



Article

The Dynamic Monitoring and Driving Forces Analysis of Ecological Environment Quality in the Tibetan Plateau Based on the Google Earth Engine

Muhadaisi Airiken ^{1,2} and Shuangcheng Li ^{1,2,*}

¹ College of Urban and Environmental Sciences, Peking University, Beijing 100871, China; 2101112067@stu.pku.edu.cn

² Key Laboratory for Earth Surface Processes of The Ministry of Education, Peking University, Beijing 100871, China

* Correspondence: scli@urban.pku.edu.cn

Abstract: As a region susceptible to the impacts of climate change, evaluating the temporal and spatial variations in ecological environment quality (EEQ) and potential influencing factors is crucial for ensuring the ecological security of the Tibetan Plateau. This study utilized the Google Earth Engine (GEE) platform to construct a Remote Sensing-based Ecological Index (RSEI) and examined the temporal and spatial dynamics of the Tibetan Plateau's EEQ from 2000 to 2022. The findings revealed that the RSEI of the Tibetan Plateau predominantly exhibited a slight degradation trend from 2000 to 2022, with a multi-year average of 0.404. Utilizing SHAP (Shapley Additive Explanation) to interpret XGBoost (eXtreme Gradient Boosting), the study identified that natural factors as the primary influencers on the RSEI of the Tibetan Plateau, with temperature, soil moisture, and precipitation variables exhibiting higher SHAP values, indicating their substantial contributions. The interaction between temperature and precipitation showed a positive effect on RSEI, with the SHAP interaction value increasing with rising precipitation. The methodology and results of this study could provide insights for a comprehensive understanding and monitoring of the dynamic evolution of EEQ on the Tibetan Plateau amidst the context of climate change.



Citation: Airiken, M.; Li, S. The Dynamic Monitoring and Driving Forces Analysis of Ecological Environment Quality in the Tibetan Plateau Based on the Google Earth Engine. *Remote Sens.* **2024**, *16*, 682. <https://doi.org/10.3390/rs16040682>

Academic Editors: Shin Nagai and Jeroen Meersmans

Received: 20 December 2023

Revised: 4 February 2024

Accepted: 6 February 2024

Published: 14 February 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: Google Earth Engine; Remote Sensing-based Ecological Index; SHAP; climate change

1. Introduction

The unique geography and dynamic processes of the Tibetan Plateau have a significant impact on the climate of East Asia and the world. The plateau's ecosystem is delicate, vulnerable, and sensitive to natural changes and human interference [1]. Climate change and human intervention profoundly affect the atmospheric and hydrological cycles of the plateau, potentially limiting ecological environments and regional sustainable development [2,3]. Therefore, maintaining the Ecological Environment Quality (EEQ) of the Tibetan Plateau is crucial for ensuring downstream areas' social, economic, and ecological security and stability.

The use of holistic ecological indices, such as the Remote Sensing-based Ecological Index (RSEI), has become increasingly popular in EEQ studies. RSEI integrates data on greenness, humidity, dryness, and heat degree [4,5]. Hu and Xu [6] proposed RSEI specifically designed to identify EEQ characteristics in southeast China, utilizing principal component analysis (PCA). Xu et al. [7] utilized RSEI and feature inversion techniques to investigate the ecological effects of population growth and impervious surface area increase. Xu et al. [8] developed an RSEI-change vector analysis methodology to examine the change characteristics of China's EEQ in the past 16 years. Other studies have also demonstrated the usefulness of RSEI in evaluating EEQ in diverse settings. RSEI has been

widely used, not only in regional studies [9–11] but also in EEQ studies in developed countries [12,13], including urban agglomerations [11,14–16], watersheds [9,17], croplands [18], wetlands [4], land-use change [19], and land degradation [20]. Recent studies have also been conducted on the Tibetan Plateau: Tu et al. [21] selected patches with the highest RSEI values as alternative ecological sources, ultimately determining 123 ecological sources and 333 ecological corridors; Zhang et al. [22] analyzed the spatiotemporal changes in EEQ on the Tibetan Plateau from 2000 to 2020 and discussed the response of EEQ to climate and land-use changes. Liu et al. [23] constructed an RSEI model for the cold and high-altitude pastoral areas in the northeastern part of the Tibetan Plateau from 2000 to 2020. The results indicated a good correlation between the Comprehensive Ecological Security Index and RSEI, demonstrating that the assessment framework could effectively reflect the actual ecological security status of the study area. Moreover, the Google Earth Engine (GEE) platform could invoke the medium-resolution imaging spectroradiometer (MODIS), Landsat, and other massive remote sensing (RS) data products. With its robust cloud computing and storage capabilities, GEE has become a valuable tool for evaluating large-scale, long-term dynamics to calculate the RSEI [24–28].

In the realm of machine learning research, the interpretation of models assumes paramount significance [29]. Traditional machine learning models fall short in elucidating individual predictions or justifying model decisions [30]. The SHAP (Shapley Additive Explanation) method, grounded in the TreeExplainer framework, emerges as a valuable tool capable of providing localized explanations for machine learning model predictions. It proficiently identifies non-linear interactions, facilitating adaptable modeling, interpretation, and visualization of intricate geographic phenomena and processes [31]. The TreeExplainer-based SHAP method has found applications across diverse domains, encompassing research on heat-related mortality [29], environmental disasters [32], social sciences [33], ecology [34], and geography [35]. While some studies delve into the EEQ conditions of the Tibetan Plateau, a dearth of explanations concerning the driving factors behind modeling outcomes persists. Consequently, this study leverages the capabilities of the GEE platform to address the gap in the long time series evaluation of RSEI and undertakes a comprehensive analysis of the influence exerted by both natural and anthropogenic factors in the Tibetan Plateau. The primary objective of this paper is not only to analyze the spatial–temporal dynamic change characteristics of the RSEI in the Tibetan Plateau and assess its effectiveness and reliability but also to utilize XGBoost (eXtreme Gradient Boosting) and SHAP to identify and quantify the contributions of individual factors. This research aims to provide a foundational basis for monitoring the dynamic changes in the EEQ of the Tibetan Plateau under the context of climate change.

2. Study Area and Methodology

2.1. Study Area

The Tibetan Plateau is characterized by sparse air and intense solar radiation, which lead to marked regional climate differences due to the impact of monsoons and westerly winds [36,37]. The temperature and moisture conditions gradually vary from the northwest, with a cold and dry climate, to the southeast, with a relatively warm and humid climate. The unique topography, high elevations, and complex surface features of the Tibetan Plateau significantly influence East Asian climate patterns, Asian monsoon processes, and Northern Hemisphere atmospheric circulation via powerful dynamic and thermal effects [36]. The ecological environment of the Tibetan Plateau is somewhat vulnerable, and it exhibits a distinct response to global climate change and human activities [38,39].

2.2. Data Sources and Preprocessing

2.2.1. Raster Data Utilized for Constructing the RSEI Model

The development of the RSEI model incorporated the use of MODIS data, complemented by land use data obtained from NASA LP DAAC at the USGS EROS Center (USGS, Earth Explorer, <https://earthexplorer.usgs.gov/> (accessed on 23 February 2023)), with de-

tailed specifics presented in Table 1. Supplementary Table S3 provides detailed information on the specific land use types. Diverse data processing tasks, encompassing remote sensing data acquisition, cloud removal, image mosaicking, clipping, resampling, and projection, were executed on the Google Earth Engine (GEE) platform.

Table 1. The data source of ecological components.

