



Article

Evolution and Spatiotemporal Response of Ecological Environment Quality to Human Activities and Climate: Case Study of Hunan Province, China

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Abstract: Human beings are facing increasingly serious threats to the ecological environment with industrial development and urban expansion. The changes in ecological environment quality (EEQ) and their driving factors are attracting increased attention. As such, simple and effective ecological environment quality monitoring processes must be developed to help protect the ecological environment. Based on the RSEI, we improved the data dimensionality reduction method using the coefficient of variation method, constructing RSEI-v using Landsat and MODIS data. Based on RSEI-v, we quantitatively monitored the characteristics of the changes in EEQ in Hunan Province, China, and the characteristics of its spatiotemporal response to changes in human activities and climate factors. The results show the following: (1) RSEI-v and RSEI perform similarly in characterizing ecological environment quality. The calculated RSEI-v is a positive indicator of EEQ, but RSEI is not. (2) The high EEQ values in Hunan are concentrated in the eastern and western mountainous areas, whereas low values are concentrated in the central plains. (3) A total of 49.40% of the area was experiencing substantial changes in EEQ, and the areas with significant decreases (accounting for 2.42% of the total area) were concentrated in the vicinity of various cities, especially the Changsha–Zhuzhou–Xiangtan urban agglomeration. The areas experiencing substantial EEQ increases (accounting for 16.97% of the total area) were concentrated in the eastern and western forests. (4) The areas experiencing substantial EEQ decreases, accounting for more than 60% of the area, were mainly affected by human activities. The areas surrounding Changsha and Hengyang experienced noteworthy decreases in EEQ. The areas where the EEQ was affected by precipitation and temperature were mainly concentrated in the eastern and western mountainous areas. This study provides a valuable reference for ecological environment quality monitoring and environmental protection.

Keywords: ecological environment quality; human activity; climate change; Google Earth Engine (GEE); Hunan Province; China; RSEI-v



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1. Introduction

According to the United Nations Environment Programme, humans are facing increasingly severe environmental challenges: humans are the direct drivers of environmental change and the dominant forces currently shaping the earth [1]. Against the backdrop of global climate change [2], biodiversity loss [3], accelerated urban expansion [4], and the increasing human consumption of resources [5], scientifically and efficiently assessing the spatiotemporal dynamics of regional ecological environment quality is crucial to achieving the goal of sustainable development.

Remote sensing, a method characterized by reliability, strong periodicity, easy access, wide coverage, and rich information, has been widely used in ecological environment quality assessment and monitoring [6]. Early remote sensing ecological monitoring mainly involved the use of single indicators, such as NDVI [7], TVDI [8], or NDBI [9], to reflect the richness of a certain surface feature. The trend in the use of remote sensing ecological monitoring indicators has gradually shifted toward integration and diversification with the gradual development of remote sensing technology and ecological environment research. In 2006, the Chinese government issued the Technical Specifications for Ecological Conditions Evaluation, proposing the use of remote sensing technology to establish an ecological conditions index (EI). Xu et al. [10] drew on this standard and proposed a simple and practical remote sensing ecological index (RSEI) that relies solely on remote sensing data for calculation. The EI includes four basic indicators: greening rate, humidity, dryness, and heat, which can be used to comprehensively evaluate the quality of the ecological environment. The RSEI provides comprehensive coverage and quantifiable data and is objective and easy to use. Therefore, the RSEI is widely used in many research fields [11–17], such as ecological watershed [18] and mine [19] monitoring, urban environmental evaluation [20], and ecological risk assessment of projects [21]. In addition, the RSEI has often been used as a parameter in the research on ecological resilience [22], human landscape changes [22], and urban development strategies [23].

However, the RSEI has some limitations despite its widespread use: (1) the RSEI is unsuitable for areas with considerable water cover [24], (2) the information obtained through principal component analysis (PCA) can be lost [25], and (3) the results cannot be guaranteed to be positive indicators [26] because the direction of the eigenvector cannot be fixed during the PCA calculation [27]. Therefore, researchers are focusing on improving and perfecting the RSEI. The main ideas for improving the RSEI include the following: (1) Appropriate subindicators are added to increase the suitability of the results for a study area. For instance, in mining environments, the mine-specific eco-environment index (MSEEI), constructed using the mining intensity index [28], can be added, and for forest ecological environments, the three-dimensional greenness remote sensing ecological index (TDRSEI) constructed using the forest canopy height [29] can be added. (2) Subindicators can be preprocessed to obtain more information. For example, the four indicators can be discretized [26]. (3) A subindicator dimensionality reduction method can be modified to ensure positive indicator transformation. For instance, the entropy weight method can be used instead of PCA to integrate the four subindicators [12].

The current direction for improving RSEI involves increasing its adaptability to big data computing platforms, such as Google Earth Engine (GEE) [15,30,31], to achieve the macroscopic and long-term monitoring of the ecological environment [32].

Although scholars have extensively studied the RSEI, the uncertainty in the positive and negative directions of the RSEI has not been effectively address. Therefore, the RSEI results often require manual intervention to ensure positive results, which hinders its streamlined and efficient operation with GEE. As such, we constructed a simple and efficient remote sensing ecological index, RSEI-v, which is suitable for GEE. We then used this index to analyze the spatiotemporal response of the ecological environment quality to changes in human activities and climate elements in Hunan Province, China. We constructed a simple and easy process as well as a model for ecological environment quality monitoring; we also studied the factors driving EEQ. The research results provide new ideas and methods for long-term, regional ecological environment monitoring and assessment.

2. Materials and Methods

2.1. Study Area

Hunan, situated in the southcentral area of China, is bordered by six provincial-level administrative regions, including Chongqing, Hubei, Jiangxi, Guangdong, Guangxi, and Guizhou (Figure 1), in a clockwise direction from west to east. Hunan ranges in latitude from 24°37'N to 30°9'N and in longitude from 108°45'E to 114°15'E. This province is

characterized by diverse landform types and terrain undulations. An impact plain is widely distributed, and mountains and hills dominate the south and west. Hunan hosts many rivers, most of which merge into Dongting Lake in the north; 14 major cities are located along the rivers. The capital of Hunan, Changsha, is situated in the northeastern section of the province, serving as the provincial economic and demographic hub. Here, an urban agglomeration known as the Changsha–Zhuzhou–Xiangtan (CZT) Urban Cluster is found, which includes Changsha city along with its neighboring cities, Zhuzhou and Xiangtan. The CZT has recently become a key area for economic construction for the Hunan provincial government.

