which are correlated to ecological status. Four elements are calculated based on MODIS data (Lobser and Cohen 2007; Xu 2008). These indices can be divided into two categories:

**Table 1** Data source

Data set	Resolution	Time resolution	Platform	Coordinate system	Products	Product level
MOD13A1	500 m	16 days	Terra	Sinusoidal	NDVI	L3
MOD11A2	1000 m	8 days	Terra	Sinusoidal	LST	L3
MOD09A1	500 m	8 days	Terra	Sinusoidal	Surface reflectance	L2
MCD12Q1	500 m	1 year	Terra	Sinusoidal	Land use	L3

positive and negative. Positive index means that the better the ecological quality, the higher the index value; negative index means that the better the ecological quality, the lower the index value. In reference to existing research (Wei et al. 2019), NDVI and Wet were positive indices, and NDBSI and LST were negative indices. In order to unify the magnitudes of these indicators, the normalization of each indicator was required, where Eq. (1) and Eq. (2) are the standard calculation formulas. Positive index dimensionless evaluation dataset was obtained by Eq. (1), while negative index dimensionless evaluation dataset was obtained by Eq. (2).

$$Y_i = (X_i - X_{\min}) / (X_{\max} - X_{\min}) \quad (1)$$

$$Y_i = (X_{\max} - X_i) / (X_{\max} - X_{\min}) \quad (2)$$

where  $Y_i$  is the standardized value,  $X_i$  is the primitive value, and  $X_{\max}$  and  $X_{\min}$  are the maximum and minimum values of the  $X_i$ , respectively.

### Calculation of the RSEI

Based on the normalized elements, the first principal component after principal component analysis (PCA) was used to develop the RSEI, as shown in Eq. (3) (Yuan et al. 2021). In addition, our study normalized the RSEI derived by PCA to facilitate the spatial and temporal analysis of the ecological quality of the study region, which can be calculated as Eq. (4).

$$RSEI_0 = PC1(\textit{Greenness}, \textit{Wetness}, \textit{Heat}, \textit{Dryness}) \quad (3)$$

$$RSEI = (RSEI_0 - RSEI_{0\min}) / (RSEI_{0\max} - RSEI_{0\min}) \quad (4)$$

where the MOD13A1 product characterizes the *Greenness*, the MOD11A2 product characterizes the *Heat*, and the MOD19A1 image band calculates the *Wetness* and *Dryness*; *PC1* is the first principal component in principal component analysis;  $RSEI_0$  is the un-normalized raw of RSEI;  $RSEI_{0\min}$  is the minimum value of the  $RSEI_0$ ;  $RSEI_{0\max}$  is the maximum value of the  $RSEI_0$ .

### Methods of MRSEI

The RSEI integrates information on greenness, wetness, heat, and dryness, which can reflect the spatial variability of the ecological status. Whereas, as mentioned in the introduction, the non-applicability of RSEI in an arid region is still not effectively resolved. Since Inner Mongolia is a typical arid region; there are large areas of desertified and salinized land (Zhang et al. 2018; Zhao et al. 2020). Therefore, in order to improve the application of the remote sensing ecological index in this study area, we used the salinization

monitoring index (SMI) and desertification monitoring index (DMI) as one of the indicators for constructing MRSEI. In addition, SMI and DMI are negative indexes.

### Soil salinization

Soil salinization is land degradation caused by fragile arid environments, as well as unreasonable human activity (Guo et al. 2019a). In accordance with previous research, there was a strong correlation between vegetation cover and soil salinity. This relationship could be seen in remote sensing imagery as the modified soil-adjusted vegetation index (MSAVI) decreased as soil salinity increased (SI) (Guo et al. 2019b). Based on this, Lu et al. (2020) established the salinization monitoring index (SMI) by using MSAVI and SI to monitor soil salinization. The calculation formulas are shown as Eq. (5)–Eq. (7).

$$MSAVI = \frac{2b_2 + 1 - \sqrt{(2b_2 + 1)^2 - 8(b_2 - b_1)}}{2} \quad (5)$$

$$SI = \sqrt{b_3 \times b_1} \quad (6)$$

$$SMI = \sqrt{(MSAVI - 1)^2 + SI^2} \quad (7)$$

where  $b_1$ ,  $b_2$ , and  $b_3$  denote band 1, band 2, and band 3 in the MOD09A1.

### Land desertification

The ecological quality in the arid region has been significantly impacted by the development of desertification (Sandeeep et al. 2021). Desertification has been shown to have an impact on surface albedo, vegetation cover, and land sanding degree (Chen et al. 2020; Wang et al. 2021b). As a result, Bai et al. (2022). developed a desertification monitoring index (DMI) which incorporates three indicators: MSAVI, Albedo, and sanding feature index (SFI). The calculation formulas of MSAVI are shown as Eq. (5), and the calculation formulas of Albedo and SFI are shown as Eq. (8) and Eq. (9). Where SFI is the index proposed by Meng (2005), because the reflectance value is between 0 and 100%, the sum of the sixth and seventh band values of the reflectance image after stretching will not be larger than 200; thus, the constant in the denominator of Eq. (9) is chosen to be 200 to ensure that the denominator is nonnegative. At present, the SFI was used to extract the sandy land, and obtain satisfactory results (Yang et al. 2017). Therefore, SFI is appropriate for Inner Mongolia because Inner Mongolia includes large areas of sandy land.

According to research by Guo et al. (2020) and Wei et al. (2020), spatial distance models can more accurately and realistically evaluate the effects of different indicators in ecological evaluation. This study fitted three indicators, MSAVI, Albedo, and SFI, based on spatial distance models with reference to the research by Bai et al. (2022).

$$Albedo = 0.160 \times b_1 + 0.291 \times b_2 + 0.243 \times b_3 + 0.116 \times b_4 + 0.112 \times b_5 + 0.081 \times b_7 - 0.0015 \tag{8}$$

$$SFI = (b_6 - b_3)/(200 - b_6 - b_7) \tag{9}$$

$$DMI = \sqrt{(M - M_{max})^2 + (A - A_{min})^2 + (S - S_{min})^2} \tag{10}$$

where  $b_1$ – $b_7$  denote band 1 ~ band 7 of in the MOD09A1;  $DMI$  is the desertification monitoring index; and  $M$ ,  $A$ , and  $S$  are the normalized MSAVI, Albedo, and SFI, respectively.  $M_{max}$  is the maximum value of  $M$ , and  $A_{min}$  and  $S_{min}$  are the minimum values of  $A$  and  $S$ , respectively.

