Ecological environment quality evaluation of the Sahel region in Africa based on remote sensing ecological index postprint

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Abstract

Long-term monitoring of the ecological environment changes is helpful for the protection of the ecological environment. Based on the ecological environment of the Sahel region in Africa, we established a remote sensing ecological index (RSEI) model for this region by combining dryness, moisture, greenness, and desertification indicators. Using the Moderate-resolution Imaging Spectroradiometer (MODIS) data in Google Earth Engine (GEE) platform, this study analyzed the ecological environment quality of the Sahel region during the period of 2001–2020. We used liner regression and fluctuation analysis methods to study the trend and fluctuation of RSEI, and utilized the stepwise regression approach to analyze the contribution of each indicator to the RSEI. Further, the correlation analysis was used to analyze the correlation between RSEI and precipitation, and Hurst index was applied to evaluate the change trend of RSEI in the future. The results show that RSEI of the Sahel region exhibited spatial heterogeneity. Specifically, it exhibited a decrease in gradient from south to north of the Sahel region. Moreover, RSEI in parts of the Sahel region presented non-zonal features. Different land-cover types demonstrated different RSEI values and changing trends. We found that RSEI and precipitation were positively correlated, suggesting that precipitation is the controlling factor of RSEI. The areas where RSEI values presented an increasing trend were slightly less than the areas where RSEI values presented a decreasing trend. In the Sahel region, the areas with the ecological environment characterized by continuous deterioration and continuous improvement accounted for 44.02% and 28.29% of the total study area, respectively, and the areas in which the ecological environment was changing from improvement to deterioration and from deterioration to improvement accounted for 12.42% and 15.26% of the whole area, respectively. In the face of the current ecological environment and future change trends of RSEI in the Sahel region, the research results provide a reference for the construction of the ゜Green Great Wall'' (GGW) ecological environment project in Africa.

Full Text

Preamble

Ecological Environment Quality Evaluation of the Sahel Region in Africa Based on Remote Sensing Ecological Index

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Abstract: Long-term monitoring of ecological environment changes is essential for effective ecological protection. Focusing on the Sahel region in Africa, we established a remote sensing ecological index (RSEI) model by integrating dryness, moisture, greenness, and desertification indicators. Using Moderate-resolution Imaging Spectroradiometer (MODIS) data on the Google Earth Engine (GEE) platform, this study analyzed the ecological environment quality of the Sahel region from 2001 to 2020. We employed linear regression and fluctuation analysis to examine RSEI trends and variability, utilized stepwise regression to assess the contribution of each indicator to RSEI, applied correlation analysis to investigate the relationship between RSEI and precipitation, and used the Hurst index to evaluate future RSEI change trends.

The results reveal significant spatial heterogeneity in RSEI across the Sahel region, with values decreasing from south to north. Additionally, some areas exhibited non-zonal characteristics. Different land-cover types showed distinct RSEI values and trends. RSEI and precipitation were positively correlated, indicating that precipitation is the controlling factor for RSEI. Areas with increasing RSEI values were slightly fewer than those with decreasing values. During the study period, regions characterized by continuous ecological deterioration and continuous improvement accounted for 44.02% and 28.29% of the total study area, respectively, while areas transitioning from improvement to deterioration and from deterioration to improvement represented 12.42% and 15.26% of the region, respectively. These findings provide a scientific reference for the implementation of the "Green Great Wall" (GGW) ecological project in Africa.

Keywords: ecological environment; remote sensing ecological index; human activities; climate change; Sahel region; "Green Great Wall" (GGW)

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1 Introduction

Over the past 100 years, global mean temperature has increased by 0.7°C (IPCC, 2014). Numerous studies have demonstrated that climate change significantly impacts polar, temperate, and tropical ecosystems (Vitousek, 1994; Walther et al., 2002). Human activities further complicate ecological environment changes, making them increasingly multidimensional (Sih et al., 2011). Advances in science and technology provide the foundation for monitoring Earth' s ecological variability and its responses to anthropogenic and natural conditions (Moss et al., 2010). Such monitoring contributes to improved understanding of Earth system mechanisms, reveals ecological responses to intensified human activities (Qureshi et al., 2020), and helps minimize negative impacts of global changes on human survival and development (Ji et al., 2020).