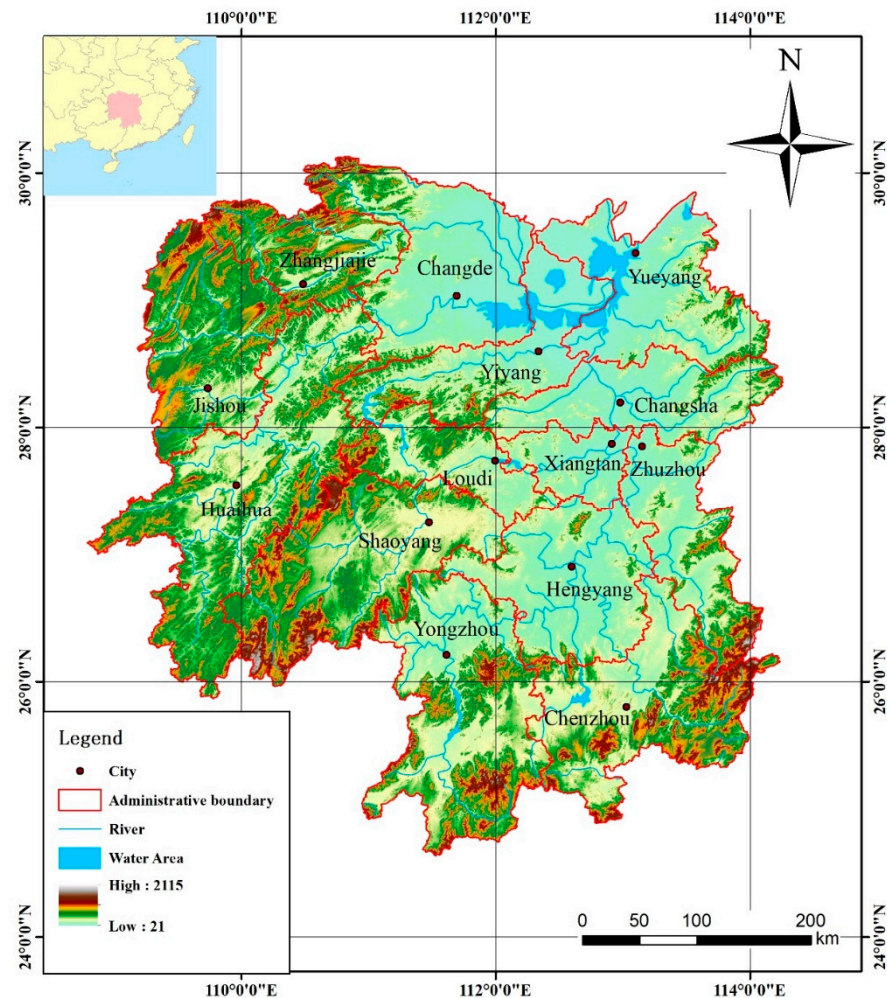


Figure 1. The location, major cities, elevation, and main water systems of the study area.

Since the beginning of the 21st century, with economic development and population growth, Hunan's urbanization rate has continued to increase, placing constant pressure on the regional ecological environment [33].

2.2. Data Sources

The main focus of our study was exploring the characteristics of the spatiotemporal response of environmental ecological quality (EEQ), which is driven by changes in climate and human activities. We used the RSEI-v, which we constructed analogously to the RSEI, to characterize the regional EEQ. Both indices rely on the use of four key indicators: greenness, heat, humidity, and dryness. These indicators can all be derived or extracted from remote sensing satellite data. Xu et al. first used Landsat 5/8 satellite data to construct indicators and verified and used them on a smaller scale [24]. Scholars have usually applied MODIS data for EEQ indicator calculations when used on a larger scale [34]. Data from

Landsat satellites have a high spatial resolution and contain rich band information, so these data are suitable for calculating humidity, dryness, and greenness index. However, the data from Landsat satellites are unsuitable for accurately calculating surface temperature due to the strong impact of clouds [35]. In addition, the Landsat series of datasets poses certain challenges: In the study area, the datasets contain large areas of irreparable defects in the thermal infrared band, which were generated during the data processing project (Figure 2) (<https://www.usgs.gov/landsat-missions/landsat-collection-2-known-issues> (accessed on 1 May 2024)). This issue is still being fixed, so the surface temperature cannot be calculated using Landsat satellite data; instead, lower-resolution MODIS data are used. The remaining three indicators are calculated using Landsat satellite data. The details of the remote sensing data used to construct the indicators are shown in Table 1.

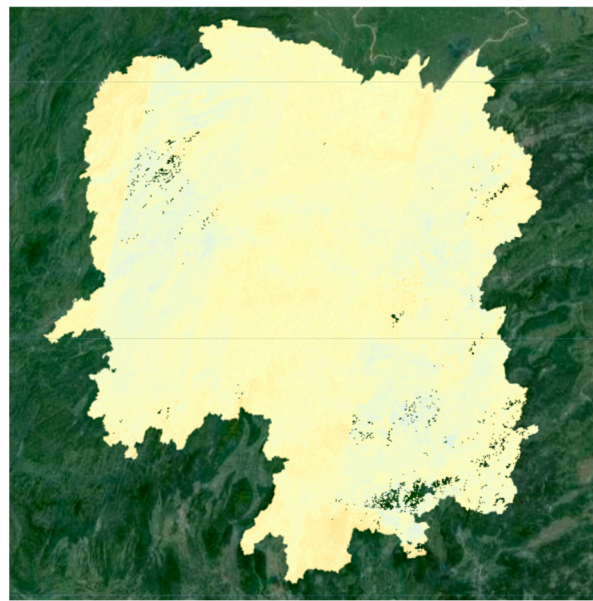


Figure 2. Null value of thermal infrared band image of Landsat5TM satellite (image mean synthesized using Google Earth Engine for the year 2000).

Table 1. Description of data sources used in this study.

Data	Data Source	Year	Name of Image Collection	Spatial Resolution
Satellite Data	Landsat8	2013–2020	LANDSAT/LC08/C02/T1_L2	30 m/100 m
	Landsat7	2012	LANDSAT/LE07/C02/T1_L2	30 m/60 m
	Landsat5	2000–2011	LANDSAT/LT05/C02/T1_L2	30 m/120 m
	MODIS	2000–2020	MODIS/006/MOD11A2	1 km
Temperature	ERA5	2000–2020	ECMWF/ERA5/DAILY	0.1°
Precipitation	ERA5	2000–2020	ECMWF/ERA5/DAILY	0.1°
Human Activities	GHF	2000–2020	GHF	1 km

The commonly used Landsat data are currently obtained from three sensors: TM, ETM+, and OLI. The ETM+ sensor has a fault, so the data from this sensor were used as little as possible. We selected all the Landsat5TM data from 2000 to 2011, Landsat7ETM+ from 2012, and Landsat8OLI from 2013 to 2020. These data were synthesized into a multispectral image for each year according to the annual median value after screening and declouding. Similarly, all MODIS surface temperature data from 2000 to 2020 were synthesized into an LST image for each year using the median synthesis method. Finally, the corresponding Landsat and MODIS data were combined into an image set according to year for calculating the EEQ. The above steps were all completed using Google Earth Engine (<https://earthengine.google.com/> (accessed on 1 May 2024)).

The factors driving EEQ mainly include climate change and human activity intensity. We characterized climate change during the study period using data on temperature and annual precipitation, which exhibited sufficiently large variations. These meteorological data were obtained from the ERA5 dataset, which is provided by the Copernicus Climate Change Service (C3S) of the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset has been providing the daily observations and forecasts of seven global climate parameters since 1975. Two of the parameters, 2 m surface temperature and daily precipitation, were used in this study. The datasets of these two parameters were synthesized into one scene image per year according to the annual mean using GEE.

The nondiscrete index data for describing human activities are relatively limited. The human footprint dataset developed by Mu et al. [36], which is based on eight factors reflecting the intensity of human activities, such as building environment, population density, and night light, was used to represent the dynamic spatiotemporal changes in the intensity of human activities in the study area. The details of the data used are shown in Table 1.