**Calculation of the MRSEI**

The previous method constructed the RSEI using the first principal component of the principal component analysis (Jia et al. 2021; Hang et al. 2020; Yang et al. 2021). However, a high contribution rate is not guaranteed by the RSEI obtained with the first principal component (PC1), which has a contribution rate of 60 to 90% (Shan et al. 2019; Hang et al. 2020). Additionally, the contribution rate of the first principal component would steadily decrease as the number of indicators increases (Li 2017). While the entropy method not only makes full use of each indicator’s information, it also solves the problem of overlapping information across multiple indications (Wang et al. 2013). As a result, the entropy method was used to determine the weights of NDVI, LST, NDBSI, and Wet, then calculated the remote sensing ecological index (Cheng et al. 2021; Xu et al. 2022). Furthermore, Wang et al. (2022) proposed the Remote Sensing Ecological Index considering Full Elements (RSEIFI) by replacing the original PCA with the entropy method to integrate four ecological indicators (NDVI, LST, NDBSI, and Wet), and the study results showed that the calculation process of RSEIFE is more stable than that of RSEI, and the RSEIFE results are consistent with the real eco-environment on the surface. Therefore, our study used the entropy method to calculate the weights of the NDVI, Wet, LST, NDBSI, SMI, and DMI to construct the MRSEI. The calculation formulas are as follows:

$$w_i = \frac{1 - H_i}{n - \sum_{i=1}^n H_i} \tag{11}$$

$$MRSEI_0 = \sum_{i=1}^n w_i a_i \tag{12}$$

where  $MRSEI_0$  is the un-normalized raw of MRSEI;  $n$  is the number of indicators;  $w_i$  is the weight of the  $i$ th indicator;  $H_i$  is the entropy of the  $i$ th indicator; and  $a_i$  is the value of the  $i$ th indicator.

In addition, numerous studies normalize the indexes to unify the magnitudes, but the normalization process of anomalous samples can have a large impact on the distribution of the data (Wang et al. 2021a; Yang et al. 2021), while standardization can effectively solve this problem and has good interference resistance (Zheng et al. 2022). Therefore, we used Eq. (13) to standardize  $MRSEI_0$  to facilitate subsequent discretization.

$$MRSEI = \frac{MRSEI_0 - \mu}{\sigma} \tag{13}$$

where  $MRSEI$  is the modified remote sensing environment index;  $\mu$  and  $\sigma$  are the mean and standard deviation of variables set  $MRSEI$ .

**Dynamic detection**

Mapping analysis can not only efficiently monitor but also visualize changes in ecological status over long time series. Therefore, our study used Jenks’ natural breaks to classify the ecological index into five grades, excellent, good, moderate, fair, and poor, and assign values of 5, 4, 3, 2, and 1, respectively. Referring to the study of Li et al. (2022b), the calculation formulas of ecological changing conditions are as follows:

$$code = \sum_{i=1}^4 10^{4-i} (code_{i+1} - code_i) \tag{14}$$

$$C = code_5 - code_1 \tag{15}$$

where  $code$  is the ecological change code;  $code_1$ ,  $code_2$ ,  $code_3$ ,  $code_4$ , and  $code_5$  are the ecological code of 2000, 2005, 2010, 2015, and 2020, respectively; if  $code_{i+1} - code_i = 0$ , then assign it to 0 which indicates that the ecological status has remained unchanged; if  $code_{i+1} - code_i > 0$ , then assign it to 1, which indicates that the ecological status of area has been improved; if  $code_{i+1} - code_i < 0$ , then assign it to 2, which means that the ecological status of area has been destroyed.  $C$  refers to the difference in ecological status between 2020 and 2000.

In order to more effectively analyze the changing status of ecological quality in the study area, we divided the ecological changes into six categories (Table 2) based on Eqs. (14) and (15).

**Table 2** Classification explanation

Code	Class	Classification basis
Stable	0000	Sustained stability
	1111, 1110, 1100, 1000, and so on	Stability improvement
	2222, 2220, 2200, 2000, and so on	Stability deterioration
Undulated	Other codes	$C=0$ Undulated stability
		$C>0$ Undulated improvement
		$C<0$ Undulated deterioration

**Driver analysis**

Although interaction detectors in geographic detectors can quantitatively describe the relative importance of influencing factors in studying the driving mechanisms of ecological quality evolution, geographic detectors can suffer from data upper limit problems. For the reasons mentioned above, our study refers to the mechanism of NDVI response to climate change studied by Lin et al. (2020) to calculate multiple correlation coefficients to analyze the driving mechanisms of ecological quality. The calculation formulas of multiple correlation coefficients are shown in Eqs. (16)–(19).

$$\rho_{ya} = \frac{\sum_{i=1}^n (y_i - \bar{y})(a_i - \bar{a})}{\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2 \sum_{i=1}^n (a_i - \bar{a})^2}} \tag{16}$$

$$\rho_{yab} = \frac{\rho_{ya} - \rho_{yb}\rho_{ab}}{\sqrt{(1 - \rho_{yb}^2)(1 - \rho_{ab}^2)}} \tag{17}$$

$$\rho_{y,ab} = \sqrt{1 - (1 - \rho_{ya}^2)(1 - \rho_{ab}^2)} \tag{18}$$

$$t_{y,ab} = \frac{\rho_{y,ab}}{\sqrt{1 - \rho_{y,ab}^2}} \sqrt{n - m - 1} \text{ or } t_{ya,b} = \frac{\rho_{ya,b}}{\sqrt{1 - \rho_{ya,b}^2}} \sqrt{n - m - 1} \tag{19}$$

where  $y$  is the dependent variable,  $a$  and  $b$  are the independent variables;  $m$  is the number of independent variables ( $m=2$  in the study);  $n$  is the number of samples ( $n=5$  in the study);  $\rho_{ya}$ ,  $\rho_{yb}$ , and  $\rho_{ab}$  are the correlation coefficients

between  $y$  and  $a$ ,  $y$  and  $b$ , and  $a$  and  $b$ ;  $\bar{y}$  and  $\bar{a}$  are the average of  $y$  and  $a$ ;  $\rho_{ya,b}$  is the partial correlation coefficients between  $y$  and  $a$ , excluding the influence of  $b$  on  $y$  and  $a$ ;  $\rho_{y,ab}$  is the multiple correlation coefficients between  $y$ ,  $a$ , and  $b$ .  $t_{y,ab}$  and  $t_{ya,b}$  are the  $t$ -test result for determining the significance of linear regression.