Remote sensing (RS) technology offers advantages of broad observation coverage, timeliness, and periodicity, making it widely applicable for fire monitoring, land-cover change analysis, forestry investigation, and large-scale real-time air pollutant monitoring (Biswal and Gorai, 2020; Ebrahimi et al., 2020; Gu et al., 2020; Yim, 2020). This technology plays a crucial role in ecological environment monitoring (Xu et al., 2019). The ecological environment encompasses both living and non-living components (Liao and Jiang, 2020). Due to varying research themes, scholars have proposed different definitions of ecological environment quality (Miao et al., 2016; Jing et al., 2020). Based on relevant research, we define ecological environment quality in this study as the degree of suitability for organism survival.

Ecological environment quality evaluation employs comprehensive assessment methods based on selected indicators to quantitatively evaluate regional ecological-environmental quality (Zhou, 2000). Xu (2013) proposed monitoring and evaluating ecological environment quality through remote sensing ecological index (RSEI) derived from RS technology. Currently, many scholars have applied RSEI to assess different regions. For example, Xu et al. (2019) quantified and monitored ecological environment changes in Fujian Province, China, using change vector analysis and four ecological indicators (moisture, greenness, heat, and dryness). Liao and Jiang (2020) established China' s RSEI model based on the same four indicators, monitoring national ecological environment quality from 2000 to 2017 and identifying drought as the most important factor.

Ecological environment changes are typically accompanied by variations across the entire environment, including changes in surface vegetation, temperature, and soil moisture (Walther et al., 2002; Zheng et al., 2020). Therefore, comprehensive evaluation of multiple indicators is necessary when using RS to monitor ecological changes. However, previous research has predominantly used moisture, greenness, heat, and dryness as evaluation indicators while ignoring ecological environment diversity (Xiong et al., 2020). Different ecological environments require different indicators. Additionally, RS images are susceptible to data loss due to adverse weather conditions (Steven et al., 1998; Zhang et al., 2020). Some studies cover broad areas and often select images at 5- or 10-year intervals to reduce workload (Fan et al., 2020), but this approach can lead to misjudgment of ecological changes due to data selection limitations, surface feature variations, and extreme climate events (Hang et al., 2020). Historically, single ecological factors such as vegetation index (Dardel et al., 2014), soil moisture index (Gu et al., 2019), precipitation (Dai, 2011), and temperature (Wu et al., 2020) were used to evaluate ecological environment quality, with few studies addressing the overall ecological environment of the Sahel region. This paper comprehensively assesses Sahel region ecological environment quality based on the RSEI model.

As natural resources are consumed and global climate changes, the global ecological environment is undergoing corresponding transformations (Singh et al., 2014). The Sahel region, a transitional zone between the Sahara Desert and savanna, has a fragile ecological environment extremely sensitive to climate change and human activities (Held et al., 2005; Issa et al., 2014). Severe desertification occurs due to harsh ecological conditions. The "Green Great Wall" (GGW) ecological project was proposed to combat desertification by constructing a tree belt across Africa from west to east (Goffner et al., 2019). This shelterbelt aims to regulate temperature, reduce wind erosion, and increase local microclimate moisture (Wade et al., 2018; You et al., 2019).

The main objectives of this study are to: (1) identify appropriate RS ecological indicators for the Sahel region; (2) determine ecological environment change trends over the past 20 years; (3) construct an RSEI model for the Sahel region; and (4) predict future ecological environment changes. This research provides an academic reference for GGW construction.