3. Methods

3.1. Remote Sensing Ecological Index Based on Coefficient of Variation Weighting (RSEI-v)

The RSEI-v was derived by improving the dimensionality reduction method used for the RSEI without changing the data composition of the RSEI. Similarly, RSEI-v is composed of four indicators: greenness, humidity, dryness and heat. The calculation formulas and references for the four subindicators are shown in Table 2. The detailed calculations for each indicator are provided in Appendix A. Each indicator needs to be normalized and positively processed before calculating the RSEI-v. The formulas are also listed in Appendix A.

Table 2. Calculation formula and references of the subindicators of the RSEI-V.

Subindicator	Index	Formula	References
Greenness	NDVI	Appendix A Formula (A1)	[7]
Humidity	Tasseled cap Transform	Appendix A Formulas (A2) and (A3)	[37,38]
Dryness	NDBSI	Appendix A Formulas (A4)–(A6)	[10,39]
Heat	Surface temperature	MODIS surface temperature products	

Principal component analysis (PCA) was used by Xu et al. to synthesize the information contained in the above four subindicators [24]. However, PCA has the following two limitations: (1) The contribution rate of the first principal component (PC1) may not be large enough when analyzing a sufficiently large research area or a sufficiently long time series because of the large number of samples. (2) The results of the first principal component (PC1) for each period of data often have both positive and negative results when analyzing long time series, so manual supervision and adjustment are often required in practice. These two shortcomings strongly impact the results of time-series analysis and cloud platform processing.

Objectivity should be considered as much as possible in the improvement of the RSEI algorithm because one of the advantages of the RSEI is its use of an objective weighting method to avoid the influences of subjective factors.

The coefficient of variation weighting method is a commonly used objective weighting method. With this method, weights are assigned according to the degree of variation in the sample. The larger the differences in the sample, the higher the weight assigned to it [40]. Data with large differences contain more information, so the spatial differences in the EEQ are more accurately reflected, enabling the judging of the characteristics of the spatiotemporal variation in the EEQ. The coefficient of variation is also one of the indicators commonly used to reflect EEQ [41]. Therefore, we used the coefficient of variation weighting

method to separately weight the four indicators. The formula for calculating the coefficient of variation weighting is as follows:

$$\omega_i = \frac{v_i}{\sum_{i=1}^n v_i} \quad (1)$$

$$v_i = \frac{s_i}{a_1} \quad (2)$$

$$a_i = \frac{1}{k} \sum_{j=1}^k \gamma_{ij}, S_i = \sqrt{\frac{1}{k} \sum_{j=1}^k (\gamma_{ij} - a_i)^2} \quad (3)$$

where ω_i is the weight of the i th subindicator, v_i is the coefficient of variation of the i th subindicator, s_i is the standard deviation of the i th subindicator, a_i is the mean of the i th subindicator, and r_{ij} is the j th sample's value of the i th subindicator. In $i \in (1, n)$, $n = 4$, $j \in (1, k)$, k is the total number of pixels in the image.

The weighted summation method is used to calculate the RSEI-v after the weight calculation is completed. The weighted summation is calculated as

$$RSEI_v = \sum_{i=1}^n w_i \cdot I_i \quad (4)$$

where RSEI-v is the indicator used to characterize EEQ, I_i is the value of the i th subindicator, and w_i is the weight of the i th subindicator, $i \in (1, n)$, $n = 4$.

The obtained RSEI-v values are all positive indicators; the values require neither positive processing based on manual supervision nor the consideration of whether most of the information of the subindicators has been integrated.

The calculated RSEI-v needs to be normalized again to facilitate subsequent time series and correlation analyses. The formula for this process is provided in Appendix A Formula (A6). We also calculated the RSEI for the study area from 2000 to 2020 using the method used by Xu et al. to examine the performance of RSEI-v by comparing the two methods using random point sampling.

3.2. Trend Analysis

One-dimensional linear regression analysis is commonly used for time-varying trends:

$$slope = \frac{n \sum_{i=1}^n i \cdot x_i - \sum_{i=1}^n i \cdot \sum_{i=1}^n x_i}{n \cdot \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2} \quad (5)$$

where slope is the trend of indicator x ; i represents the year, which ranged from 2000 to 2022 in this study; x is the indicator that represents the quality of the ecological environment in the study area, which was the RSEI-v in this study. The Mann-Kendall test was used to determine the significance of the trend in the changes in the RSEI-v in the study area. The EEQ in the study area was considered to have significantly changed when $p < 0.05$. The characteristics of the spatial distribution of EEQ in the study area were obtained by applying the above method for each pixel.

3.3. Pixel-Based Correlation Analysis

The pixel-based correlation analysis method was used to identify the response of the EEQ to changes in human activities and the natural environment. A schematic diagram of the method is shown in Figure 3. The results of conventional image correlation show the spatial correlation between two images. The correlation coefficient reflects whether the spatial distribution patterns of the values in the two images are similar. The data structure is reduced from two dimensions to one dimension during the calculation process. Conversely, the pixel-based correlation analysis method focuses on whether different indices in the

same location have similar temporal variation patterns. With this method, the data structure is reduced from three to two dimensions during the calculation process.

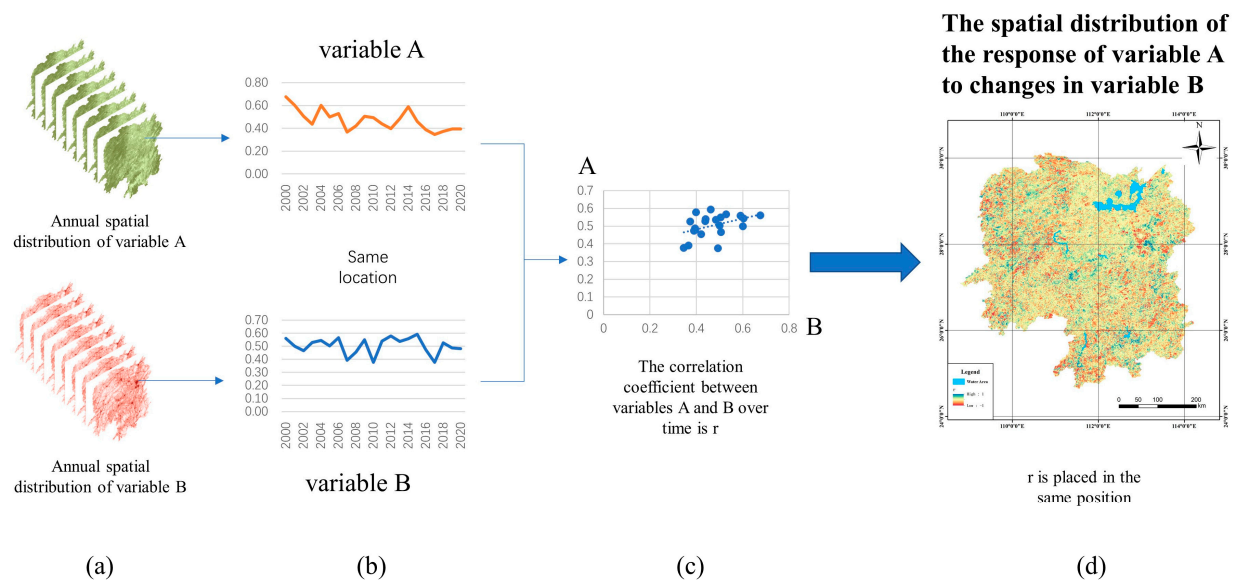


Figure 3. Schematic of pixel-based correlation analysis method: (a) distribution of variables A and B over N years; (b) relationship between the two variables and time for a certain pixel; (c) relationship between the two variables; (d) spatial distribution of the correlation between the two variables.