With reference to existing studies, we analyzed the drivers of ecological change in terms of both social and natural factors, respectively (Guo et al. 2020; Yang et al. 2021; Lu et al. 2022). Natural factors include precipitation (P) and temperature (T), a combination of precipitation and temperature (P&T), and other factors (N). Social factors include population density (D) and GDP per capita (G), a combination of population density and GDP per capita (D&G), and other factors (N). The single driver is determined by the partial correlation coefficients described by Eqs. (16) and (17). The combination of drivers is determined by the multiple correlation coefficients described by Eqs. (16) and (18). The statistical significance of all correlation coefficients in the study was based on Student’s  $t$ -test described by Eq. (19) (Song and Ma 2011) and the significance level was set to 0.05.

**Results**

**Comparison and selection of the ecological index**

Table 3 shows the correlation coefficients ( $r$ ) between MRSEI (RSEI) and each ecological component for 2020, which can be found that there were differences in the correlations of RSEI and MRSEI with each ecological indicator. The average  $r$  between MRSEI (RSEI) and NDVI, LST, Wet, NDBSI, DMI, and SMI are 0.942 (0.926),  $-0.849$  ( $-0.802$ ), 0.748

**Table 3** Correlation of ecological index and factors

	NDVI	LST	NDBSI	Wet	DMI	SMI
MRSEI	0.942	$-0.849$	$-0.852$	0.748	$-0.947$	$-0.906$
RSEI	0.926	$-0.802$	$-0.838$	0.744	–	–

(0.744),  $-0.852$  ( $-0.838$ ),  $-0.947$  ( $-$ ), and  $-0.906$  ( $-$ ), respectively. According to this result, MRSEI is more indicative of the comprehensive information of each indicator than RSEI since its correlation coefficients with each element are higher than those of RSEI. The correlation coefficients of DMI, SMI, and MRSEI are all higher than 0.9, demonstrating the critical role that DMI and SMI play in the development of MRSEI for arid regions.

In order to compare the differences between RSEI and MRSEI in characterizing ecological status, we selected four experiment areas (case A, case B, case C, case D) in Inner Mongolia which covered different land types and ecological quality. As shown in Fig. 2, in case A, the ecological status is harsh, and the land cover is predominantly unused, including a large area of desert and salinized land. Case B is located in the southwest of Inner Mongolia, where the land use is mainly cultivated land and grassland, but there are minor areas of unused land and forest land. The predominant land use in case C and case D is grassland and forestland, respectively.

Considering the information for 2020 as an example, we created two transect lines that crossed as many different land-type pixels as possible in order to ensure a change in ecological status between pixels (Fig. 2). Then, the pixel cross-section fluctuation curves of the RSEI and MRSEI

in the research area were compared. In addition, we performed a linear regression analysis based on the pixels of RSEI and MRSEI on the transect lines;  $R^2$  is the correlation coefficient between RSEI and MRSEI (Fig. 3). Figure 3 shows the pixel fluctuations in the diagonal direction of the transects in the four cases and the correlation coefficients of RSEI and MRSEI. Because the four cases have varied ecological conditions, the value domains of MRSEI on transect lines are also different. Case B contains both unused and forest land; therefore, the ecological status varies widely, resulting in a maximum MRSEI of 1.63 and a minimum value of  $-1.24$  on the transect line in case B, indicating that the difference between the maximum and minimum values is greater. Furthermore, in other cases, the greater the ecological quality, the higher the value of MESEI, i.e., the overall low value of MESRI in case A and the overall high value of MRSEI in case D. The results in Fig. 3 show that although there are differences in certain regions, the RSEI and MRSEI fluctuation curves in the four cases show good agreement in the overall trend. In addition, the RSEI and MRSEI of cases B, C, and D show an extremely high linear correlation with  $R^2 > 0.85$ , which is consistent with the pixel fluctuations. RSEI and MRSEI showed correlation coefficients of 0.7889 and 0.7552 on the transect of case A, respectively, which are slightly