2.1 Study Area

The Sahel region extends from Senegal in the west to Eritrea in the east of Africa, lying between the Sudan savanna zone and the arid Sahara Desert with a mean width of approximately 350 km. The region includes numerous wetlands such as the Senegal Delta, Niger River, and Lake Chad region (Moser et al., 2014). The area is primarily delineated by annual precipitation. As shown in Figure 1 [Figure 1: see original paper], the Sahel region is bounded by 150 mm annual isohyet on its northern border and 700 mm on its southern border (Le and Henri, 1989). The region has a dry climate with frequent sandstorms. Rapid population growth has led to continuous expansion of farmland and pastoral areas, resulting in ecological deterioration and desertification spread (Tucker et al., 1985; Scheffer et al., 2001). The GGW concept was introduced to manage ecological conditions caused by climate change and human activities in the Sahel region, gradually developing into the current GGW ecological project (Goffner et al., 2019). The latitude of GGW project areas is similar to that of the African Sahel region, with substantial spatial overlap between them.

2.2 Data

Moderate-resolution Imaging Spectroradiometer (MODIS) data (https://lpdaac.usgs.gov/products/, 2001–2020) with 500 m spatial resolution were used, including MOD09A1 surface reflectance (8-day composite) and MCD43A3 albedo (16-day composite). Google Earth Engine (GEE) was used to remove clouds from MOD09A1 surface reflectance data (https://earthengine.google.com/). Due to limited and unevenly distributed meteorological stations in Africa, precipitation data from the ERA5 (ECMWF Reanalysis v5) dataset (https://cds.climate.copernicus.eu/#!/home) were used to calculate annual mean precipitation. Annual isohyets of 150 mm and 700 mm were extracted to delineate the Sahel region. Total precipitation from May to October during 2001–2019 was calculated. GlobeLand30 land classification data for 2020 (http://www.globallandcover.com/) were used. Joint Research Centre (JRC) water products (https://global-surface-water.appspot.com) were adopted to reduce water influence on results, using water areas from 2001–2020 as masks to remove water bodies from MODIS imagery. Detailed data information is shown in Table 1 .

3.1 RSEI

RSEI, proposed by Xu et al. (2019), monitors ecological environment based on four indicators (moisture, greenness, heat, and dryness) using RS data. The RSEI model has demonstrated good performance in evaluating regional ecological environments (Gou and Zhao, 2020; Jing et al., 2020; Wen et al., 2020). However, limitations exist: the heat indicator is based on urbanization, potentially causing large errors when evaluating environments without cities (Shao et al., 2020). The Sahel region has a fragile ecological environment with serious desertification (Toure et al., 2019) and increasing temperatures in recent decades (Diedhiou et al., 2018). Therefore, using the heat indicator may yield inaccurate results. In this study, we removed the heat indicator and incorporated the reverse desert difference index (RDDI) into an improved RSEI model tailored for the Sahel region. The improved RSEI model is as follows:

where RSEI is the remote sensing ecological index; NDSI (normalized dry soil index) represents ecological environment dryness; WETI (wet index) represents ecological environment moisture; NDVI (normalized difference vegetation index) represents ecological environment greenness; RDDI represents ecological environment desertification degree; and f is the principal component analysis (PCA) method used to extract the first principal component band. PCA is a statistical method that transforms correlated variables into uncorrelated variables through orthogonal transformation, reducing dimensionality and simplifying datasets (Jolliffe and Cadima, 2016).

Generally, high RSEI values represent healthy ecological environments, while low values represent poor environments (Xu et al., 2019; Ning et al., 2020). However, after conducting PCA for 2004, 2005, 2008, 2010, 2018, 2019, and 2020, we found that low RSEI values represented healthy environments while high values represented poor environments. Therefore, we subtracted RSEI values for these years from 1, so that high values represented healthy environments and low values represented poor environments (Xu et al., 2019; Ning et al., 2020).