A change curve (Figure 3b) exists for variables A and B (Figure 3a) within N years for any pixel point, which represents the trend of the changes in the variables at that location over N years. A scatter plot of the values of variables A and B in the same year was created (Figure 3c). We then calculated the correlation index r of the two variables as follows [42]:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (6)$$

where r is the Pearson correlation coefficient between the two variables; x_i is the i th sample value of the first variable; y_i is the i th sample value of the second variable; and $\bar{x}$ and $\bar{y}$ are the means of the two variables, respectively.

r indicates whether the trends of the changes in the two variables are sufficiently connected within the same time period. The spatial distribution of the connection between the trends of the changes in the two variables over time was obtained by calculating the r value for each pixel and performing spatial mapping (Figure 3d).

Changes in EEQ are simultaneously driven by changes in multiple natural and human factors at the same time. The influence of natural factors needed to be eliminated in correlation analysis to more accurately judge the relationship between EEQ and human factors and vice versa. Introducing a third variable in the correlation calculation process effectively eliminates the influence of the third factor, so the spatiotemporal response of EEQ to changes in a single variable could be more accurately identified [43]. Therefore, partial correlation analysis was used to eliminate the influence of the third factor, which is calculated as [42].

$$r_{ab(c)} = \frac{r_{ab} - r_{ac} \cdot r_{bc}}{\sqrt{1 - r_{ac}^2} \sqrt{1 - r_{bc}^2}} \quad (7)$$

where a and b are the independent variable and dependent variable, respectively; c is the control variable; $r_{ab(c)}$ is the correlation coefficient of variable a - b after eliminating the influence of c ; and r_{ab} , r_{ac} and r_{bc} are the Pearson correlation coefficients of variables a - b , a - c , and b - c , respectively.

4. Results

4.1. RSEI-v Performance Verification

We used the traditional PCA method to calculate the RSEI of the study area from 2000 to 2020 for comparison with the performance of RSEI-v.

We constructed a total of 500 random sampling points, obtained the mean RSEI-v and RSEI values to determine the differences between their results, and plotted the results as scatter plots (Figure 4a). Then, we constructed 50 artificially supervised sampling points, obtained the RSEI-v and RSEI values in each period, and plotted them as scatter plots in chronological order to verify whether RSEI-v successfully solves the uncertainty problem experienced with RSEI. Figure 4b depicts the result of one of the sampling points.

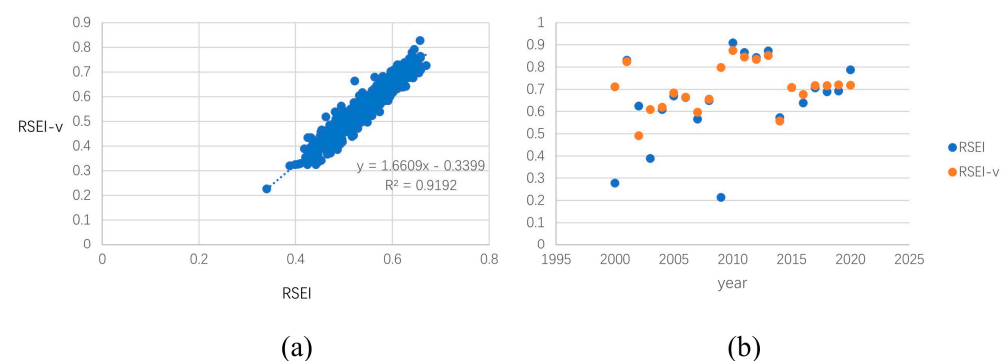


Figure 4. Performance comparison of RSEI-v and RSEI: (a) scatter plot of one random sampling point; (b) scatter plot of distribution over time for a certain artificial supervised sampling point.

The RSEI-v strongly correlates with the RSEI, with the R^2 reaching 0.92, as shown in Figure 4a. These results indicate that the RSEI-v and RSEI results are similar for most sampling points. The RSEI-v performs well, similarly to the RSEI, in reflecting the spatial distribution of EEQ. The sampling points are located in undeveloped forests with little human activity, which is a high-value EEQ cluster, as shown in Figure 4b. Therefore, an effective indicator should have high values with almost no mutations. The RSEI produced abnormally low values in 2000, 2003, and 2009. The above three years were used as the experimental group, and 2002, 2012, and 2020 were used as the control group to conduct significance tests. Natural areas and man-made surfaces for RSEI and RSEI-v in the experimental and control groups were sampled using manual supervised sampling, and significance tests were performed using independent samples T-tests. The results show that for the experimental group $\text{sig. (two-tailed)} = 0.000 < 0.05$, there is a significant difference, while for the control group $\text{sig. (two-tailed)} = 0.200 > 0.05$, there is no significant difference. The calculated RSEI results were found to be negative in these years through manual inspection. The RSEI-v and RSEI values were similar in the remaining years. The characteristics of the two indices were similar at other manually supervised sampling points. Therefore, the performance of the RSEI-v was verified to be substantially better than that of the RSEI in terms of reflecting the temporal changes in EEQ.

In summary, the RSEI-v is similar to the RSEI in spatial distribution but notably more accurate than the RSEI in time-series analysis. We thus used the RSEI-v to represent the regional EEQ, as well as to analyze the spatiotemporal variation in and the response of the EEQ to various factors in Hunan.

4.2. Spatial Pattern of and Changes in EEQ

Figure 5a shows the pattern of the spatial distribution of the mean RSEI-v value in the study area from 2000 to 2020, which we used to represent the EEQ in this study. The overall EEQ in the study area was good, with a multiyear mean of 0.71. The high-value EEQ areas were mainly distributed in the eastern, western, and southern mountainous areas. The low-value areas are mainly concentrated around the rivers and lakes in the central province.

Spatially, the high-value areas surrounded the low-value areas on three sides. The images in Figure 5a were classified using the natural breakpoint method, and five EEQ levels were identified by area from low to high, accounting for 8.88%, 21.08%, 25.20%, 24.78%, and 20.06% of the total area. The classified vector boundaries were superimposed on the high-definition Google Earth remote sensing images, and Figure 5b shows the areas with low EEQ levels. We found that the areas with low EEQ levels were characterized by (1) a generally low altitude, (2) a location around watersheds, and (3) frequent human activities, hosting many towns and large amounts of cultivated land.