Component	MODIS Data Collection	Layer	Spatial/Temporal Resolution
Greenness	MOD13A1_v6	Normalized Difference Vegetation Index (NDVI)	500 m/16 days
Heat	MOD11A2_v6	Daytime Land Surface Temperature (DLST)	1 km/8 days
Wetness	MOD09A1_v6	Corrected surface spectral reflectance for bands 1 to 7	500 m/8 days
Dryness	MOD09A1_v6	Corrected surface spectral reflectance for bands 1 to 7	500 m/8 days
Water	MOD09A1_v6	Corrected surface spectral reflectance for bands 1 to 7	500 m/8 days
LUCC	MCD12Q1_061	MODIS Global Land Cover Type	500 m Yearly

2.2.2. Multi-Source Data for Driving Factor Analysis

This study aims to explore the contribution of natural and anthropogenic factors to the ecological and environmental quality of the Tibetan Plateau. For this purpose, 10 representative driving factors were selected (Table 2) and analyzed using the XGBoost model and SHAP to elucidate the importance ranking of each factor. The vector boundary of the Tibetan Plateau was defined based on previous work [40]. Table 2 reveals differences in the spatial and temporal resolution of each driving factor. Therefore, comprehensive preprocessing was conducted on all data: five typical land use and land cover (LUCC) types (Barren, Grasslands, Mixed Forests, Evergreen Needleleaf Forests, and Woody Savannas) were selected and reordered according to RSEI values. The distance to roads was calculated using ArcGIS, and the average values of all indicators from 2014 to 2020 were computed. Finally, all data were spatially resampled to 1 km; a grid was created in ArcGIS, and voids were removed, resulting in a final dataset comprising 11,747 sample points.

Table 2. Independent variable descriptions.

Factors Category	Variable	Description	Resolution	Source
Natural factors	Digital Elevation Model (DEM)	DEM Dataset of China	1 km	Resource and environmental science data center of Chinese Academy of Science (http://www.resdc.cn (accessed on 23 February 2023))
	Relief Degree of Land Surface Dataset (Rdls)	Relief Degree of Land Surface Dataset of China	1 km	Global Change Research Data Publishing & Repository, (http://www.geodoi.ac.cn (accessed on 23 February 2023))
	Mean temperature (TMP)	1 km monthly mean temperature dataset for China (°C)		National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdac.ac.cn/ (accessed on 23 February 2023))
	Precipitation (PRE)	1 km monthly precipitation dataset for China (mm)	1 km, 1901–2021	National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdac.ac.cn/ (accessed on 23 February 2023))
	Soil moisture dataset (SMCI)	A 1 km daily soil moisture dataset over China based on situ measurement (10 cm) (m^3/m^3)	1 km, 2000–2020	National Tibetan Plateau/Third Pole Environment Data Center (https://data.tpdac.ac.cn/ (accessed on 23 February 2023))
	LUCC	MCD12Q1_061: MODIS Global Land Cover Type	1 km, 2000–2020	NASA LP DAAC at the USGS EROS Center (USGS, https://earthexplorer.usgs.gov (accessed on 23 February 2023))

Table 2. Cont.

Factors Category	Variable	Description	Resolution	Source
Anthropogenic factors	Worldpop (POP)	WorldPop estimates the number of people per 100 m × 100 m grid square on Earth, population density, etc.	100 m, 2000–2020	(https://www.worldpop.org/ (accessed on 23 February 2023))
	Nighttime Light Data (NTL)	An Extended Time Series (2000–2022) of Global NPP-VIIRS-Like Nighttime Light Data from a Cross-Sensor Calibration	500 m, 2000–2022	National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn) (accessed on 23 February 2023))
	Distance to roads (DR)	OpenStreetMap Data	2014–2022	(https://download.geofabrik.de (accessed on 23 February 2023))
	Human impact index (HAI)	Human Activity Intensity Dataset of the Qinghai-Tibet Plateau	1 km, 2000–2020	Digital Journal of Global Change Data Repository, (https://www.geodoi.ac.cn/ (accessed on 23 February 2023))

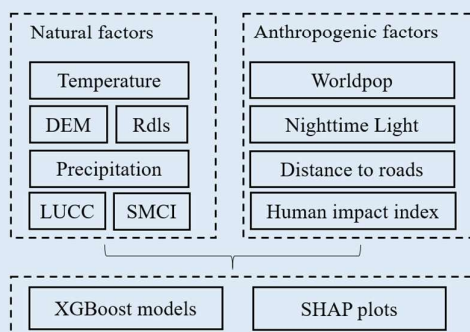
2.3. Methods

The main workflow of this study is illustrated in Figure 1. Further detailed content can be categorized into the following five points: (1) obtained the RSEI index in the study area from 2000 to 2022 using GEE; (2) analyzed spatiotemporal changes based on the multi-year RSEI dataset; (3) introduced XGBoost-SHAP to assess the response of RSEI to natural and socio-economic factors; (4) explored the interactive effects of climate factors; and (5) validated and discussed the applicability of RSEI in the ecological assessment of the Tibetan Plateau.

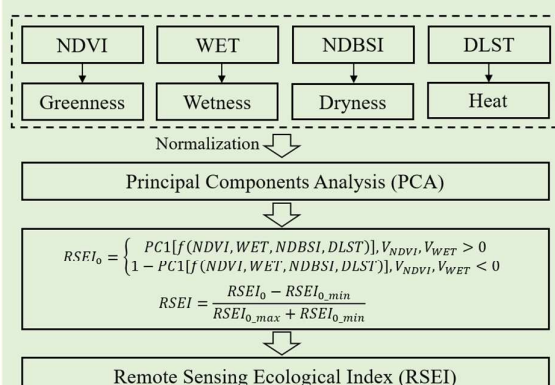
I. MODIS Data Collections



IV. Quantification of the SHAP values of drivers



II. Long time series RSEI calculation



III. Change detection of RSEI

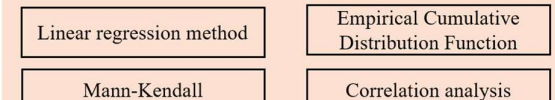


Figure 1. Methodological framework applied in the present analysis.

2.3.1. Construction of the RSEI Model

RSEI has gained widespread applicability due to its ability to integrate various natural factors, providing a more comprehensive reflection of land conditions compared to a single index, as proposed by Xu, Wang, Shi, Guan, Fang, and Lin [7]. The primary calculation process is illustrated in Figure 1, and the principal component analysis results are presented in Supplementary Figure S1. The specific calculation formulas for each remote sensing index can be referenced from previous works [41,42], and the calculation formulas for each

index are provided in Table 3. Since the units of various indicators differ, normalization is required. The normalization formula is given by

$$N_i = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where N_i represents the normalized value for the i -th index, X is the original value of the i -th index, $X_{\min}$ and $X_{\max}$ denote the minimum and maximum values of the i -th index, respectively.

Table 3. Formula and description of the ecological indicators.

Indicators	Calculation Formula	Explanation
Wetness	$\text{Wet} = c_1\rho_{\text{red}} + c_2\rho_{\text{nir1}} + c_3\rho_{\text{blue}} + c_4\rho_{\text{green}} + c_5\rho_{\text{nir2}} + c_6\rho_{\text{swir1}} + c_7\rho_{\text{swir2}}$	where ρ_{red} , ρ_{blue} , ρ_{green} , ρ_{swir1} , ρ_{swir2} represent the reflectance of the 7 bands of the MOD09A1_v6 images, respectively. For MODIS multi-band images, the coefficient of each band is $c_1 = 0.1147$, $c_2 = 0.2489$, $c_3 = 0.2408$, $c_4 = 0.3134$, $c_5 = -0.3122$, $c_6 = -0.6416$, $c_7 = -0.5087$ [43].
Dryness	$\text{NDBSI} = \frac{\text{IBI} + \text{BI}}{2}$ $\text{IBI} = \frac{\frac{2\rho_{\text{swir1}}}{\rho_{\text{swir1}} + \rho_{\text{nir1}}} - \left[\frac{\rho_{\text{nir1}}}{\rho_{\text{nir1}} + \rho_{\text{red}}} + \rho_{\text{green}} / (\rho_{\text{green}} + \rho_{\text{swir1}}) \right]}{\frac{2\rho_{\text{swir1}}}{\rho_{\text{swir1}} + \rho_{\text{nir1}}} + \left[\frac{\rho_{\text{nir1}}}{\rho_{\text{nir1}} + \rho_{\text{red}}} + \rho_{\text{green}} / (\rho_{\text{green}} + \rho_{\text{swir1}}) \right]}$ $\text{BI} = \frac{[(\rho_{\text{swir1}} + \rho_{\text{red}}) - (\rho_{\text{nir1}} + \rho_{\text{blue}})]}{[(\rho_{\text{swir1}} + \rho_{\text{red}}) + (\rho_{\text{nir1}} + \rho_{\text{blue}})]}$	where ρ_{red} , ρ_{blue} , ρ_{green} , ρ_{nir1} , and ρ_{swir1} are the surface reflectance of the corresponding bands in the MOD09A1 V6 images, respectively.
MNDWI	$\text{MNDWI} = (\rho_{\text{green}} - \rho_{\text{swir1}}) / (\rho_{\text{green}} + \rho_{\text{swir1}})$	where ρ_{green} and ρ_{swir1} represent the reflectance of the 7 bands of the MOD09A1_v6 images, respectively.