3.1.1 Dryness Indicator

The dryness indicator reflects regional surface dryness degree, obtained by combining bare soil indicator and index-based built-up indicator (Rikimaru, 2002; Xu, 2008; Liao and Jiang, 2020). The dryness indicator is expressed as:

where SI is the bare soil indicator; $_{1}$- $_{7}$ denote bands 1-7 of MODIS image data, corresponding to red, near infrared 1, blue, green, near infrared 2, short-wavelength infrared 1, and short-wavelength infrared 2 bands, respectively; and IBI is the index-based built-up indicator.

3.1.2 Moisture Indicator

The moisture indicator reflects water body, vegetation, and soil humidity. Based on Lobser and Cohen (2007), we adopted the Tasseled Cap Transformation method to obtain the moisture indicator using MODIS09A1 data. The formula is as follows:

3.1.3 Greenness Indicator

NDVI represents surface vegetation characteristics (Carlson and Ripley, 1997) and was selected as the greenness indicator. The calculation formula is as follows:

3.1.4 Desertification Indicator

This study used the desertification difference index (DDI) model (Ma et al., 2011). We subtracted the normalized DDI value from 1 to obtain RDDI. RDDI values closer to 1 indicate more serious desertification. The extraction steps were: MCD43B3 and MOD13A1 images from May 1 to October 1 each year during 2001-2020 were mosaicked using GEE; albedo and NDVI values for the Sahel region during 2001-2020 were extracted and averaged; 19,847 sampling points were established. The DDI model was built using albedo and mean NDVI values of sampling points, then the RDDI model was derived. The formulas are as follows:

where a is the DDI value; K is the slope of correlation between albedo and NDVI values; b and c are NDVI and albedo values, respectively; and d is the RDDI value.

3.2 Linear Regression

Linear regression was used to analyze interannual RSEI variation characteristics from 2001 to 2020 (Bashir et al., 2020; Wu et al., 2020). The formula is as follows:

where is the slope of RSEI variations; n is the number of monitoring years; and M_{RSEI} is the RSEI for the ith year. When > 0, RSEI showed an increasing trend; when < 0, RSEI showed a decreasing trend; when $= 0$, RSEI remained constant.

3.3 Fluctuation Analysis

The coefficient of variation (CV) method effectively reveals data fluctuation (Kesteven, 1946) and was used to analyze RSEI fluctuation in the Sahel region from 2001 to 2020. The formula is:

where CV_{RSEI} is the coefficient of variation of RSEI; *σ{RSEI} is the standard deviation of RSEI data; and RSEI*{mean} is the mean RSEI value. CV measures overall ecological environment variation in the Sahel region, with higher values indicating greater temporal volatility (Wu et al., 2020).

3.4 Stepwise Regression Analysis

Stepwise regression combines forward introduction and backward elimination methods, incorporating advantages of both (Pope, 1970). The principle is that selected variables may be removed when they become unimportant after introducing new variables (Birth, 1985). Removed variables can be reintroduced if new variables prove unimportant. To ensure the regression equation contains only variables with significant influence, each variable introduction or removal was subject to F-test. This method was used to deduce and test four indicators affecting RSEI, eliminate insignificant variables, and establish the RSEI model for the Sahel region.

3.5 Correlation Analysis

Correlation analysis reveals relationships between different variables. This method was used to study the relationship between RSEI and precipitation.

3.6 Hurst Index

The Hurst index is an important tool for analyzing time series data changes (Liu et al., 2017; Tong et al., 2018) and has been used to monitor vegetation trends (Tong et al., 2018). We used it as a key indicator for monitoring RSEI changes, selecting RSEI values from the past 10 years for analysis. When Hurst index (HI) = 0.5, the time series is completely independent with no evident correlation or only short-term correlation. When $0.0 < \text{HI} < 0.5$, future changes oppose past changes, with stronger anti-persistence as HI approaches 0.0. When $0.5 < \text{HI} < 1.0$, future changes are consistent with past changes, with stronger persistence as HI approaches 1.0.