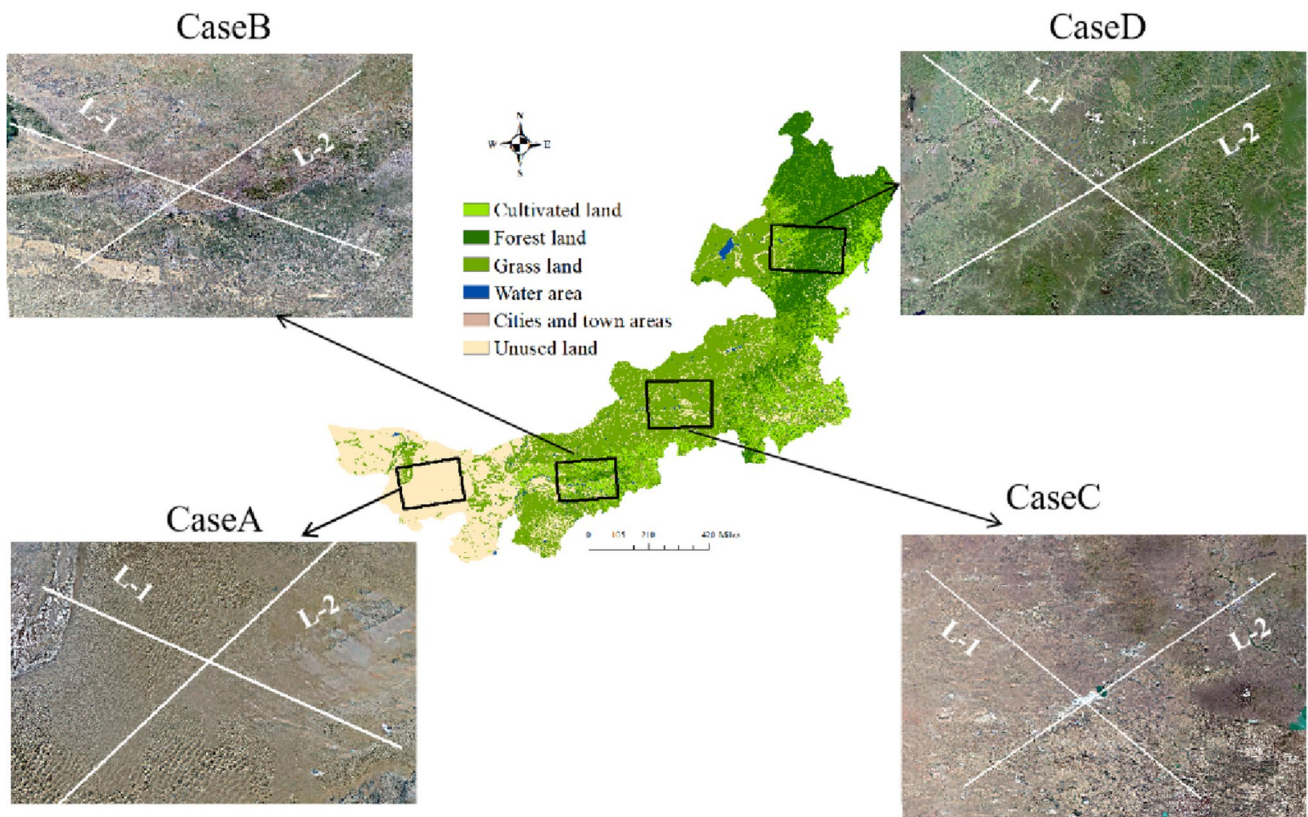
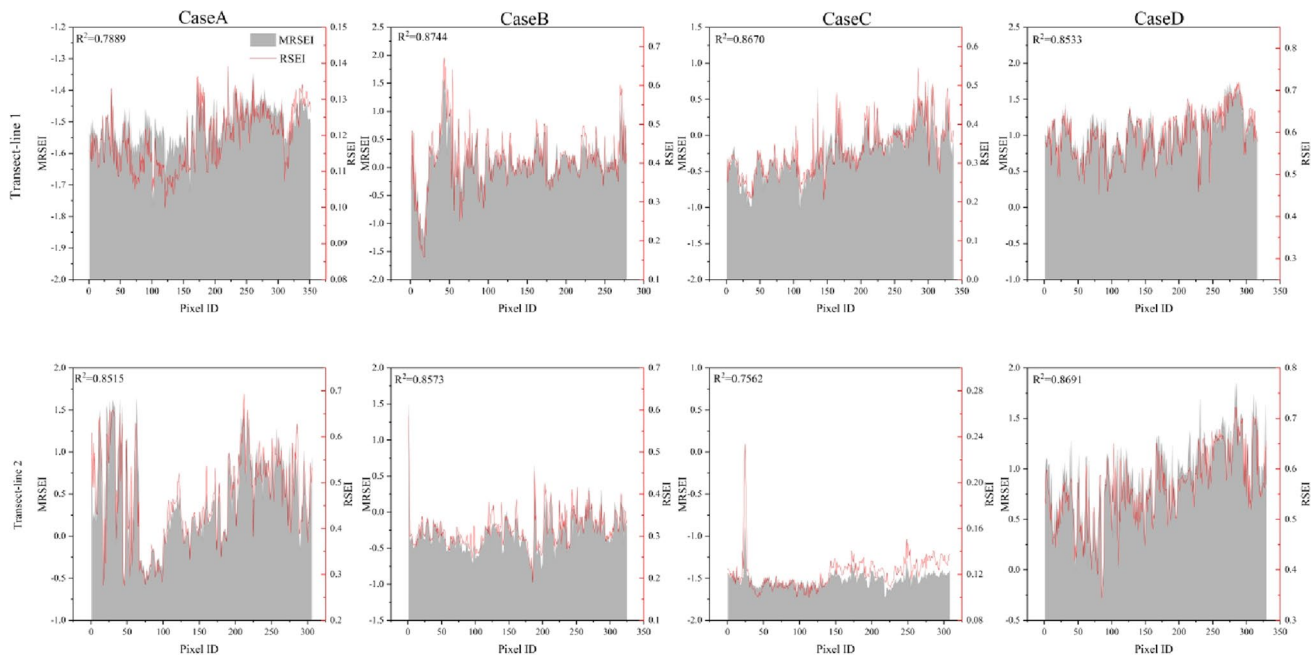


Fig. 2 The location map of four case areas



**Fig. 3** The pixel fluctuations in the diagonal direction of the cross-section within the four cases

lower than the other cases. Therefore, we can consider that in bare ground with poor biological circumstances, there will be differences between RSEI and MRSEI.