RSEI is normalized within the range [0, 1]. A higher RSEI value indicates a better eco-environmental quality for the region.

2.3.2. Linear Regression Method and Mann–Kendall

The trend analysis method is a widely used statistical approach aimed at analyzing changes over time by performing a linear regression analysis on preset variables [44]. To calculate the slope of the pixel regression equation, researchers use Equation (2):

$$\text{Slope} = \frac{n \sum_{i=1}^n (i \times RSEI_i) - \sum_{i=1}^n i \sum_{i=1}^n RSEI_i}{n \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2} \quad (2)$$

where Slope represents the slope of the pixel regression equation, $RSEI_i$ stands for the mean value of $RSEI$ in the i -th year, and n indicates the number of years under investigation. $\text{Slope} > 0$ suggests increasing $RSEI$ values, $\text{Slope} = 0$ indicates no significant change, and $\text{Slope} < 0$ reflects a decrease in $RSEI$.

The Mann–Kendall test is an important non-parametric statistical method frequently used to analyze the significance of trends in time series. This test is usually conducted alongside linear regression analysis [45,46]. The calculation formula for the test is presented below:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & , S > 0 \\ 0 & , S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & , S < 0 \end{cases} \quad (3)$$

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(RSEI_j - RSEI_i) \quad (4)$$

$$Var(S) = \frac{n(n-1)(2n+5)}{18} \quad (5)$$

$$sign(RSEI_j - RSEI_i) = \begin{cases} 1, RSEI_j - RSEI_i > 0 \\ 0, RSEI_j - RSEI_i = 0 \\ -1, RSEI_j - RSEI_i < 0 \end{cases} \quad (6)$$

where S represents the summation of the rank correlation coefficient. The variance of S , which is represented by $Var(S)$, is calculated using Formula (5). Once the slope and confidence interval of the Mann–Kendall test's Z-value are computed, statistical plotting of RSEI change trend ($p < 0.05$) can be executed based on these two results.

2.3.3. Attribution Analysis

The eXtreme Gradient Boosting (XGB) model, an ensemble learning algorithm built on iterative decision trees, has been extensively utilized in the realms of classification and regression [34,35]. Situated within the framework of gradient-boosting trees, this ensemble learning approach showcases robustness, exceptional performance, and precise handling of low-dimensional data [31,47]. The algorithm's core lies in optimizing the objective function value within the gradient-boosting framework. This study specifically employed the regression function of the algorithm. After the training of the XGBoost model, the Shapley Additive Explanation (SHAP) method was employed to delineate the marginal contribution of each predictor to the target variable. The implementation of the XGBoost model was carried out using the xgboost Python package.

Shapley Additive Explanations (SHAP), serving as a machine learning interpreter, utilizes game theory methods to compute the marginal contributions of each feature to the model's output. It assigns specific predictive importance values to each feature, ensuring robust global and local interpretability [48]. SHAP finds widespread applications across various domains [35]. The amalgamation of the SHAP algorithm with feature selection enhances both the speed and quality of the feature selection process. The SHAP values for an XGBoost model are computed using the Python package shap.

For a specific input sample x with M features, the Shapley additive mechanism expresses an individual prediction by decomposing it into feature contributions [49]:

$$f(x) = g(x') = \varphi_0 + \sum_{i=1}^M \varphi_i x'_i \quad (7)$$

where f and g represent the original model and the explanation model, respectively. The function g should match the output of the original model for a simplified input x' of x . φ_0 is the mean value of the prediction values [50], and $\varphi_i x'_i$ represents the SHAP value for feature i in sample x .

The SHAP method also provides a global explanation [34]. The SHAP feature importance of a specific variable is calculated as the average of the absolute SHAP values, denoted as I_{SHAP}^j , where j is the input variable, i is the data sample, and n is the number of samples:

$$I_{SHAP}^j = \frac{1}{n} \sum_{i=1}^n |\varphi_j^i| \quad (8)$$

3. Results

3.1. Spatial–Temporal Variation Characteristics of RSEI in Long Time Series

Figure 2 illustrates the annual spatial distribution characteristics of the RSEI computed via the GEE platform from 2000 to 2022. The spatial distribution pattern of the ecological and environmental quality on the Tibetan Plateau displayed a distinct regularity, depicting a decreasing trend from southeast to northwest. The average RSEI value for the Tibetan Plateau during the period 2000–2022 reached 0.404. The RSEI values were classified into five categories, where higher values indicated greater vegetation coverage, a healthier

ecological environmental, and a more stable ecosystem, while lower values suggested adverse regional conditions [51].

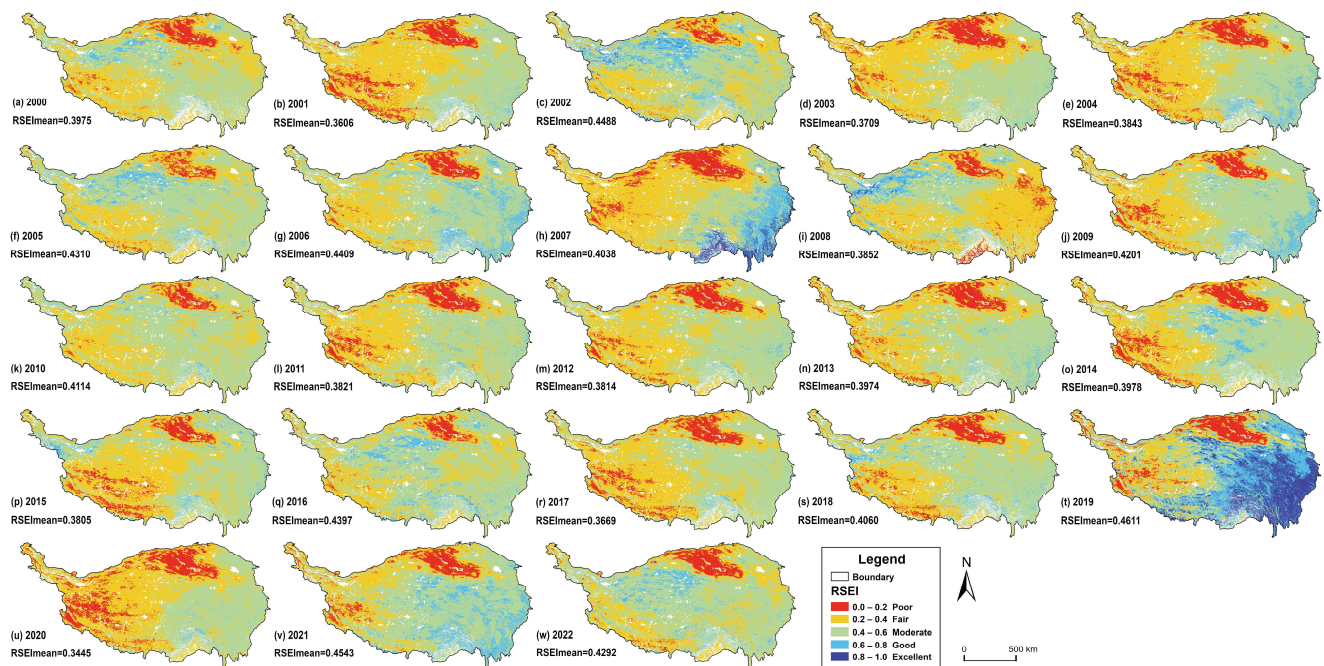


Figure 2. Visualized spatial distribution of RSEI over the Tibetan Plateau.

Significantly, dynamic changes in RSEI levels on the Tibetan Plateau from 2000 to 2022 were observed. The northern Qaidam Desert region and the southwestern part consistently exhibited Poor or Fair levels, with a substantial area falling into these categories in 2020, resulting in the lowest RSEI value reaching 0.3445. In the southeastern region, most of the time was spent in Moderate or Good levels, with rare occurrences of large areas categorized as Fair and Poor in 2008. In 2007 and 2019, extensive areas were classified as Excellent, contributing to the high RSEI value of 0.4611 in 2019. The central region predominantly fell into Good, Moderate, and Fair levels.