4.1 Extraction of RDDI

Figure 2 [Figure 2: see original paper] shows a clear negative correlation between albedo and NDVI, with albedo increasing as NDVI decreases. Frequency analysis indicates most albedo and NDVI values ranged from 0.23–0.68 and 0.20–0.60, respectively. The RDDI model for the Sahel region was obtained as:

$$\text{RDDI} = 1 - 1.2563 \times \text{NDVI} + \text{Albedo}$$

As shown in Figure 3 [Figure 3: see original paper], RDDI values in the Sahel region were unevenly distributed (mean = 0.50), demonstrating spatial heterogeneity in desertification degree. RDDI showed gradient characteristics, gradually increasing from south to north. RDDI values around rivers (Senegal River and Niger River), lakes (Lake Chad), and wetlands were significantly lower than at the same latitudes because soils were relatively moist and vegetation growth was well-developed (Zoffoli et al., 2008; Thakur et al., 2012).

4.2 Principal Component Analysis (PCA) of RSEI

Due to large data volume, we present PCA results only for 2001, 2006, 2011, and 2016. Table 2 shows that the first principal component (PC1) contribution rates for these four periods exceeded 90.00%, indicating PC1 accounted for over 90% of original data characteristics after PCA, thus better reflecting the four indicators. For PC1, NDVI and WETI were greater than zero while NDSI and RDDI were less than zero, showing NDVI and WETI had positive effects on RSEI whereas NDSI and RDDI had negative effects. Finally, PC1 contribution rates remained almost constant across different years, providing a basis for obtaining RSEI and analyzing its trends.

4.3 RSEI in the Sahel Region

Figure 4 [Figure 4: see original paper] shows the spatial distribution of mean RSEI in the Sahel region during 2001–2020. The mean RSEI value was 0.40, with southern values obviously larger than northern values, though some areas showed non-zonal characteristics. For example, RSEI near Lake Chad was higher than at the same latitude due to the humid microclimate and abundant vegetation. Meanwhile, RSEI in the eastern Nile River region was high due to extensive cultivated land, resulting in higher greenness and moisture but lower desertification and dryness.

We selected regions A (13°35 N, 30°44 E; Sudan), B (14°50 N, 15°10 W; Senegal), and C (11°06 N, 34°39 E; Sudan) shown in Figure 4 for analysis using high spatial resolution images from Google Earth (Fig. 5 [Figure 5: see original paper]). Mean RSEI values were 0.20, 0.40, and 0.75 for regions A, B, and C, respectively. Region A had no vegetation cover with dry sandy soil; region B had sparse vegetation with scattered shrubs and some cultivated land; region C had high vegetation coverage with tall trees (Fig. 5). These regions represented completely different ecological environments, and RSEI results supported this conclusion, demonstrating that the improved RSEI could effectively monitor the Sahel region' s ecological environment.

Land cover in the Sahel region was divided into seven types: cultivated land, forest, grassland, shrubland, wetland, artificial surface, and bare land (Fig. 6 [Figure 6: see original paper]; Table 3). Grassland occupied the largest area (113.92$\times10^{4}$ km^2), while artificial surface occupied the smallest (1.02$\times10^{4}$ km^2). Area decreased in the order: grassland > cultivated land > shrubland > forest > wetland > artificial surface > bare land. However, RSEI values differed considerably among land-cover types. Wetland had the highest RSEI (0.64), while bare land had the lowest (0.27). RSEI values decreased as: wetland > forest > shrubland > cultivated land > grassland > artificial surface > bare land.