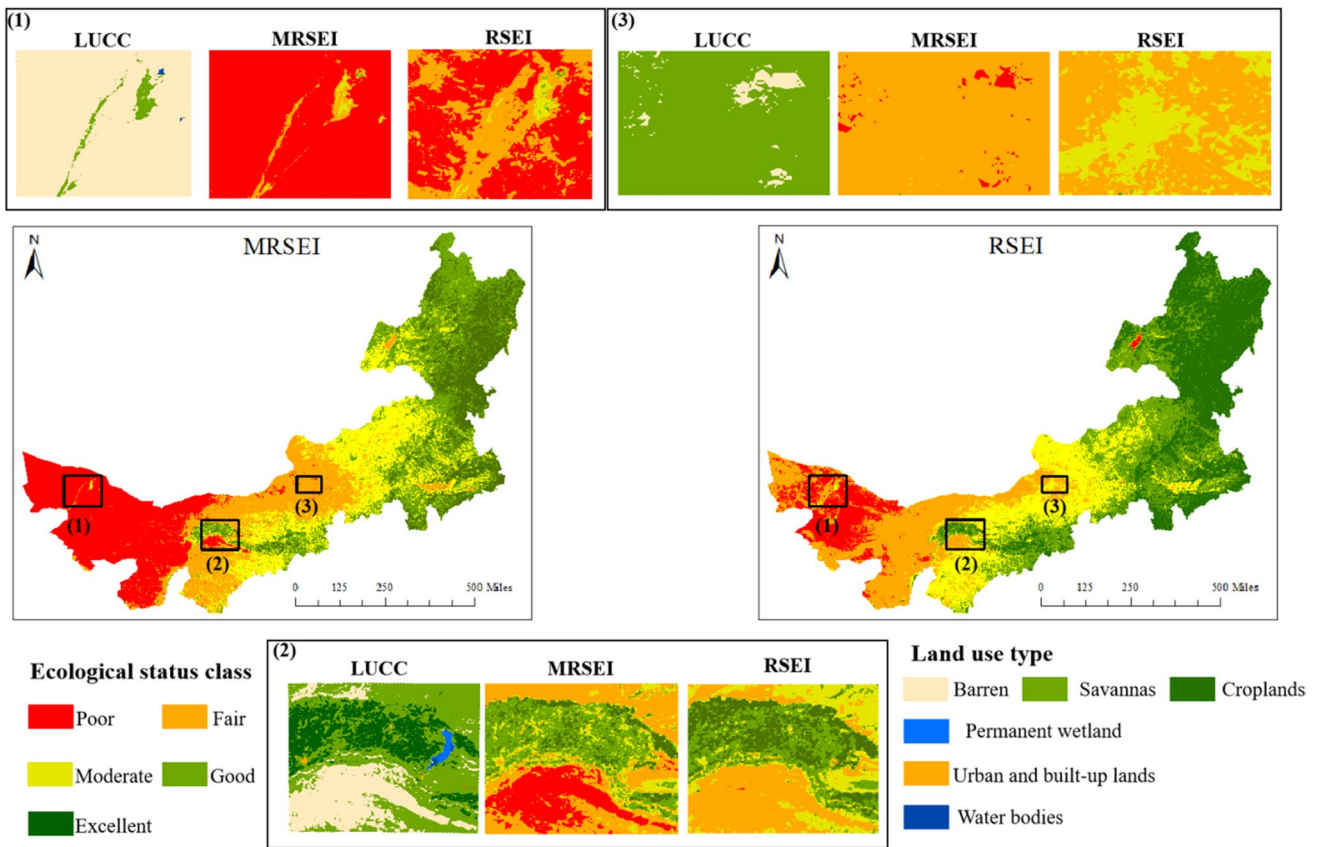
In order to further verify the reliability of the RSEI and MRSEI, we selected three regions as sample areas (sample 1, sample 2, sample 3), each of which had various areas of bare ground. The differences between RSEI and MRSEI in the three sample areas were then compared using the land-type data from MCD12Q1 (Fig. 4). The areas with relatively high ecological status grades were mainly croplands and savannas with dense vegetation. While urban built-up areas with very little vegetation cover and barren land, including desert and saline land, are the majority of the areas with relatively low ecological status grades. The findings in Fig. 4 demonstrate that in sample 1, there is an obvious difference between the two inversion results, that is, the RSEI categorizes a portion of the desert land as having fair ecological conditions while the MRSEI characterizes this area as having poor ecological level. Additionally, MRSEI outperforms RSEI in recognizing the strip oasis in the middle of sample 1. The ecological conditions reflected by the RSEI and MRSEI of the cropland in sample 2 were well consistent with the land type. However, in the barren portion of sample 2, MRSEI identified it as a poor ecological status, and RSEI identified it as a fair ecological status. The MRSEI is more accurate than the RSEI in reflecting the ecological conditions of sample 3 and agrees well with the land types. In summary, for extreme environmental areas, the differences between MRSEI and RSEI will be more pronounced, and the results of MRSEI will be significantly cautious and realistic.

## Dynamic monitoring and trend analysis of MRSEI

### Spatiotemporal characteristics of MRSEI evolution in Inner Mongolia

Considering the above findings, we selected the MRSEI to analyze the spatial distribution of ecological status. It has been demonstrated that Jenks' natural breaks can most correctly group similar data in order to optimize the differences between categories (Li and Xu 2020), and Jenks' natural breaks have been widely used in ecological condition assessment (Bai et al. 2022; Liu et al. 2019). Therefore, we used Jenks' natural breaks to classify MRSEI into five categories, excellent, good, moderate, fair, and poor, and evaluate the ecological state of Inner Mongolia from 2000 to 2020. In these 5 years of monitoring (Fig. 5), the ecological quality in the northeast of Inner Mongolia was generally better than that of the southwest, and the majority of the middle part of the region has fair ecological conditions, while the areas with good or excellent conditions are mostly concentrated in the oasis. In 2000, area of both poor and fair levels account for 48.58% of the whole area, and good and excellent levels account for 30.31%, but in 2020, poor and fair levels account for 41.35%, and good and excellent levels account for 38.08%, which illustrates that the ecological quality of Inner Mongolia has gradually improved in the past 20 years.