The RSEI trend analysis on the Tibetan Plateau from 2000 to 2022 was visualized via linear regression and MK test, as shown in Figure 3. Its trend was categorized into four types using a significance level of 0.05. Figure 3 reveals that the RSEI change trend in the Tibetan Plateau is mainly characterized by slight degradation (45.9%) and slight improvement (40.8%). The areas that experienced slight degradation are primarily clustered in the northeastern parts of the Tibetan Plateau. Conversely, the areas with slight improvement are mainly concentrated in regions with low elevation, gradually widening from west to east, including Qamdo, Garze, Aba, and surrounding areas. Some areas depicted considerable degradation (5.1%) scattered across locations such as Haixi and Xigaze. Moreover, 7.9% of areas remained stable, with no significant RSEI changes. Lastly, only 0.3% of regions represented a significant improvement.

To further examine the five-year variation characteristics of RSEI on the Tibetan Plateau using the Empirical Cumulative Distribution Function (ECDF) in MATLAB software, fluctuations were observed (Figure 4a). In comparison to the year 2020, the ECDF values for the remaining years exhibited a notable rightward deviation, with the most significant deviation observed in 2005. This suggested a relatively superior overall ecological environment in 2005 as opposed to 2020, reaching a value of 0.431. The ECDF value for the year 2000 was positioned at a mid-range level. Moreover, in 2010 and 2005, corresponding to lower RSEI values, a similar probability distribution was evident; however, as RSEI gradually improved, distinctions became apparent.

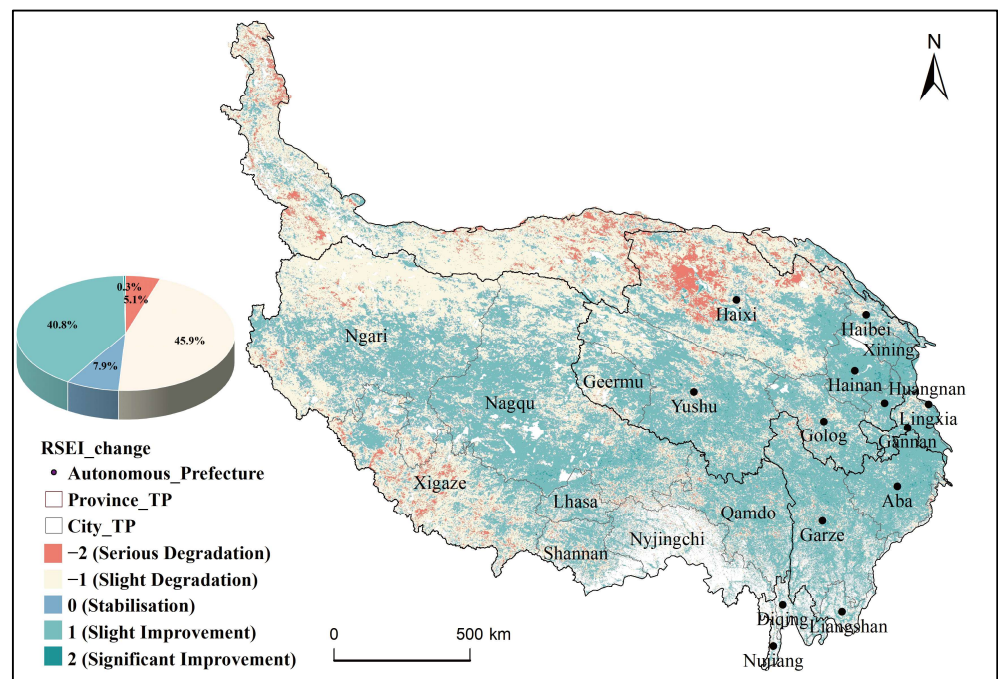


Figure 3. The spatial distribution of the RSEI change trend in the Tibetan Plateau from 2000 to 2022.

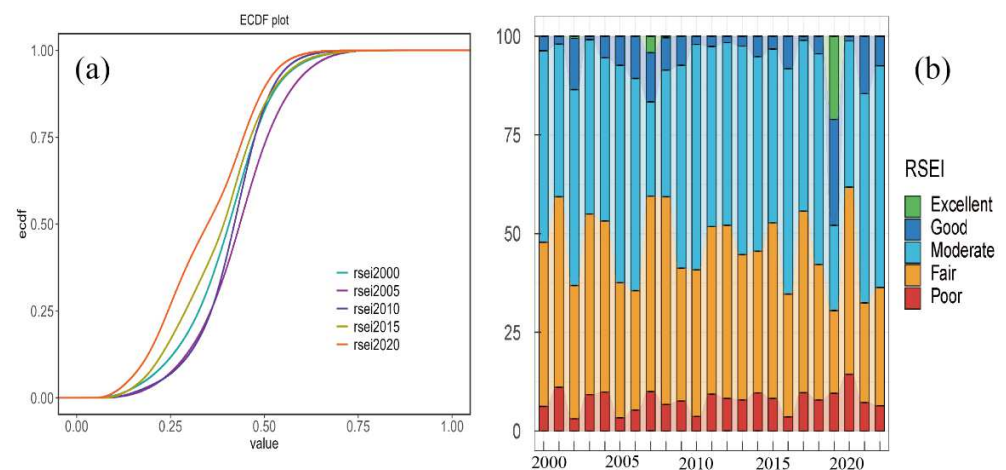


Figure 4. The ECDF effects of mean RSEI value in the Tibetan Plateau from 2000 to 2022 (a) and Alluvial diagram of RSEI grades (b).

To further elucidate the annual variations in the area proportion of each RSEI level, a chart depicting the impact of grade changes was generated (Figure 4b). Figure 4b illustrates that all RSEI levels underwent varying changes in area proportion. The ecological environmental quality (EQ) of the Tibetan Plateau was predominantly categorized as either Fair or Moderate from 2000 to 2022. Specifically, the Moderate grade reached its peak in 2010 (57.08%) and 2016 (56.99%), followed by 2022 (56.11%). The Fair grade achieved its highest percentage in 2008 (52.57%) and then gradually declined to 49.56%, 48.25%, and 47.32% in 2007, 2001, and 2020, respectively. The Poor and Good grades constituted a relatively small percentage, with $\text{Good}_{2019} (26.9\%) > \text{Good}_{2002} (12.96\%) > \text{Good}_{2007} (12.45\%)$. The highest incidence of Poor (14.41%) was recorded in 2020, indicating a poor EQ level in the Tibetan Plateau during that year, a trend more evident in Figure 2 portraying the spatial distribution. Notably, the region with an Excellent level accounted for 4.2% in 2007 and 21% in 2019.

3.2. Influence of LUCC on RSEI Response

To evaluate the influence of LUCC on RSEI, the LUCC dataset for each year was superimposed onto the RSEI map (see Supplementary Figure S3). Employing zoning statistical methods, RSEI values of each land use category were calculated from 2001 to 2020, offering insights into the specific contribution of different LUCC changes to RSEI (Figure 5).