Figure 7 [Figure 7: see original paper] shows correlation coefficients between RSEI and precipitation varied from -0.92 to 0.91, demonstrating evident spatial heterogeneity. Areas with positive and negative correlations accounted for 67.44% and 32.56% of the entire region, respectively, indicating that RSEI in most areas was positively correlated with precipitation. Figure 8 [Figure 8: see original paper] exhibits an obvious positive correlation between RSEI and normalized precipitation, with RSEI increasing as precipitation increased. Frequency analysis shows most RSEI and precipitation values ranged from 0.19–0.38 and 0.11–0.31, respectively.

4.4.1 Fluctuation Analysis

Figure 9 [Figure 9: see original paper] shows RSEI spatiotemporal fluctuations. CV values varied from 0.02 to 0.48, demonstrating spatial heterogeneity. We divided CV values into five fluctuation levels: very low, low, moderate, high, and very high (Fig. 9b; Table 4) (Rey et al., 2017). Low fluctuation area was largest (31.48% of total area), followed by very low (28.99%) and moderate (22.75%). High and very high fluctuation areas were small (12.66% and 4.13%, respectively). Northern Sahel CV values were evidently larger than southern values. High-fluctuation areas were mainly in southern Mauritania, southern Mali, and central Chad, while stable areas were in northern Burkina Faso, northern Nigeria, Lake Chad, and most of central and southern Sudan.

4.4.2 Interannual Trend Characteristics of RSEI

Figure 10 [Figure 10: see original paper] shows spatial heterogeneity in annual RSEI change trends during 2001–2020. Areas with decreasing and increasing trends accounted for 53.43% and 46.57% of the study area, respectively. The proportion of areas with increased RSEI was less than those with decreased RSEI. Areas with significantly changing trends accounted for 23.09% of the region, with significantly increasing and decreasing areas representing 43.52% and 56.48%, respectively. RSEI showed decreasing trends in eastern Senegal, central and western Mali, northeastern Burkina Faso, southwestern Niger, and southern Sudan, while increasing trends occurred along the Chad-Nigeria and Chad-Sudan borders.

Interannual RSEI trends varied by land-cover type. Grassland (-0.23\$$\times 10^{\{-3\}), forest(-1.33\times 10}${-3}), $and cultivated land(-0.36\times 10^{\{-3\})showed declining trends, with forest being most significant. Wetland(0.93\times 10}${-3}), $shrubland(0.30\times 10^{\{-3\}), and artificial surface(0.17\times 10}${-3}\$) showed upward trends, with wetland being most significant. Bare land showed no obvious trend. Table 5 shows statistical analysis of RSEI and trends by country. Burkina Faso and Sudan had higher RSEI values (0.46 and 0.45), while Mauritania and Niger had lower values (both 0.26). RSEI showed obvious spatial heterogeneity at national scale, with Senegal and Mauritania showing large decreasing trends while Sudan and Chad showed large increasing trends.

4.5 Ecological Environment Modeling in the Sahel Region

To quantitatively describe the Sahel region' s ecological environment, we established an ecological quality model. We extracted 3,000 random points annually, including RSEI, NDVI, NDSI, RDDI, and WETI values, then screened them to obtain 59,394 effective sample points. The RS ecological environment quality model was obtained through stepwise regression:

$$RSEI = 0.441WETI + 0.303NDVI - 0.351RDDI - 0.204NDSI \ (R^2 = 0.99)$$

Figure 11 [Figure 11: see original paper] shows WETI and NDVI were positive indicators for RSEI, while RDDI and NDSI were negative indicators. All four indicators were retained after stepwise regression, indicating their key roles in the RSEI model. WETI had the largest influence, followed by RDDI and NDVI, with NDSI having the smallest influence. Three-dimensional projections show RSEI decreased with increasing NDSI and RDDI, while NDSI increased with RDDI (Fig. 11a). This may be because NDSI represents urban building scale and surface exposure degree, and desertification probability increases with impervious surface expansion. Additionally, RSEI increased with WETI and NDVI, while NDVI increased with WETI (Fig. 11b), attributable to precipitation being a key factor restricting vegetation growth in arid and semi-arid regions where WETI correlates highly with precipitation.