**Fig. 4** Comparison of the land use classification of the case area in 2020 with RSEI, MRSEI

**Trend analysis of MRSEI**

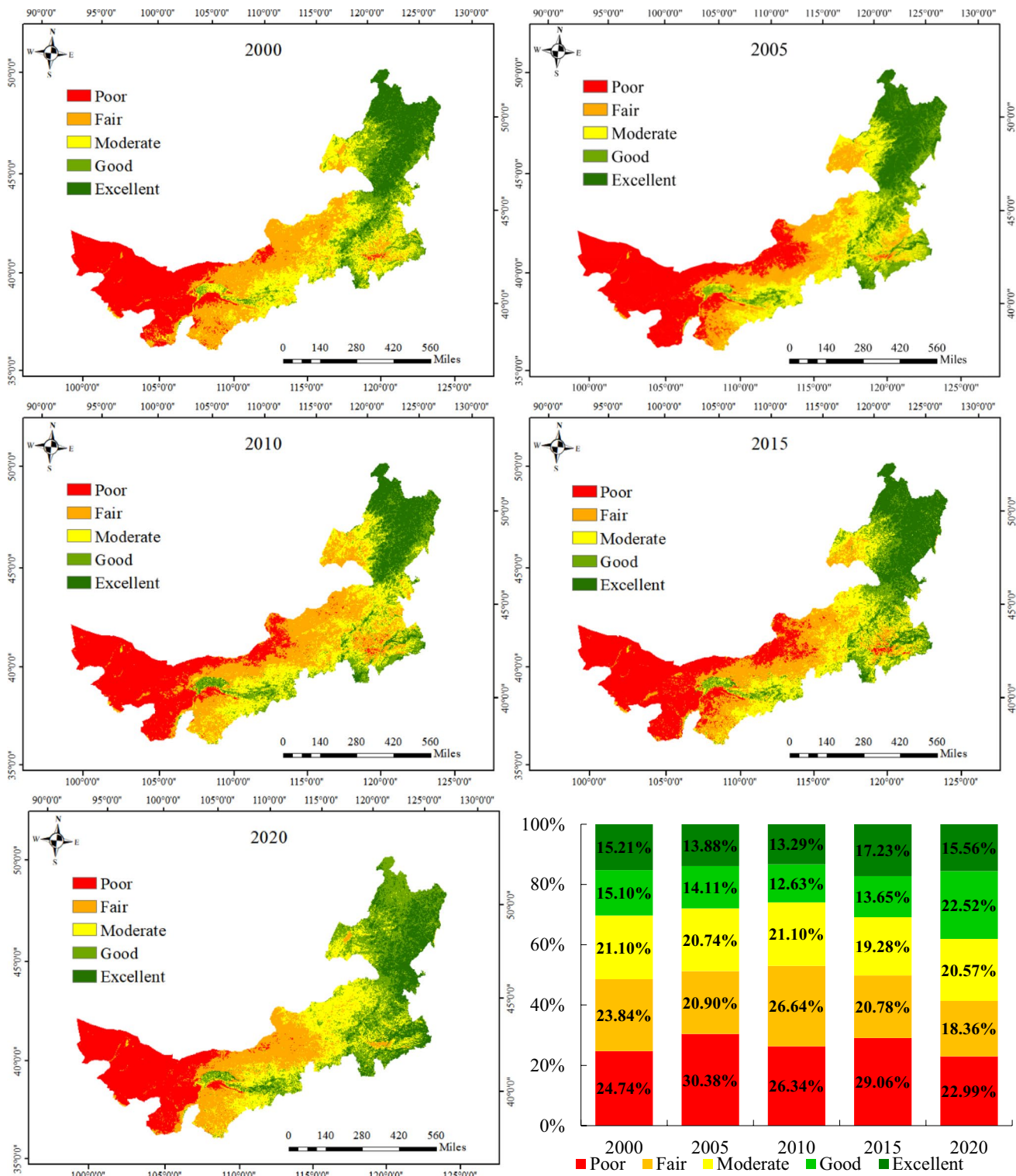
Figure 6 a shows the dynamic ecological recovery or destruction in Inner Mongolia over the previous 20 years. The cropland or oasis with good environmental governance and improved vegetation conservation was primarily showing undulated improvement and stability improvement. The undulated deterioration and the stability deterioration regions were primarily concentrated in oasis urban regions (urbanization continues, indicating that settlements continue to develop into oasis), as well as certain oasis and desert areas where the ecosystem was still damaged. Figure 6 b shows the statistical percentage pie chart of the area for each change type. According to Fig. 6 b, the categories of sustained stability and fluctuating stability account for 61.69% of the study area; the fluctuating improvement and stability improvement categories account for 26.07% of the study area; and the fluctuating deterioration and stability deterioration categories account for 12.33%. To summarize, the ecological environment quality in Inner Mongolia generally improved between 2000 and 2020. However, there was no discernible improvement in wide barren areas to the southwest of the study area. As a result, the region’s environmental

governance should continue to focus on barren, and efforts to safeguard vegetation should be accelerated.

**MRSEI response to driving factors**

We selected LST (T) and precipitation (P) as natural factors to analyze the driving mechanism of the two on the MRSEI spatiotemporal evolution in Inner Mongolia (Fig. 6 a). Natural factors (P, T, P&T) drive MRESI change among 37.46% of the whole area. Among them, T, P, and the T&P explain approximately 1.33%, 9.46%, and 26.67% of the MRSEI changes, respectively. Thus, T&P appears to be the most important MRSEI driver factor. Figure 7 a shows that the region of the T&P driver is mainly distributed in the Hulunbuir, north of the Hinggan, southeast and north-central of the Alxa, east and north of the Chifeng, and the Xilingol.

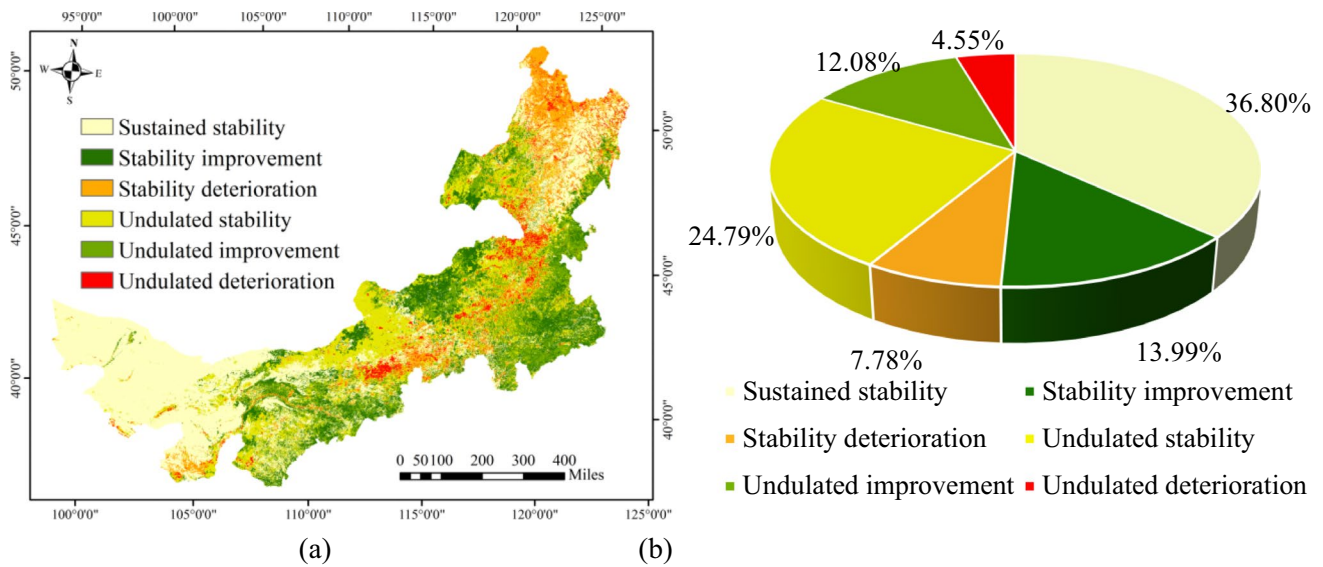
Social developments such as population density (D) and GDP per capita (G) have also impacted the ecological status to a certain extent. As shown in Fig. 7 b, social factors (D, G, D&G) drive MRSEI change among 25.85% of Inner Mongolia. G driving factors mainly explain the