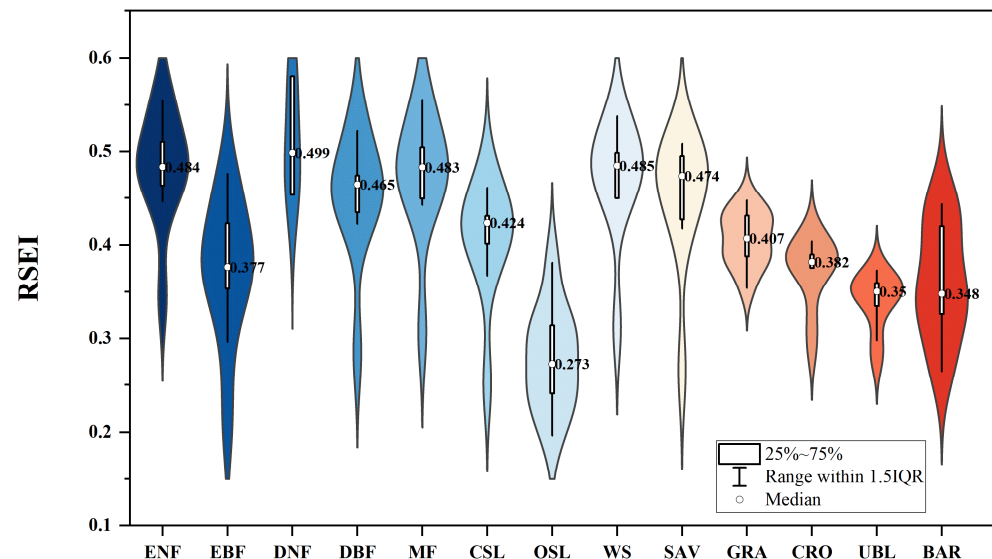


Figure 5. Responses of land use types to RSEI in the Tibetan Plateau. (ENF, Evergreen Needleleaf Forests; EBF, Evergreen Broadleaf Forests; DNF, Deciduous Needleleaf Forests; DBF, Deciduous Broadleaf Forests; MF, Mixed Forests; CSL, Closed Shrublands; OSL, Open Shrublands; WS, Woody Savannas; SAV, Savannas; GRA, Grasslands; CRO, Croplands; UBL, Urban and Built-up Lands; BAR, Barren).

In Figure 5, the highest RSEI median was observed for DNF at 0.499. This observation was primarily attributed to the limited extent of DNF coverage in the Tibetan Plateau. The second-highest RSEI median value was for WS, with a median of 0.485. Meanwhile, ENF and MF exhibited nearly identical RSEI medians, both at 0.484 and 0.483, respectively. These results indicated that the land use types with the most significant contribution to RSEI were WS, ENF, and MF. Subsequent land use categories include SAV, DBF, CSL, and GRA, with RSEI medians of 0.474, 0.465, 0.424, and 0.407, respectively. Notably, GRA displays the most concentrated response values to RSEI, with 0.407, exceeding the medians of CRO at 0.382, EBF at 0.377, UBL at 0.35, and BAR at 0.348. The smallest RSEI median value was observed for OSL, reaching 0.273, indicating that the RSEI of OSL was more vulnerable. Its corresponding maximum RSEI value is only 0.314, classified as Fair.

3.3. Quantification of the SHAP Values of Drivers

To further quantify the contributions of both natural and anthropogenic factors to RSEI, various factors underwent data preprocessing operations. Subsequently, SHAP values for each factor influencing RSEI were computed across 11,747 fishnet points (Figure 6). A negative SHAP value signifies an RSEI loss from a base value caused by a specific variable, while a positive value indicates the opposite.

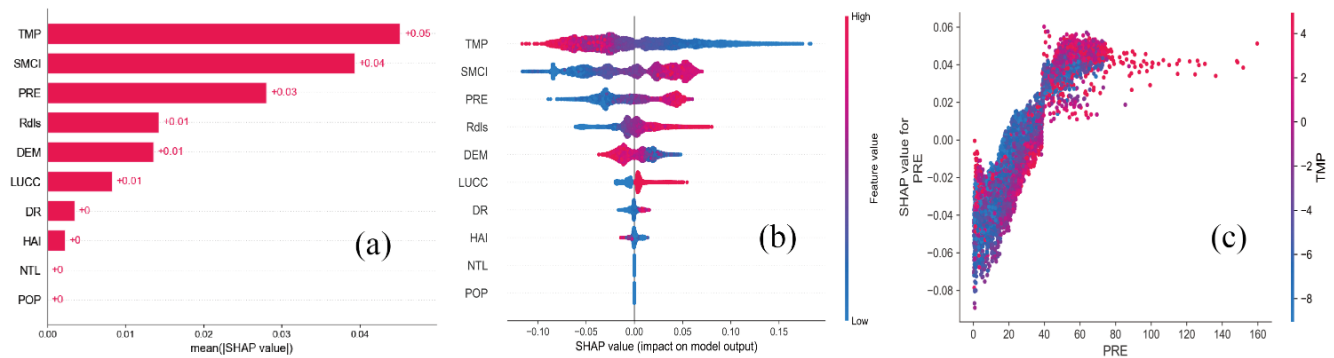


Figure 6. SHAP values of RSEI drivers. (a) Bar plot of the mean absolute SHAP values of drivers affecting RSEI. (b) The Bees warm plots visualize SHAP values, with each dot representing a fishnet point in this study. The dot's position on the x-axis indicates the influence that a variable has on the XGBoost model's prediction for that specific fishnet point. In instances where multiple dots align at the same x position, they aggregate to denote density. (c) SHAP interaction plot of features. TMP, temperature; SMCI, soil moisture; PRE, precipitation; Rdls, relief degree of land surface; DEM, digital elevation model; DR, distance to roads; HAI, human impact index; NTL, nighttime light data; POP, population density.

The results revealed that TMP, SMCI, and PRE were the three most influential factors affecting RSEI sensitivities (Figure 6a). The average contributions of Rdls, DEM, and LUCC to RSEI-XGB were consistently measured at 0.01 each (Figure 6a). Conversely, factors associated with human activities (DR, HAI, NTL, and POP) demonstrated the least degree of contribution. In summary, the relative importance of natural factors exceeded that of anthropogenic factors.

A lower TMP could result in more substantial variations in RSEI dynamics, characterized by long right tails of SHAP values (Figure 6b). Conversely, higher RSEI values were generally associated with elevated SHAP values of SMCI and PRE. To further analyze the interaction between temperature and precipitation on RSEI, TMP and PRE were examined for their interactive effect using a SHAP interaction plot (Figure 6c). An evident coupling effect between TMP and PRE was identified: when the temperature was high, an increase in precipitation led to an augmentation in the SHAP interaction value between TMP and PRE. Similarly, at lower temperatures, the SHAP interaction value with PRE exhibited a positive effect, albeit lower than the value at higher temperatures. In contrast, minimal precipitation and higher temperature resulted in a negative impact on the SHAP interaction value. In summary, the substantial interactive effects between TMP and PRE had a more pronounced impact on RSEI.

4. Discussion

4.1. Applicability of RSEI in the Ecological Environment Assessment of the Tibetan Plateau

The ecological environment, serving as a vital natural resource and human habitat, is a prerequisite for human development and social progress [16,52]. Previous research on ecological environment assessment has predominantly relied on statistical data, exhibiting some ambiguity and low spatial resolution characteristics due to subjectivity in index construction [16,53–56]. Advances in Earth observation satellites and open access to remote sensing data have facilitated a more precise identification of environmental processes across various scales, supporting regional-scale Earth observation research [56] and introducing novel methods for a comprehensive evaluation of regional ecological environment quality [5,12,42]. RSEI emerges as a more comprehensive reflection of the genuine environmental situations than a single-index evaluation, encompassing various natural elements. In a recent study, researchers combined factors such as vegetation coverage, biological richness, Net primary productivity (NPP), soil salinization, soil erosion, water conservation, and PM_{2.5} concentration to construct the eco-environmental quality index

(EQI) for the Tibetan Plateau, openly disclosing the results for the years 2000, 2010, and 2020 [57]. To further validate the legitimacy of the RSEI obtained in this study, a comparison was made with the latest research findings. The results indicated that in this study, leveraging the GEE platform for an extended time series monitoring of ecological environmental quality in the Tibetan Plateau, detailed dynamic inter-annual fluctuations were captured (Figures 2 and 4). Furthermore, a substantial correlation with the EQI index was observed, reaching 0.526 (Figure 7). This suggested that RSEI holds the potential for assessing the ecological environmental quality of the Tibetan Plateau.