4.6 Predicting Ecological Environment in the Sahel Region

RSEI from 2001-2020 cannot reflect recent trends, making future predictions less reliable. Therefore, we selected RSEI values from the past 10 years for Hurst index analysis. Figure 12 [Figure 12: see original paper] shows spatial distributions of predicted RSEI trend slope, HI, and future RSEI change trends. Areas with increasing RSEI (slope > 0.00) and decreasing RSEI (slope < 0.00) accounted for 40.71% and 59.29% of the study area, respectively. In the last decade, areas with ecological deterioration exceeded those with improvement (Fig. 12a), similar to the 2001-2020 trend. Deteriorating areas were mainly in western Niger, while improving areas concentrated in eastern Niger.

The mean HI for the Sahel region was 0.57. Areas with HI > 0.50 accounted for 72.31% of the region, while HI < 0.50 accounted for 27.69%. Combining past 10-year RSEI trends with HI values, we classified future RSEI change trends into four types: continuous reduction, continuous increase, reduction-increase, and increase-reduction. These accounted for 44.02%, 28.29%, 15.26%, and 12.42% of the study area, respectively. Continuously deteriorating areas were mainly in the western Sahel (Senegal-Mauritania-Mali border area, northeastern Burkina Faso, southwestern Sudan). Continuously improving areas were in southern Niger and northern Lake Chad. Areas changing from improvement to deterioration were mostly in southeastern Sudan. Areas changing from deterioration to improvement were widely distributed across the Sahel region.

Different land-cover types showed different RSEI change trends (Fig. 13 [Figure 13: see original paper]). For bare land, the largest proportion (37.52%) showed continuous RSEI increase, as did shrubland (33.12%) and artificial surface (33.37%). Forest showed the largest proportion (67.80%) of continuous RSEI reduction. Grassland and bare land showing continuous reduction accounted for 45.73% and 43.23% of the area, respectively. The overall RSEI change trend across land-cover types was: wetland > bare land > artificial surface > shrubland > cultivated land > grassland > forest.

5 Discussion

Previous studies often focused on single indicators such as NDVI, pollutant concentration, or biodiversity while ignoring ecological environment integrity (Adams et al., 2012; Firth et al., 2014; Mutti et al., 2020). The current RSEI method is considered more reasonable than single indicators for ecological assessment (Liu et al., 2019; Gao et al., 2020; Ji et al., 2020). However, using constant indicators for different ecological environments may cause deviations. Therefore, we selected evaluation indicators appropriate for Sahel region conditions. As a semi-arid region with severe desertification (Wu et al., 2020), we added RDDI (representing desertification degree) to the RSEI model. With few large-scale urban agglomerations and less human disturbance in tropical areas, we removed the heat indicator from the original RSEI model.

Our evaluation based on the improved RSEI model revealed spatial heterogeneity in Sahel region RSEI, with a gradual decrease from south to north. The Sahel is a transitional region between Sahara Desert and savanna. The northern part near the Sahara has sparse vegetation, high land exposure, severe desertification, and poor soil moisture, while the southern part shows opposite characteristics (Foley et al., 2003; Lee et al., 2015). Notably, this gradient trend was disturbed in some regions like Lake Chad and the eastern Nile River. Abundant aquatic vegetation near Lake Chad (Leblanc et al., 2011) improves greenness and moisture indicators while reducing desertification and dryness. Substantial cultivated land in the eastern Nile River region yielded higher NDVI and RSEI values than same-latitude areas.

RSEI values for different land-cover types decreased as: wetland > forest > shrubland > cultivated land > grassland > artificial surface > bare land. In the RSEI model, WETI and NDVI are positive indicators while RDDI and NDSI are negative. Wetland had high WETI and NDVI but low NDSI and RDDI, while bare land showed the opposite pattern. Grassland, forest, and cultivated land showed interannual RSEI decline, possibly related to grazing, deforestation, and excessive reclamation (van Keulen and Breman, 1990; Mainali, 2006; Epule et al., 2014). Wetland, shrubland, and artificial surface showed upward trends, possibly due to greening projects and climate change (Fensholt et al., 2012; Abiodun et al., 2013).