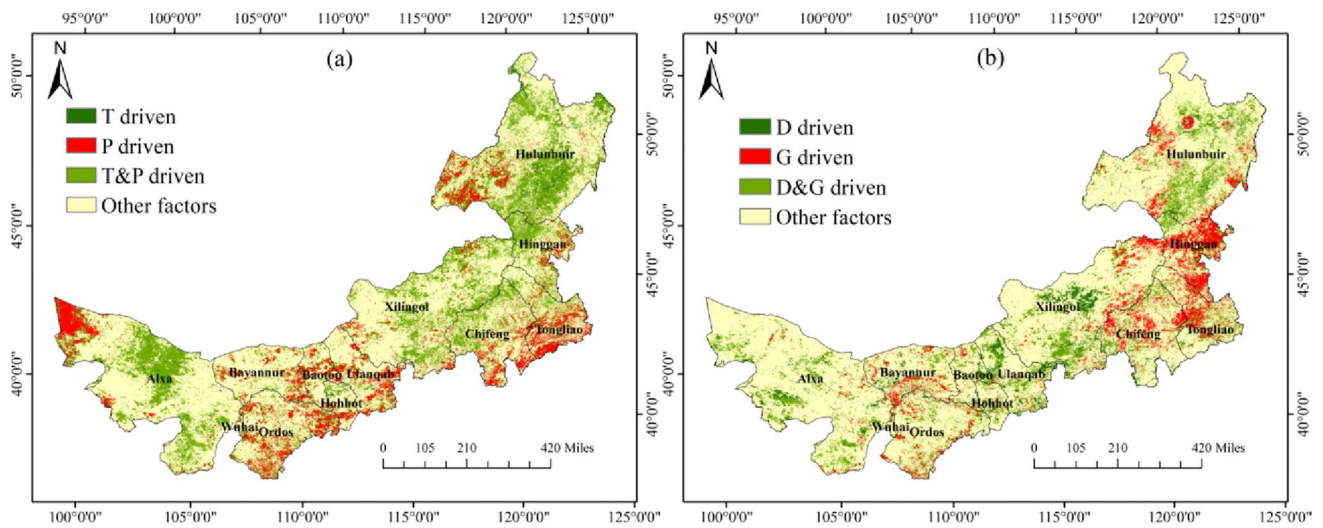
**Fig. 5** The temporal and spatial changes of MRSEI in Inner Mongolia during 2000 to 2020, areas of different MRSEI quality levels

Hinggan, the northeast of the Tongliao, and the Chifeng, which account for 8.32% of the whole area. D&G driver

is mainly distributed in the Hulunbuir, the Ulanqab, east of the Baotou, and the Alxa, which account for 13.23% of the whole area.



**Fig. 6** Ecological status changing trends from 2000 to 2020 (a), and the area distribution of ecological status changing trends from 2000 to 2020 (b)



**Fig. 7** Distribution of the MRSEI natural drivers (a) and social drivers (b) in Inner Mongolia

## Discussions

### Advantages of MRSEI

The RESI is widely used in ecological monitoring. Yang et al. (2021) used the RSEI to study the spatial and temporal changes in the ecological environment of Xinjiang in China. In addition, Huang et al. (2021) used RSEI to evaluate and monitor the eco-environmental quality of Lhasa. However, the RESI only considers the four factors of greenness, humidity, dryness, and heat, ignoring problems like desertification and salinization in arid regions.

In our study, the DMI and SMI were added to the RSEI to construct the MRSEI for arid regions. The results show that compared to the RSEI, the evaluation result of the MRSEI for extreme environmental areas (e.g., desertification, salinization) is more cautious and more realistic. In summary, MRSEI is especially suitable for monitoring ecological environments in arid regions.

Although it is difficult to verify the accuracy of the results for ecological environment quality evaluation with specific data, the statistical yearbooks and relevant conclusions of literature can effectively prove it. Since 2000, a number of ecological restoration projects have been carried out in Inner Mongolia in an effort to reduce the spread of sandy land and

enhance the living conditions of the population. These projects include the management of Beijing-Tianjin wind and sand sources, and the 3-North Shelter Forest Program (Tian et al. 2018). This demonstrates the validity of the claim that from 2000 to 2020, Inner Mongolia's ecological quality has improved. Additionally, our study used statistical yearbooks to determine Inner Mongolia's population and cultivated status. The findings revealed that between 2000 and 2020, Inner Mongolia's population increased from 237,274,000 to 240,228,000, and its per-capita cultivated area increased from 0.25 to 0.37 hectares, indicating a decline in human demands and disturbances on the land, and an improvement in ecological quality. In Inner Mongolia, the area of reforestation expanded from 590,000 to 650,000 hectares between 2000 and 2020, the area of green space increased from 15,392 to 68,540.88 hectares, and the number of natural areas protected climbed from 80 to 216. This shows that ecological management has advanced somewhat in the government. This supports the finding in “Spatiotemporal characteristics of MRSEI evolution in Inner Mongolia” and “Trend analysis of MRSEI” of this study that, overall, from 2000 to 2020, Inner Mongolia's ecological environment has improved. Additionally, it demonstrates the accuracy and reliability of the MRSEI application in arid regions.

### Partition for ecological protection and management

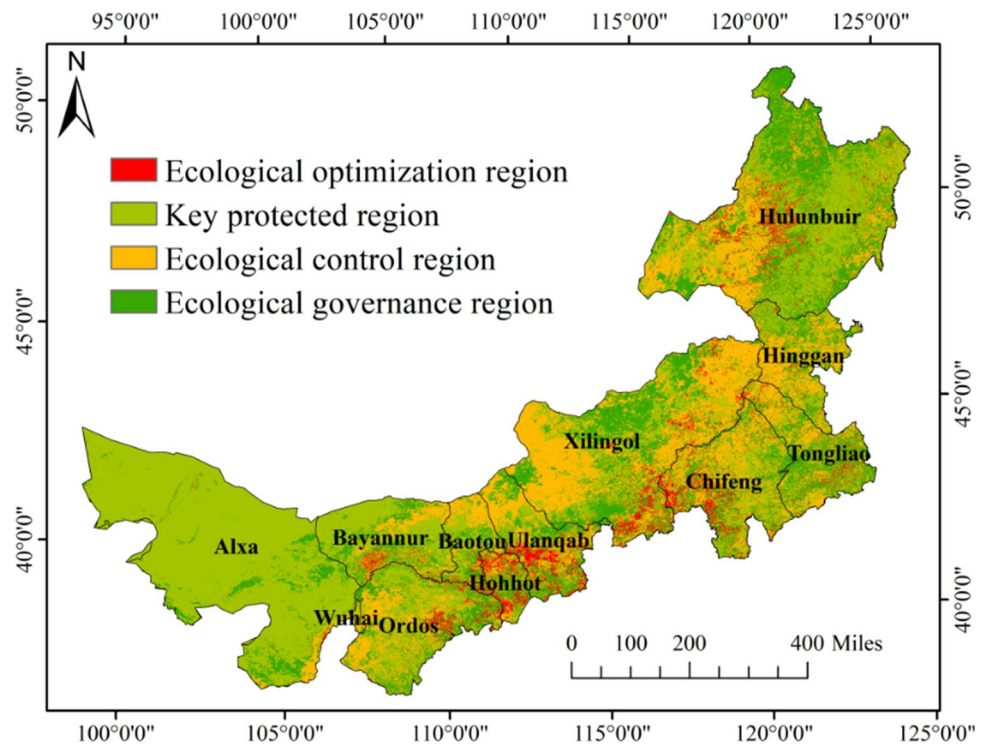
Scholars are currently conducting studies on ecological management partition. Jiang et al. (2023) divided Inner Mongolia into four regions based on the spatial and temporal evolution characteristics of desertification: key protection region, environmental improvement region, environmental management region, and key management region. Based on the results of a desertification sensitivity evaluation in 2015, Tian et al. (2018) categorized Inner Mongolia into ecological protection regions, desertification control regions, comprehensive development regions, and ecological migration regions. The aforementioned studies show that the majority of current research on the delineation of ecological reserves focuses on either a single “static” status or “dynamic” evolution, while there are few studies on the delineation of ecological that