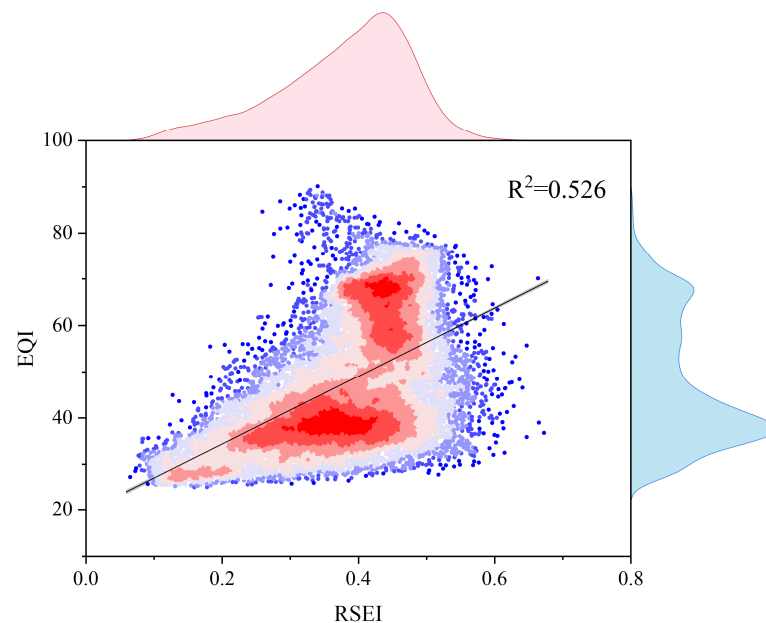


Figure 7. Correlation analysis of RSEI and EQI in Tibet Plateau. The red and blue curves illustrate the distribution of RSEI and EQI values, respectively. The color intensity of each data point shifts towards red, indicating a higher concentration of sample points at corresponding values.

4.2. Analysis of RSEI Driving Factors

Several studies have highlighted that the composition of the RSEI model itself led to higher NDBSI performance when regional vegetation coverage was lower. Consequently, drought emerged as the primary determinant of ecological environment quality in such areas. Conversely, NDVI displayed greater sensitivity, with greenness emerging as a major factor influencing the ecological environment [51].

The SHAP values obtained in this study revealed that natural factors had a more significant impact on RSEI, with TMP, SMCI, and PRE identified as the top three crucial feature factors. Soil moisture had played a pivotal role in shaping the response of alpine grassland plant productivity and community composition [58]. In the high-altitude, low-temperature environment of the Tibetan Plateau, plant growth had been predominantly constrained by the availability of soil moisture. Therefore, the ranking of soil moisture among the top three driving factors in the RSEI model aligned with this result. Additionally, lower temperatures had yielded larger SHAP values, attributed to the relatively lower optimal temperature on the Tibetan Plateau [59].

Interaction results indicated that a decrease in precipitation and higher temperature had a negative impact on the SHAP interaction value. This was because, with warming and reduced precipitation (i.e., warming and drying phenomena), vegetation growth had been minimized [60]. Moreover, temperature had a positive effect on plant growth only in humid regions and a negative impact in arid regions [61].

4.3. Limitations and Priorities for Future Work

This study utilized the GEE platform to evaluate the long-term ecological environment of the Tibetan Plateau and developed interpretable machine learning models, specifically XGBoost and SHAP. The objective was to offer a fresh attempt and establish a research foundation for monitoring the ecological environment of the Tibetan Plateau. However, there are several limitations in this study. Firstly, the RSEI model is not flawless. The application of Principal Component Analysis (PCA) with different sequences of component bands during the calculation introduces stochasticity to the computed PC1 [62]. Controversies arise regarding the utilization of PC1, whether in its original form [63–65] or as 1-PC1 [66–68]. To address this, the study exercised judgment during computation to derive the final RSEI value. Secondly, the study solely employed XGBoost and SHAP as interpretable machine learning methods to identify primary driving factors. Future research should diversify the range of models used for a more comprehensive evaluation and selection of the optimal model for further analysis. Lastly, the study concentrated on the entire Tibetan Plateau, overlooking its extensive spatial heterogeneity. Moreover, in recent years, the Chinese government has initiated numerous ecological restoration projects in this region. Whether these projects have impacted the ecological environment quality of the Tibetan Plateau remains an important question for exploration in future studies, especially at finer spatial scales.

5. Conclusions

This study utilized the GEE platform to construct an RSEI model for the long-term ecological environment quality of the Tibetan Plateau. The objective was to identify spatiotemporal trends, investigate the contributions of natural and anthropogenic activities to the ecological environment, and determine the impact of climate factor interactions on the ecological environment quality of the Tibetan Plateau. The primary conclusions are summarized as follows.

The ecological environment quality trend on the Tibetan Plateau from 2000 to 2022 primarily exhibited a slight degradation trend (45.9%), predominantly observed in the northern regions, including Xinjiang, Nagari, Xigaze, and areas along provincial roads. Overall, the ecological environment quality of the Tibetan Plateau was mainly categorized as Fair and Moderate, with a multi-year RSEI averaging 0.404. The land-use types with the most significant impact on RSEI were Woody Savannas, Evergreen Needleleaf Forests, Mixed Forests, and Grasslands, corresponding to RSEI values of 0.485, 0.484, 0.483, and 0.407, respectively. Moreover, natural factors were the predominant influencers of ecological environment quality on the Tibetan Plateau, with temperature, soil moisture, and precipitation identified as the most critical factors. Due to the relatively lower optimal temperature on the Tibetan Plateau, lower temperatures exhibited larger SHAP values. The interaction between temperature (TMP) and precipitation (PRE) showed a positive effect on RSEI, with an increase in the SHAP interaction value as precipitation increased. These findings contribute to a comprehensive understanding of the dynamics of the ecological environment on the Tibetan Plateau in the context of climate change.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/rs16040682/s1>. Figure S1: The result of eigenvalue contribution rate of PC1 (%); Figure S2: Spatial distribution of land use types on the TP in 2020; Figure S3: Land use transition matrix during 2001–2020 (km²) in Tibetan Plateau; Table S1: Land use transition matrix during 2001–2020 (km²); Table S2: Land use/cover data were extracted from MCD12Q1 dataset (2001–2020).

Author Contributions: Conceptualization, M.A.; methodology, M.A.; software, M.A.; validation, M.A.; formal analysis, M.A.; data curation, M.A.; writing—original draft preparation, M.A.; writing—review and editing, M.A.; visualization, M.A.; supervision, S.L.; project administration, S.L.; funding acquisition, S.L.; resources, S.L. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Second Tibetan Plateau Scientific Expedition and Research Program of China, grant number 2019QZKK1001.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Conflicts of Interest: The authors declare no conflict of interest.