Our predictions show bare land' s high continuous RSEI increase associated with "greening" from large-scale afforestation and increased precipitation (Giannini et al., 2008; Kusserow, 2017), while grassland' s continuous RSEI reduction may relate to desertification spread. Forest' s high RSEI reduction may relate to decreased woody plant coverage from increased grazing and wood demand (Leroux et al., 2017).

Precipitation was positively correlated with RSEI. In arid and semi-arid areas, precipitation changes significantly affect local ecosystems, with increases generally improving ecological conditions (Fensholt et al., 2012; Xu et al., 2020). RSEI fluctuations showed spatial heterogeneity, with northern CV values significantly larger than southern values, likely related to precipitation fluctuations. Figure 14 [Figure 14: see original paper] shows precipitation CV values were larger in the northern Sahel. Among four indicators, moisture is directly precipitation-related. The Sahel' s semi-arid climate makes precipitation a key factor restricting vegetation growth (Huber et al., 2011; Fensholt et al., 2013), so annual precipitation fluctuations importantly influence RSEI variability.

Areas with increasing RSEI were smaller than decreasing areas. Figures 10 and 15 show similar RSEI and precipitation trends, though local differences existed. For example, Burkina Faso' s population increased 56% since 2000 (from 11.60$\times10^{6}$ in 2000 to 18.10$\times10^{6}$ in 2015) (FAO, 2010), placing great pressure on agriculture and contributing to land degradation (Knauer et al., 2017). RSEI largely depended on the moisture indicator, confirming precipitation as a key factor affecting ecological changes in arid and semi-arid areas (Fensholt et al., 2012). Predictions show the western Sahel' s ecological environment will continue deteriorating.

According to Monerie et al. (2020), western Sahel precipitation is expected to decrease in the future. Precipitation changes directly relate to greenness and moisture indicators, confirming our prediction of continued western Sahel deterioration. The eastern Nile River region shows a trend from improvement to deterioration due to cultivated area expansion from 3.90×10^{4} to 5.00×10^{4} km^2 between 2000–2020 (Zika and Erb, 2017).

This study has limitations. First, RSEI can observe ecological changes, but attribution of change trends can only be expressed qualitatively rather than quantitatively measuring human activity and climate change contributions. Second, specific land-cover types directly affect RSEI monitoring. Large water areas directly affect the moisture indicator. Cultivated land changes at different periods (high vegetation coverage before harvest vs. bare land after harvest) affect positive indicators. Wasteland reclamation and shelterbelt planting increase NDVI and RSEI in the short term (Estel et al., 2015; Mark, 2019; Zhou et al., 2020), but this RSEI increase consumes groundwater and fertility, damaging the original ecological environment. Future research should combine field investigations to clarify phenological changes for different land-cover types and select specific periods for RSEI observations. Attribution analysis of RSEI changes is also important.

6 Conclusions

RSEI in the Sahel region showed obvious spatial heterogeneity. From 2001–2020, RSEI of grassland, forest, and cultivated land declined, while wetland, shrubland, and artificial surface increased. RSEI and precipitation were positively correlated. CV values in the northern Sahel were larger than in the southern region. Areas with increasing RSEI were slightly less than decreasing areas. We constructed the RSEI model for the Sahel region. Based on HI analysis, areas with continuous reduction, continuous increase, increase–reduction, and reduction–increase trends accounted for 44.02%, 28.29%, 12.42%, and 15.26% of the entire area, respectively. As an afforestation project, Africa' s GGW can effectively improve RSEI positive indicators. More attention should be paid to areas with continuous deterioration and increase–reduction trends.

Acknowledgments

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