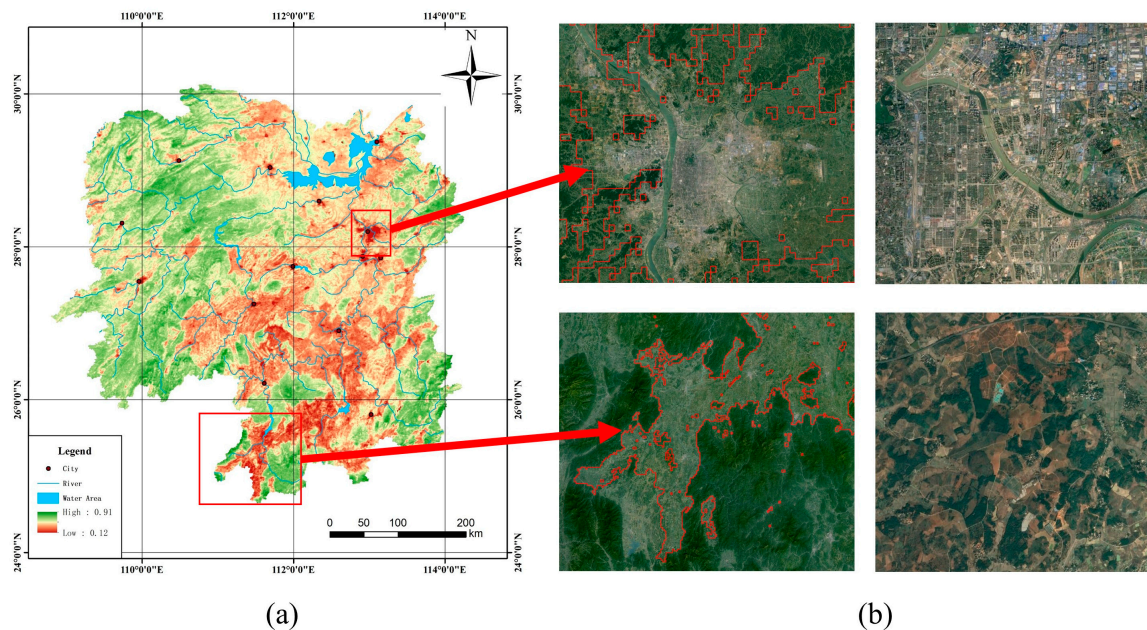


Figure 5. (a) Characteristics of the spatial distribution of EEQ; (b) range and high-definition remote sensing images of some typical study areas (Google Earth imaging date: December 2019).

Figure 6 shows the changes in the EEQ in the study area from 2000 to 2020. Figure 6a shows that the EEQ changes in the study area were generally small, mainly comprising small increases. The areas experiencing EEQ increases and decreases accounted for 81.41% and 18.59% of the total area, respectively. The slope $\in (-0.17, 0.09)$ indicates that the increase in the EEQ was very small relative to the decrease in the EEQ. The areas with increased and decreased EEQ are mainly concentrated in the northwestern mountainous study area. The areas with decreased EEQ mainly concentrated in the northeastern urban agglomeration, the northern Dongting Lake Basin, and some mountainous locations in the central and southern parts of the study area.

The results of the Mann–Kendall test show that the change in the EEQ in the study area was not significant because 49.40% of the area passed the test. The EEQ of most areas showed an increasing trend, accounting for 46.97% of the area, which was continuous in the northwestern mountainous area and dispersed in the eastern and southern regions. The areas with a declining EEQ accounted for 2.42% of the region and were almost entirely concentrated in the Changsha–Zhuzhou–Xiangtan urban agglomeration and Dongting Lake Plain in the north and around Hengyang city in the middle of the study area. The minimal remaining areas with a declining EEQ were scattered around the main towns. Hereafter, the regions where EEQ had substantially decreased and increased are referred to as EEQD and EEQI, respectively.

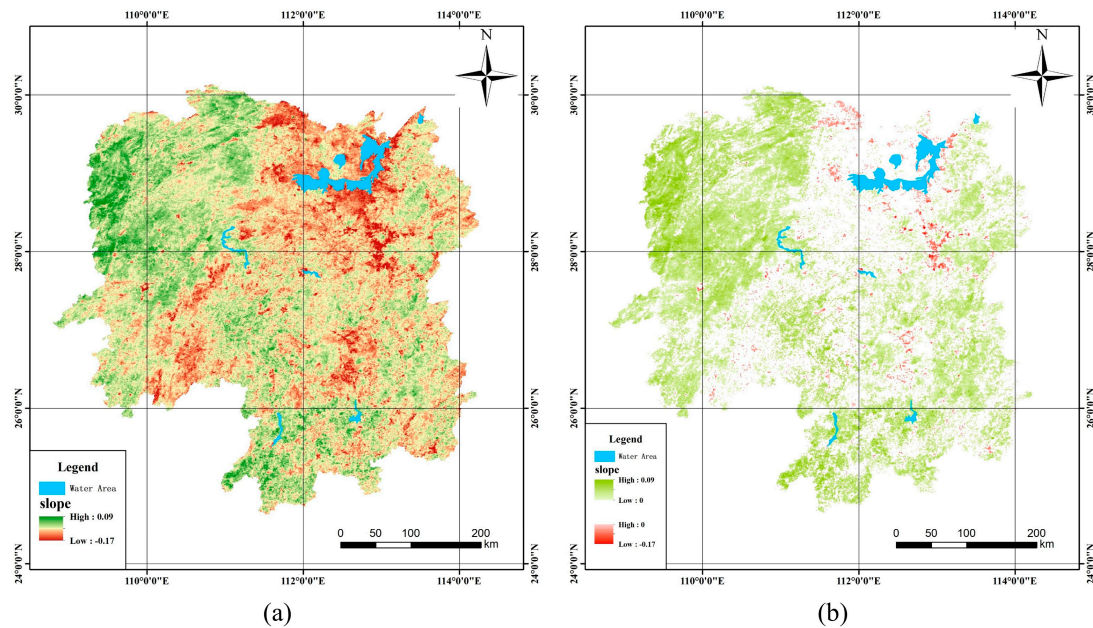


Figure 6. Pattern of the changes in the spatial distribution of EEQ over time: (a) slope index; (b) slope index that passed the Mann–Kendall test.

4.3. Spatiotemporal Responses of EEQ to Changes in Human Activities and Climate

The annual temperature (TEM) and precipitation data (PER) in the study area from 2000 to 2020 were used as independent variables representing climate change. The human footprint (HUM) was used as an independent variable representing human activities. The calculated RSEI-v was used as the dependent variable representing EEQ. The partial correlation coefficient r between the time series of the EEQ and the other factors was separately calculated. The spatial distribution of r represents the spatiotemporal response of the EEQ to the independent variable. The results are shown in Figure 7.

The human activities in most study areas negatively correlated with EEQ (Figure 7a), accounting for 56.84% of the total area. Positive and negative correlations were alternately distributed. The areas for which the significance test was passed accounted for 23.57% of the total area (Figure 7d). Among the areas that passed the significance test, the areas negatively correlated with the EEQ accounted for 68.00%, demonstrating that human activities mainly had a negative on the EEQ. The areas significantly and negatively correlated with EEQ were distributed in a ring around the cities, mainly around the Changsha–Zhuzhou–Xiangtan urban agglomeration and Hengyang. The remainder of these areas were widely distributed across the study area, and their land cover types were mainly cultivated and forest land.

Precipitation both positively and negatively correlated with EEQ in similar proportions (Figure 7b): 48.41% and 51.59%, respectively. The areas negatively correlated with the EEQ were mainly distributed in the mountainous areas in the northwest and southeast; the other areas were mainly positively correlated with EEQ. The spatial distribution was typically characterized by blocks. The areas that passed the significance test accounted for 7.90% of the total study area (Figure 7e); among these, the areas where precipitation negatively and positively correlated with EEQ accounted for 49.70% and 50.30%, respectively. The areas with significantly negative correlations were mainly concentrated in the northwestern mountainous areas, where the land cover type was mainly forest. The areas with significantly positive correlations were mainly concentrated in the cultivated southern region.