References

- Hao, S.; Zhu, F.; Cui, Y. Land use and land cover change detection and spatial distribution on the Tibetan Plateau. *Sci. Rep.* **2021**, *11*, 7531. [[CrossRef](#)] [[PubMed](#)]
- Wang, L.; Yao, T.; Chai, C.; Cuo, L.; Su, F.; Zhang, F.; Yao, Z.; Zhang, Y.; Li, X.; Qi, J.; et al. TP-River: Monitoring and Quantifying Total River Runoff from the Third Pole. *Bull. Am. Meteorol. Soc.* **2021**, *102*, E948–E965. [[CrossRef](#)]
- Wu, Y.; Long, D.; Lall, U.; Scanlon, B.R.; Tian, F.; Fu, X.; Zhao, J.; Zhang, J.; Wang, H.; Hu, C. Reconstructed eight-century streamflow in the Tibetan Plateau reveals contrasting regional variability and strong nonstationarity. *Nat. Commun.* **2022**, *13*, 6416. [[CrossRef](#)] [[PubMed](#)]
- Qureshi, S.; Alavipanah, S.K.; Konyushkova, M.; Mijani, N.; Fathololomi, S.; Firozjaei, M.K.; Homae, M.; Hamzeh, S.; Kakroodi, A.A. A Remotely Sensed Assessment of Surface Ecological Change over the Gomishan Wetland, Iran. *Remote Sens.* **2020**, *12*, 2989. [[CrossRef](#)]
- Kamran, M.; Yamamoto, K. Evolution and use of remote sensing in ecological vulnerability assessment: A review. *Ecol. Indic.* **2023**, *148*, 110099. [[CrossRef](#)]
- Hu, X.; Xu, H. A new remote sensing index for assessing the spatial heterogeneity in urban ecological quality: A case from Fuzhou City, China. *Ecol. Indic.* **2018**, *89*, 11–21. [[CrossRef](#)]
- Xu, H.; Wang, M.; Shi, T.; Guan, H.; Fang, C.; Lin, Z. Prediction of ecological effects of potential population and impervious surface increases using a remote sensing based ecological index (RSEI). *Ecol. Indic.* **2018**, *93*, 730–740. [[CrossRef](#)]
- Xu, H.; Wang, Y.; Guan, H.; Shi, T.; Hu, X. Detecting Ecological Changes with a Remote Sensing Based Ecological Index (RSEI) Produced Time Series and Change Vector Analysis. *Remote Sens.* **2019**, *11*, 2345. [[CrossRef](#)]
- Yuan, B.; Fu, L.; Zou, Y.; Zhang, S.; Chen, X.; Li, F.; Deng, Z.; Xie, Y. Spatiotemporal change detection of ecological quality and the associated affecting factors in Dongting Lake Basin, based on RSEI. *J. Clean. Prod.* **2021**, *302*, 126995. [[CrossRef](#)]
- Zhu, D.; Chen, T.; Wang, Z.; Niu, R. Detecting ecological spatial-temporal changes by Remote Sensing Ecological Index with local adaptability. *J. Environ. Manag.* **2021**, *299*, 113655. [[CrossRef](#)]
- Tang, P.; Huang, J.; Zhou, H.; Fang, C.; Zhan, Y.; Huang, W. Local and telecoupling coordination degree model of urbanization and the eco-environment based on RS and GIS: A case study in the Wuhan urban agglomeration. *Sustain. Cities Soc.* **2021**, *75*, 103405. [[CrossRef](#)]
- Boori, M.S.; Choudhary, K.; Paringer, R.; Kupriyanov, A. Spatiotemporal ecological vulnerability analysis with statistical correlation based on satellite remote sensing in Samara, Russia. *J. Environ. Manag.* **2021**, *285*, 112138. [[CrossRef](#)] [[PubMed](#)]
- Firozjaei, M.K.; Kiavarz, M.; Homae, M.; Arsanjani, J.J.; Alavipanah, S.K. A novel method to quantify urban surface ecological poorness zone: A case study of several European cities. *Sci. Total Environ.* **2021**, *757*, 143755. [[CrossRef](#)]
- Li, W.J.; Kang, J.; Wang, Y. Spatiotemporal changes and driving forces of ecological security in the Chengdu-Chongqing urban agglomeration, China: Quantification using health-services-risk framework. *J. Clean. Prod.* **2023**, *389*, 136135. [[CrossRef](#)]
- Tang, W.; Liu, S.; Feng, S.; Xiao, F.; Ogbodo, U.S. Evolution and improvement options of ecological environmental quality in the world's largest emerging urban green heart as revealed by a new assessment framework. *Sci. Total Environ.* **2023**, *858*, 159715. [[CrossRef](#)] [[PubMed](#)]
- Zhang, L.; Fang, C.; Zhao, R.; Zhu, C.; Guan, J. Spatial-temporal evolution and driving force analysis of eco-quality in urban agglomerations in China. *Sci. Total Environ.* **2023**, *866*, 161465. [[CrossRef](#)] [[PubMed](#)]
- Li, Y.; Li, Z.; Wang, J.; Zeng, H. Analyses of driving factors on the spatial variations in regional eco-environmental quality using two types of species distribution models: A case study of Minjiang River Basin, China. *Ecol. Indic.* **2022**, *139*, 108980. [[CrossRef](#)]
- Sui, H.; Song, G.; Liu, W.; Zhang, Y.; Su, R.; Wang, Q.; Ren, G.; Mi, Y. Spatiotemporal variation of cultivated land ecosystem stability in typical regions of Lower Liaohe Plain China based on stress—Buffer—Response. *Sci. Total Environ.* **2023**, *858*, 160213. [[CrossRef](#)] [[PubMed](#)]
- Yang, Y.; Li, H. Spatiotemporal dynamic decoupling states of eco-environmental quality and land-use carbon emissions: A case study of Qingdao City, China. *Ecol. Inform.* **2023**, *75*, 101992. [[CrossRef](#)]
- Chen, A.; Yang, X.; Guo, J.; Zhang, M.; Xing, X.; Yang, D.; Xu, B.; Jiang, L. Dynamic of land use, landscape, and their impact on ecological quality in the northern sand-prevention belt of China. *J. Environ. Manag.* **2022**, *317*, 115351. [[CrossRef](#)]
- Tu, W.; Du, Y.; Yi, J.; Liang, F.; Wang, N.; Qian, J.; Huang, S.; Luo, P.; Wang, X. Assessment of the dynamic ecological networks on the Qinghai-Tibet Plateau using human's digital footprints. *Ecol. Indic.* **2023**, *147*, 109954. [[CrossRef](#)]
- Zhang, Y.; Wang, S.; Li, Y.; Gao, B.; Gong, J. Spatiotemporal patterns of ecological quality across the Qinghai-Tibet Plateau during 2000–2020. *Chin. J. Ecol.* **2023**, *42*, 1464–1473. [[CrossRef](#)]
- Liu, C.; Li, W.; Xu, J.; Zhou, H.; Wang, W.; Wang, H. Temporal and spatial variations of ecological security on the northeastern Tibetan Plateau integrating ecosystem health-risk-services framework. *Ecol. Indic.* **2024**, *158*, 111365. [[CrossRef](#)]