combine “static” and “dynamic.” In view of this, our study combined the ecological status trends with the current situation of ecology in 2020, and set protection weights referring to the research of Wei et al. (2020) and Li et al. (2022b), the ecology functional protection regions were divided. The specific steps are as follows: (1) first, determine the ecological current status protection weight: 1 for excellent regions, 3 for good regions, 5 for moderate regions, 7 for fair regions, and 9 for poor regions. (2) Secondly, the ecological trend type protection weight was determined: the protection weight of sustained stability was 1, the protection weight of a stable improving region was 3, the protection weight of an unstable improving region was 5, the protection weight of an unstable stable region was 7, the protection weight of undulated deterioration region was 9, and the protection weight of a stability deterioration region was 11. (3) Finally, the final result was calculated by adding the ecological current status protection weight and the corresponding ecological trend protection weight, and the final result was divided to obtain the ecology protection function partition. Table 4 displays the specific classification statistics table.

According to Table 4, Inner Mongolia was classified into four ecological protection zones, including ecological optimization region, key protected region, ecological control region, and ecological governance region (Fig. 8). Among them, the ecological optimization region has a lower score (2–6) and better ecological status, which only needs to maintain and optimize the status quo. The key protected areas have moderate scores (8–10), in order to effectively protect this region, that is necessary to build a variety of ecological functional zones under the key protection system, as well as to achieve regional environmental sustainability. Ecological control regions have scores ranging from 12 to 14, and in these regions, human intervention should be limited when necessary. Ecological management regions have high scores (16–20) and poor ecological conditions, which must be comprehensively managed to prevent their spread from affecting normal human production and living. From the spatial distribution of ecological management zones, ecological optimization regions are scattered and distributed in Hohhot, the south of Ulanqab, the southeast of Xilinguole, and the

**Table 4** Ecological protection functional area classification statistics. Note: the 0, 1, 2, 3, 4, and 5 in the trend represent sustained stability, stability improvement, undulated improvement, undulated stability, undulated deterioration, and stability deterioration respectively

	Trend	0	1	2	3	4	5
Ecological status in 2020	Protection weight	1	3	5	7	9	11
Excellent	1	2	4	6	8	10	12
Good	3	4	6	8	10	12	14
Moderate	5	6	8	10	12	14	16
Fair	7	8	10	12	14	16	18
Poor	9	10	12	14	16	18	20

**Fig. 8** Ecological protection zone

southwest of Chifeng. Key protection regions are primarily distributed in Alax and Hulunbuir, while ecological control and governance regions are primarily distributed in the north-central and eastern parts of Inner Mongolia. According to the results of their spatial distribution, the ecological situation in Inner Mongolia is still severe, and the comprehensive improvement of ecology is still one of the main tasks of ecological civilization construction, which should strictly comply with ecological protection-related policies.

### Limitations and future perspectives

In a word, our research provides a solid scientific foundation for evaluating the ecological status of Inner Mongolia in a timely manner. MRSEI is effective in detecting ecological pressure brought by salinization or desertification, but it is unable to distinguish the ecological difference caused by human sabotage. As a result, future study needs to fully consider the anthropogenic factors when constructing remote sensing ecological indexes. In addition, our study lacks a forecast of future ecological quality. Machine learning models may be introduced in future studies to forecast ecological quality. In the application of MRSEI, the MRSEI proposed in this study can be theoretically applied to the same other arid regions because of the same characteristics of environmental pressure (desertification and salinization). However, the regional environment is complex, comprehensive, and fuzzy; as a result, the specific reference values of the MRSEI in different arid regions, as well as the applicability of the

assessment methodologies used in this work, need to be investigated further.

### Conclusions

Monitoring and tracking ecological status in a timely, effective, and accurate manner is beneficial for understanding the condition of local ecosystems and developing environmental protection strategies. The widespread use of RSEI demonstrates that ecological components derived from remote sensing images have tremendous potential for describing the ecological status. However, when using RSEI in arid regions, there are some uncertainties which should be improved. As a result, based on the existing RSEI, we proposed the MRSEI, which takes into account desertification and salinization in arid regions. The results of this study show that:

1. There is a high consistency between RSEI and MRSEI in regions with favorable ecological conditions, but in extreme environmental areas, MRSEI results are evaluated more cautiously than RSEI.
2. The northeastern region of Inner Mongolia has superior environmental conditions than the southwest. From 2000 to 2020, 61.59% of the ecological quality in Inner Mongolia remains stable, 26.07% of the regional ecological quality is improving, and 12.33% of the regional ecological quality is declining.

3. In the natural factors, the area that is driven by T, P, and P&T accounted for 1.33%, 9.46%, and 26.67% respectively. In the social factors, the area that is driven by D, G, and D&G accounted for 4.30%, 8.32%, and 13.23% respectively.

**Author contribution** Bai Zongfan: conceptualization; methodology; software; validation; investigation; writing—original draft. Han Ling: supervision, project administration, funding acquisition. Liu Huiqun: resources; writing—review and editing. Jiang Xuhai: validation. Li Liangzhi: writing—review and editing.

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**Data availability** All required data and materials are included in the manuscript.

## Declarations

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Conflict of interest** The authors declare no competing interests.

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