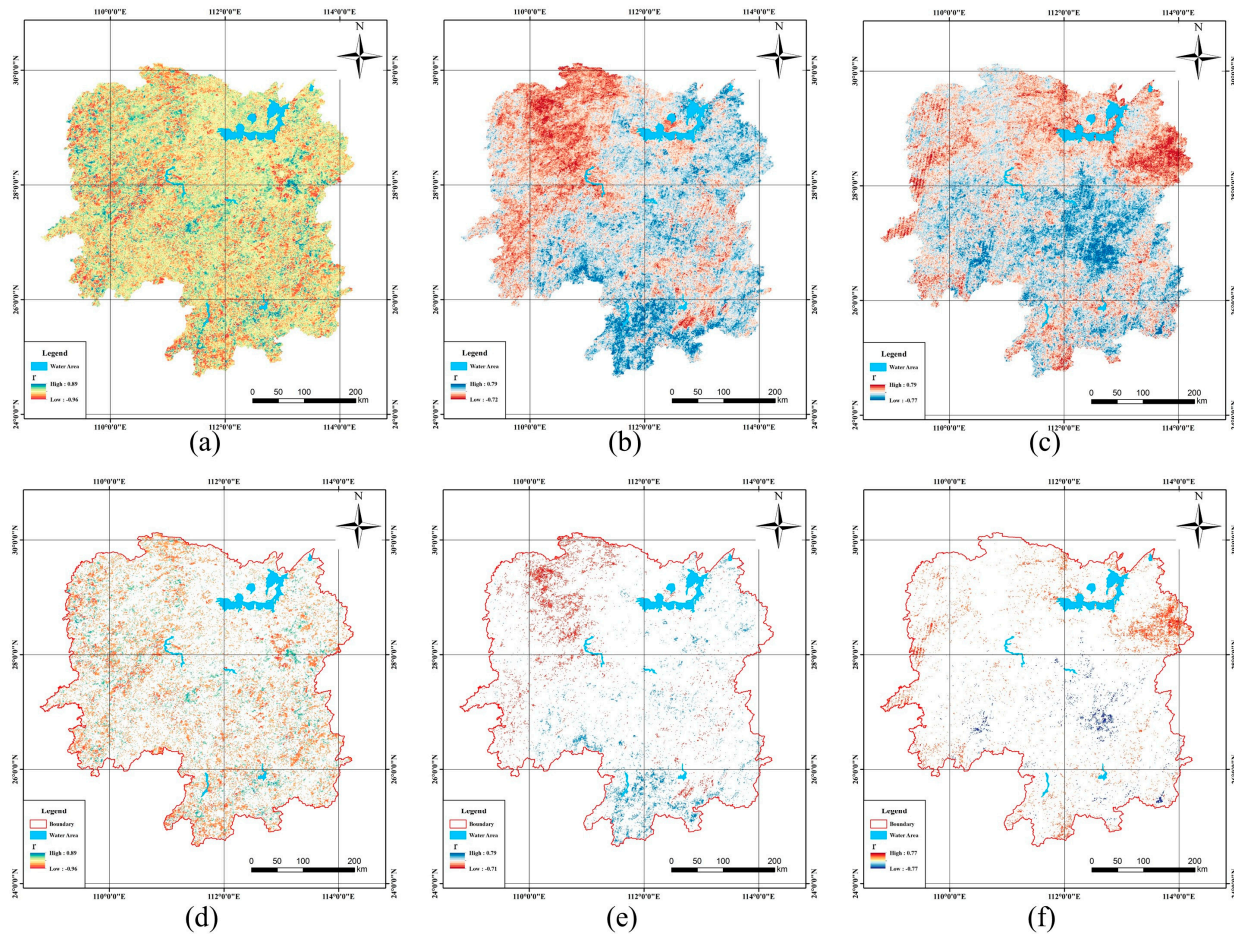


Figure 7. Spatial distribution of correlation coefficient r between the EEQ and independent variables: (a) EEQ–HUM, (b) EEQ–PER, (c) EEQ–TEM, and (d) EEQ–HUM passed the significance test; (e) EEQ–PER passed the significance test; (f) EEQ–TEM passed the significance test.

The temperature mainly showed positive correlations with the EEQ (Figure 7c), accounting for 65.14% of the total area. The areas positively correlated with the EEQ were mainly distributed in the northeastern and northwestern mountainous study areas. The areas where temperature negatively correlated with the EEQ were mainly concentrated in the plains around Hengyang, in the middle of the study area. The areas that passed the significance test accounted for 6.18% of the total region (Figure 7f); among these, the areas where temperature negatively and positively correlated with the EEQ accounted for 16.82% and 83.18% of the total, respectively. The areas where temperature significantly positively correlated with the EEQ were mainly distributed in the northeastern mountainous study area, and the land cover type was mainly forest land. Areas that were significantly negatively correlated with the EEQ were mainly distributed in the cultivated land in the middle of the study area.

5. Discussion

5.1. The Effect of Various Variables in Driving EEQ

Figure 6b is divided into two categories with 0 as the boundary. We used the natural breakpoint method to divide each category into three subcategories, which are marked as lv1–lv3, where the higher the level, the larger the change. The area and proportion of the independent variables that caused notable changes in the EEQ within each category are counted separately. The statistical results are shown in Table 3.

Table 3. Area statistics of independent variables that caused notable changes in the EEQ.

	HUM ¹	PER ¹	TEM ¹	HUM ²	PER ²	TEM ²	Proportion ³
Lv1 (negative)	3248	290	1226	68.18%	6.09%	25.73%	56.70%
Lv2 (negative)	2022	200	1330	56.93%	5.63%	37.44%	35.37%
Lv3 (negative)	454	55	392	50.39%	6.10%	43.51%	7.93%
Lv1 (positive)	10,223	3065	2223	65.91%	19.76%	14.33%	37.68%
Lv2 (positive)	18,868	4464	2423	73.26%	17.33%	9.41%	44.13%
Lv3 (positive)	9395	1663	1135	77.05%	13.64%	9.31%	18.19%

¹ Number of pixels. ² The proportion of pixels of the total number of pixels at this level. ³ The area ratio in each level passing the significance test.

As shown in Table 3, for EEQD areas, the forces driving the EEQ were HUM > TEM > PER. For EEQI areas, the driving forces were HUM > PER > TEM. The driving factors causing significant changes in the EEQ in the study area, whether increasing or decreasing, were mainly human activities. Precipitation was mainly a positive driving force, whereas temperature was a negative driving force.

We used 100 random sampling points to conduct tests for EEQD and EEQI areas. The data obtained at each sampling point were synthesized into the mean and plotted as a line graph in chronological order (Figure 8). In Figure 8a, the RSEI-v strongly decreases for EEQD areas ($R^2 = 0.7962$), HUM continuously and stably increases ($R^2 = 0.963$), TEM slowly decreases, and PER does not notably change. In Figure 8b, for EEQI areas, the RSEI-v slowly increases ($R^2 = 0.3974$); PER fluctuates with an upward trend, and the other two independent variables do not considerably change. A comparison of Figure 8a,b shows that the TEM and HUM values for EEQD areas are substantially higher than those of EEQI areas; the PER of the two types of areas are similar. The trend of the change in each variable for EEQD areas is stronger than that for EEQI areas. The changes in each variable show that human activities and temperature changes lead to a continuous decline in EEQ in EEQD areas. In EEQI areas, changes in precipitation more strongly impacted the EEQ. Human activities caused a continuous decline in EEQ that was larger than the increase in EEQ caused by changes in climate. The sampling conclusions are similar to those in Table 3.

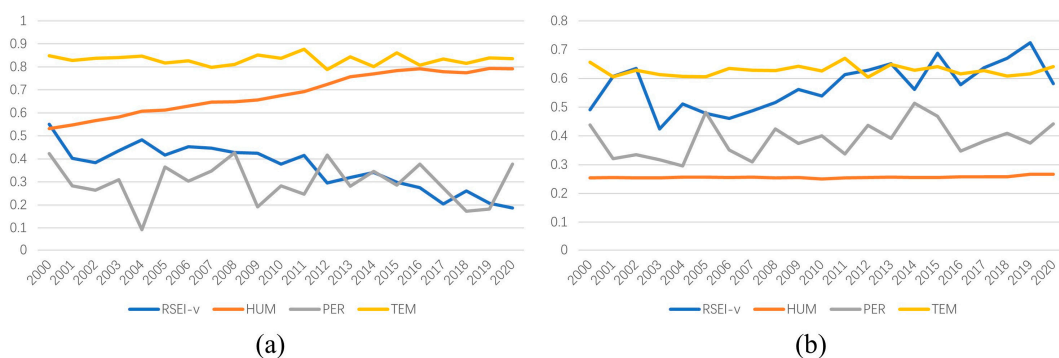


Figure 8. Line graphs of the values of the variables in areas experiencing substantial changes in EEQ: (a) EEQD and (b) EEQI areas.

5.2. Spatiotemporal Pattern of, Changes in, and Mechanisms Driving EEQ in Hunan Province

The overall ecological environment quality in Hunan Province was good, being higher in the western, eastern and southern mountainous areas and lower in the central river basin area. These results are similar to those of prior studies [16,44]. Between 2000 and 2020, the ecological environment quality of approximately half (49.4%) of the regions substantially changed, of which approximately 46.97% and 2.42% of the regions experienced ecological environment quality improvement and deterioration, respectively, the latter of which mainly occurred around various towns, especially around the provincial capital Changsha [45].

In areas where the EEQ notably changed, the most important factor was human activities. Human activities more strongly impacted the ecological environment and showed a trend of more stably changing the EEQ (Figure 8a). Human living processes require material exchanges with nature, which inevitably cause changes in land cover [46]. Different land cover types have different ecological environment quality characteristics. The production processes of humans tend to lead to the expansion of land cover types with lower ecological quality [47]. The areas where the ecological environment quality in Hunan Province significantly degraded were mainly concentrated in the peripheries of cities, where human activities are most frequent. In these areas, the land cover types are continuously progressing (natural vegetation to cultivated land, then to construction land) [48], causing degradation of the ecological environment.

Although human activities have caused a serious decline in the EEQ in Hunan, these areas accounted for 2.42% of the total. Human activities cannot directly cause substantial changes in the quality of the ecological environment on a larger scale. The EEQ of 46.97% of the total area substantially changed owing to changes in climate. These areas were mainly located in the northern study area (Figure 7), with land cover types dominated by forests and low human activity (Figure 8b). The growth and health of vegetation directly reflect the EEQ of these areas [49]. Precipitation and temperature are important factors that directly affect vegetation growth [50]: precipitation provides vegetation with the necessary substances for growth, and temperature (light) provides vegetation with the necessary energy for growth [51]. By affecting vegetation, precipitation and temperature directly drove the EEQ in Hunan Province on a larger scale.

The areas where EEQ and precipitation were strongly correlated were mainly distributed in the northwestern mountainous forests (negative correlation) and the southern plain's cultivated land (positive correlation). Precipitation is an important factor in vegetation growth; however, owing to the abundant soil water and groundwater system, the vegetation in Hunan, which has a subtropical monsoon climate, is not strongly dependent on precipitation. This is similar to the finding in a prior study [52]. In addition, excessive precipitation affects the duration of sunlight and thus inhibits vegetation growth. Therefore, in western Hunan, where the forest density was extremely high, EEQ and precipitation were negatively correlated [53]. In the plain catchment area in the south of the study area, the vegetation growth on the vast expanses of cultivated land and low-density forestland generally depends on precipitation, so this growth positively correlated with precipitation. In future studies, the hysteresis of precipitation on vegetation growth should be fully considered [52].

The driving effect of temperature on vegetation growth in the study area was limited, accounting for 6.18% of the total area, mainly in the forestland in the northeast (positive correlation) and the cities in the central and southern parts (negative correlation). Temperature changes often affect seasonal changes rather than interannual changes in vegetation growth. Temperature was a secondary factor influencing vegetation growth. In interannual scale studies [54]. This finding is verified by the small area of EEQ influenced by temperature (Figure 7) and the smooth change (Figure 8).

One finding is that the EEQ in the high-altitude areas of northeastern and northwestern Hunan was affected by different natural factors. In the northeast, EEQ was mainly positively correlated with temperature; in the northwest, EEQ was mainly negatively correlated with precipitation (Figure 7). The main vegetation community in the northwest was an evergreen coniferous forest dominated by Masson pine; the northeast was a mixed forest area of Chinese fir, bamboo forest, and artificial crop forest [55]. This difference is caused by the sensitivities of different biomes to changes in climate.

5.3. Comparison of Ideas for Improving the RSEI

Other scholars have generally adopted the following methods to address the problem of inconsistent positive and negative RSEI results:

(1) The manual supervision and adjustment method can be applied, which was also used by Xu et al. [10]. This method is convenient, clear, and effective. However, this method requires manual identification and is unsuitable for calculations with large amounts of long-time-series data. (2) Other information dimensionality reduction methods, such as the entropy weight and AHP methods, have been independently used in research [56–58]. (3) The subindicators can be appropriately processed to reduce the possibility of negative indicators. For example, Zheng et al. used discretization processing of the subindicators [26]. (4) The nonsupervised forward processing process can be applied after traditional PCA to integrate information. For example, Yang et al. used a time-filtering method to determine the errors in the time-series data and reconstruct the data [34].

Among the above methods, methods (1) and (2) (AHP) require human supervision and are unsuitable for process-based operations. Method (4) requires additional calculation steps. Additionally, if extreme calculations are needed (such as for climate or human influence), the results of the time-filtering method may be inaccurate. Method (3) may miss important information in the data processing. Xu et al., the developers of the RSEI, have noted this issue [59].

Our method (RSEI-v) has the following advantages compared with the above improved methods: (1) calculation is simple; (2) the problem of the inconsistent positive and negative properties of indicators is effectively solved; (3) the parameters are objective, so the index is suitable for use with big data platforms.

5.4. Shortcomings and Prospects

Generally, EEQ is affected by many factors, including climate change, topography, biological populations, and human activities. Only discussing changes in temperature, precipitation, and human activities is not enough to fully describe the driving factors of EEQ changes. Some scholars use multiple regression methods to mathematically model various natural factors and EEQ and use residuals to represent human impacts [60]. Some scholars also analyze the spatial relationship between EEQ and discrete data such as land cover/use, economy, and population [18]. These methods have contributed to the construction of a comprehensive driving model of EEQ changes.

In addition, the changes in EEQ due to climate change and human activities have the characteristics of changing with time and space scales. In terms of temporal scale, EEQ monitoring with higher temporal accuracy or typical seasons [34] can better reflect the ecological and environmental characteristics of different study areas. In future studies, multi-temporal EEQ, such as monthly data and mean or maximum value synthesis, deserves more attention. In terms of spatial scale, compared with administrative regions, watersheds [16], mining areas [19], and towns [22] are all common research scales, but there are few related works on different ecological functional areas [29], which can become the focus of future work.

6. Conclusions

(1) We used the coefficient of variation method to construct a new remote sensing ecological index, RSEI-v. A new data dimensionality reduction method is adopted in RSEI-v, which solves the problem of inconsistent positive and negative properties, so the proposed method is more suitable for use with big data platforms and for long-term, large-scale remote sensing ecological monitoring, providing a decision-making reference.

(2) Using RSEI-v, we calculated the characteristics of the spatiotemporal distribution of the ecological environment quality in Hunan Province. The ecological quality in the western, eastern, and southern mountainous areas of Hunan was relatively high, whereas that in the central plains was relatively low. Low ecological quality was found in the Changsha–Zhuzhou–Xiangtan urban agglomeration in the northeast and the cultivated area in the south.

(3) From 2000 to 2020, the ecological environment quality in Hunan Province slightly increased. The proportions of areas with increased and decreased ecological environment

quality accounted for 81.41% and 18.59% of the total, respectively. The areas with increased and decreased ecological environment quality are mainly concentrated in the eastern and western mountainous areas and the northern Changsha–Zhuzhou–Xiangtan urban agglomeration, Dongting Lake Plain, and Hengyang City, respectively.

(4) The main factor driving changes in the ecological environment quality in Hunan was human activities, which seriously impacted 23.57% of the study area (for temperature and precipitation, this figure was less than 10%). More than 60% of the ecological environment was significantly degraded, with human activities being the main cause of ecological environment degradation. However, the scope of this impact was relatively small, concentrated in the vicinity of cities and plains.

(5) Due to species differences, among others, the ecological environment quality in the northeastern and northwestern mountainous areas of Hunan Province was strongly affected by precipitation and temperature, respectively.

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Conflicts of Interest: The authors have no conflicts of interest to declare.

Appendix A

The greenness metric used in this study was the normalized difference vegetation index (NDVI), a reliable index that has been widely adopted to measure vegetation health and greenness [7]. The NDVI is calculated as follows:

$$NDVI = \frac{p_{NIR} - p_R}{p_{NIR} + p_R} \quad (A1)$$

where p_{NIR} and p_R represent the reflectivity of the near-infrared and red bands, respectively.

The humidity metric employed in this study is derived from the humidity component of the tasseled cap transform, a linear empirical method that leverages the reflection properties of ground objects to quantitatively assess humidity levels [37,38]. The humidity metric is calculated as

$$WET(TM) = 0.0315p_B + 0.2021p_G + 0.3102p_R + 0.1594p_{NIR} - 0.6806p_{SWIR1} - 0.6109p_{SWIR2} \quad (A2)$$

$$WET(OLI) = 0.1511p_B + 0.1973p_G + 0.3283p_R + 0.3407p_{NIR} - 0.7117p_{SWIR1} - 0.4559p_{SWIR2} \quad (A3)$$

where WET(TM) and WET(OLI) represent the humidity components based on TM and OLI sensing and calculation, respectively; p_B , p_G , p_R , p_{NIR} , and p_{SWIR2} represent the reflectivity of the blue, green, red, near-infrared, short infrared 1, and short infrared 2 bands, respectively.

The indices representing dryness in this study were the index-based built-up index (IBI) [10] and soil index (SI) [39]. Both buildings and bare soil cause surface dryness, so their impact on surface dryness needs to be comprehensively considered. The normalized bare building soil index (NDBSI) [10] is constructed using their arithmetic average, which is calculated as

$$NDBSI = \frac{SI + IBI}{2} \quad (A4)$$

$$SI = \frac{(p_{SWIR1} + p_R) - (p_{NIR} + p_B)}{(p_{SWIR1} + p_R) + (p_{NIR} + p_B)} \quad (A5)$$

$$IBI = \frac{\frac{2p_{SWIR1}}{p_{SWIR1} + p_{NIR}} - \left(\frac{p_{NIR}}{p_{NIR} + p_R} + \frac{p_G}{p_G + p_{SWIR1}} \right)}{\frac{2p_{SWIR1}}{p_{SWIR1} + p_{NIR}} + \left(\frac{p_{NIR}}{p_{NIR} + p_R} + \frac{p_G}{p_G + p_{SWIR1}} \right)} \quad (A6)$$

where NDBSI, SI, and IBI represent the dryness, bare soil, and building indices, respectively; p_B , p_G , p_R , p_{NIR} , and p_{SWIR1} represent the reflectivity of the blue, green, red, near-infrared, and short infrared 1 bands, respectively.

The above four indicators were separately normalized to avoid the four indicators having different weights due to magnitude in subsequent research as follows:

$$NI_i = \frac{I_i - I_{min}}{I_{max} - I_{min}} \quad (A7)$$

where NI_i is the normalized indicator value; I_i is the unnormalized indicator value; I_{max} and I_{min} are the maximum and minimum values of the indicator in the study area, respectively.

Among the four RSEI-v subindicators, NDVI and WET are positive indicators of EEQ, whereas NDBSI and LST are negative indicators. The negative subindicators need to be positively processed to ensure the dimension reduction results in a positive indicator. The formula used was as follows:

$$I_1 = 1 - I_0 \quad (A8)$$

where I_0 is the value of the indicator, which was normalized but not positively processed, and I_1 is the value of the indicator after positive processing, which was used to construct the RSEI-v.

Principal component analysis (PCA) is a common method for extracting primary information. PCA is calculated as follows:

If there are n samples and p indicators, a sample matrix x of size $n * p$ can be formed.

$$x = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \dots & \dots & \dots & \dots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{bmatrix} = (x_1, x_2, \dots, x_p) \quad (A9)$$

Calculate the mean of each column:

$$\bar{x}_j = \frac{1}{n} \sum_{i=1}^n x_{ij} \quad (A10)$$

Calculate the standard deviation for each column:

$$S_j = \sqrt{\frac{\sum_{i=1}^n (x_{ij} - \bar{x}_j)^2}{n - 1}} \quad (A11)$$

Calculate standardized data:

$$X_{ij} = \frac{x_{ij} - \bar{x}_j}{S_j} \quad (A12)$$

Calculate the standardization matrix:

$$X = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1p} \\ X_{21} & X_{22} & \dots & X_{2p} \\ \dots & \dots & \dots & \dots \\ X_{n1} & X_{n2} & \dots & X_{np} \end{bmatrix} = (X_1, X_2, \dots, X_p) \quad (A13)$$

Calculate the covariance matrix of X, named R:

$$R = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1p} \\ r_{21} & r_{22} & \dots & r_{2p} \\ \dots & \dots & \dots & \dots \\ r_{n1} & r_{n2} & \dots & r_{np} \end{bmatrix} = (r_1, r_2, \dots, r_p) \quad (A14)$$

$$\gamma_{ij} = \frac{1}{n-1} \sum_{k=1}^n (X_{ki} - \bar{X}_i)(X_{kj} - \bar{X}_j) \quad (A15)$$

Calculate the eigenvalues $\lambda_1 > \lambda_2 > \dots > \lambda_p$ and eigenvector $(a_1, a_2 \dots a_p)$ of R, and the i-th principal component can be represented as:

$$f_i = a_{1i}X_1 + a_{2i}X_2 + \dots + a_{pi}X_p \quad (A16)$$

The contribution rate P of the ith principal component is

$$P = \frac{\lambda_i}{\sum_{i=1}^p \lambda_i} \quad (A17)$$

Appendix B

Some of the calculation code for this article can be found in the link below.

<https://code.earthengine.google.com/645e8f4aeeef3d0af5445bb4f37a7cc> (accessed on 26 June 2024).

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