24. Zhang, Y.; Yi, L.; Xie, B.; Li, J.; Xiao, J.; Xie, J.; Liu, Z. Analysis of ecological quality changes and influencing factors in Xiangjiang River Basin. *Sci. Rep.* **2023**, *13*, 4375. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Xiong, Y.; Xu, W.; Lu, N.; Huang, S.; Wu, C.; Wang, L.; Dai, F.; Kou, W. Assessment of spatial–temporal changes of ecological environment quality based on RSEI and GEE: A case study in Erhai Lake Basin, Yunnan province, China. *Ecol. Indic.* **2021**, *125*, 107518. [\[CrossRef\]](#)
26. Wang, X.; Yao, X.; Jiang, C.; Duan, W. Dynamic monitoring and analysis of factors influencing ecological environment quality in northern Anhui, China, based on the Google Earth Engine. *Sci. Rep.* **2022**, *12*, 20307. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Ye, X.; Kuang, H. Evaluation of ecological quality in southeast Chongqing based on modified remote sensing ecological index. *Sci. Rep.* **2022**, *12*, 15694. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Yan, Y.; Zhuang, Q.; Zan, C.; Ren, J.; Yang, L.; Wen, Y.; Zeng, S.; Zhang, Q.; Kong, L. Using the Google Earth Engine to rapidly monitor impacts of geohazards on ecological quality in highly susceptible areas. *Ecol. Indic.* **2021**, *132*, 108258. [\[CrossRef\]](#)
29. Kim, Y.; Kim, Y. Explainable heat-related mortality with random forest and SHapley Additive exPlanations (SHAP) models. *Sustain. Cities Soc.* **2022**, *79*, 103677. [\[CrossRef\]](#)
30. Rodríguez-Pérez, R.; Bajorath, J. Interpretation of machine learning models using shapley values: Application to compound potency and multi-target activity predictions. *J. Comput.-Aided Mol. Des.* **2020**, *34*, 1013–1026. [\[CrossRef\]](#)
31. Li, Z. Extracting spatial effects from machine learning model using local interpretation method: An example of SHAP and XGBoost. *Comput. Environ. Urban Syst.* **2022**, *96*, 101845. [\[CrossRef\]](#)
32. Wang, M.; Li, Y.; Yuan, H.; Zhou, S.; Wang, Y.; Adnan Ikram, R.M.; Li, J. An XGBoost-SHAP approach to quantifying morphological impact on urban flooding susceptibility. *Ecol. Indic.* **2023**, *156*, 111137. [\[CrossRef\]](#)
33. Deng, Y.; He, R.; Liu, Y. Crime risk prediction incorporating geographical spatiotemporal dependency into machine learning models. *Inf. Sci.* **2023**, *646*, 119414. [\[CrossRef\]](#)
34. Wang, H.; Yan, S.; Ciais, P.; Wigneron, J.-P.; Liu, L.; Li, Y.; Fu, Z.; Ma, H.; Liang, Z.; Wei, F.; et al. Exploring complex water stress–gross primary production relationships: Impact of climatic drivers, main effects, and interactive effects. *Glob. Chang. Biol.* **2022**, *28*, 4110–4123. [\[CrossRef\]](#) [\[PubMed\]](#)
35. Zhang, W.; Luo, G.; Hamdi, R.; Ma, X.; Li, Y.; Yuan, X.; Li, C.; Ling, Q.; Hellwich, O.; Termonia, P.; et al. Can Gross Primary Productivity Products be effectively evaluated in regions with few observation data? *GIScience Remote Sens.* **2023**, *60*, 2213489. [\[CrossRef\]](#)
36. Yao, T.; Thompson, L.; Yang, W.; Yu, W.; Gao, Y.; Guo, X.; Yang, X.; Duan, K.; Zhao, H.; Xu, B.; et al. Different glacier status with atmospheric circulations in Tibetan Plateau and surroundings. *Nat. Clim. Chang.* **2012**, *2*, 663–667. [\[CrossRef\]](#)
37. Chen, H.; Zhu, Q.; Peng, C.; Wu, N.; Wang, Y.; Fang, X.; Gao, Y.; Zhu, D.; Yang, G.; Tian, J.; et al. The impacts of climate change and human activities on biogeochemical cycles on the Qinghai-Tibetan Plateau. *Glob. Chang. Biol.* **2013**, *19*, 2940–2955. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Yang, K.; Wu, H.; Qin, J.; Lin, C.; Tang, W.; Chen, Y. Recent climate changes over the Tibetan Plateau and their impacts on energy and water cycle: A review. *Glob. Planet. Chang.* **2014**, *112*, 79–91. [\[CrossRef\]](#)
39. Shao, X.; Yao, Y. Sustainable urban system structure evaluation in sparsely populated areas: Case study of the Qinghai-Tibet Plateau in China. *Sci. Rep.* **2022**, *12*, 16067. [\[CrossRef\]](#)
40. Zhang, Y.; Li, B.; Zheng, D. Datasets of the Boundary and Area of the Tibetan Plateau. *Acta Geogr. Sin.* **2014**, *69*, 65–68. [\[CrossRef\]](#)
41. Zheng, Z.; Wu, Z.; Chen, Y.; Yang, Z.; Marinello, F. Exploration of eco-environment and urbanization changes in coastal zones: A case study in China over the past 20 years. *Ecol. Indic.* **2020**, *119*, 106847. [\[CrossRef\]](#)
42. Xu, D.; Yang, F.; Yu, L.; Zhou, Y.; Li, H.; Ma, J.; Huang, J.; Wei, J.; Xu, Y.; Zhang, C.; et al. Quantization of the coupling mechanism between eco-environmental quality and urbanization from multisource remote sensing data. *J. Clean. Prod.* **2021**, *321*, 128948. [\[CrossRef\]](#)
43. Zhang, Y.; She, J.; Long, X.; Zhang, M. Spatio-temporal evolution and driving factors of eco-environmental quality based on RSEI in Chang-Zhu-Tan metropolitan circle, central China. *Ecol. Indic.* **2022**, *144*, 109436. [\[CrossRef\]](#)
44. Liu, Y.; Guo, B.; Lu, M.; Zang, W.; Yu, T.; Chen, D. Quantitative distinction of the relative actions of climate change and human activities on vegetation evolution in the Yellow River Basin of China during 1981–2019. *J. Arid Land* **2023**, *15*, 91–108. [\[CrossRef\]](#)
45. Fattah, A.; Morshed, S.R.; Kafy, A.-A.; Rahaman, Z.A.; Hairy Ibrahim, M.; Rahman, M.T. Wavelet coherence analysis of PM_{2.5} variability in response to meteorological changes in South Asian cities. *Atmos. Pollut. Res.* **2023**, *14*, 101737. [\[CrossRef\]](#)
46. Yang, Q.; Huang, X.; Tang, Q. The footprint of urban heat island effect in 302 Chinese cities: Temporal trends and associated factors. *Sci. Total Environ.* **2019**, *655*, 652–662. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Yang, C.; Chen, M.; Yuan, Q. The application of XGBoost and SHAP to examining the factors in freight truck-related crashes: An exploratory analysis. *Accid. Anal. Prev.* **2021**, *158*, 106153. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Zhang, X.; Liu, L.; Lan, M.; Song, G.; Xiao, L.; Chen, J. Interpretable machine learning models for crime prediction. *Comput. Environ. Urban Syst.* **2022**, *94*, 101789. [\[CrossRef\]](#)
49. Aas, K.; Jullum, M.; Løland, A. Explaining individual predictions when features are dependent: More accurate approximations to Shapley values. *Artif. Intell.* **2021**, *298*, 103502. [\[CrossRef\]](#)
50. Carlsson, L.S.; Samuelsson, P.B.; Jönsson, P.G. Interpretable Machine Learning—Tools to Interpret the Predictions of a Machine Learning Model Predicting the Electrical Energy Consumption of an Electric Arc Furnace. *Steel Res. Int.* **2020**, *91*, 2000053. [\[CrossRef\]](#)

51. Wang, Z.; Chen, T.; Zhu, D.; Jia, K.; Plaza, A. RSEIFE: A new remote sensing ecological index for simulating the land surface eco-environment. *J. Environ. Manag.* **2023**, *326*, 116851. [[CrossRef](#)] [[PubMed](#)]
52. Wang, C.; Jiang, Q.O.; Shao, Y.; Sun, S.; Xiao, L.; Guo, J. Ecological environment assessment based on land use simulation: A case study in the Heihe River Basin. *Sci. Total Environ.* **2019**, *697*, 133928. [[CrossRef](#)] [[PubMed](#)]
53. Wolfslehner, B.; Vacik, H. Evaluating sustainable forest management strategies with the Analytic Network Process in a Pressure-State-Response framework. *J. Environ. Manag.* **2008**, *88*, 1–10. [[CrossRef](#)] [[PubMed](#)]
54. Ke, X.; Wang, X.; Guo, H.; Yang, C.; Zhou, Q.; Mougharbel, A. Urban ecological security evaluation and spatial correlation research—Based on data analysis of 16 cities in Hubei Province of China. *J. Clean. Prod.* **2021**, *311*, 127613. [[CrossRef](#)]
55. Vaalgamaa, S. The effect of urbanisation on Laajalahti Bay, Helsinki City, as reflected by sediment geochemistry. *Mar. Pollut. Bull.* **2004**, *48*, 650–662. [[CrossRef](#)] [[PubMed](#)]
56. Bai, T.; Cheng, J.; Zheng, Z.; Zhang, Q.; Li, Z.; Xu, D. Drivers of eco-environmental quality in China from 2000 to 2017. *J. Clean. Prod.* **2023**, *396*, 136408. [[CrossRef](#)]
57. Liu, H.; Cheng, Y.; Liu, Z.; Li, Q.; Zhang, H.; Wei, W. Conflict or Coordination? The Spatiotemporal Relationship Between Humans and Nature on the Qinghai-Tibet Plateau. *Earth's Future* **2023**, *11*, e2022EF003452. [[CrossRef](#)]
58. Ganjurjav, H.; Gao, Q.; Gornish, E.S.; Schwartz, M.W.; Liang, Y.; Cao, X.; Zhang, W.; Zhang, Y.; Li, W.; Wan, Y.; et al. Differential response of alpine steppe and alpine meadow to climate warming in the central Qinghai-Tibetan Plateau. *Agric. For. Meteorol.* **2016**, *223*, 233–240. [[CrossRef](#)]
59. Chen, A.; Huang, L.; Liu, Q.; Piao, S. Optimal temperature of vegetation productivity and its linkage with climate and elevation on the Tibetan Plateau. *Glob. Chang. Biol.* **2021**, *27*, 1942–1951. [[CrossRef](#)]
60. Liu, X.; Zhao, W.; Yao, Y.; Pereira, P. The rising human footprint in the Tibetan Plateau threatens the effectiveness of ecological restoration on vegetation growth. *J. Environ. Manag.* **2024**, *351*, 119963. [[CrossRef](#)]
61. Li, P.; Hu, Z.; Liu, Y. Shift in the trend of browning in Southwestern Tibetan Plateau in the past two decades. *Agric. For. Meteorol.* **2020**, *287*, 107950. [[CrossRef](#)]
62. Zheng, Z.; Wu, Z.; Chen, Y.; Guo, C.; Marinello, F. Instability of remote sensing based ecological index (RSEI) and its improvement for time series analysis. *Sci. Total Environ.* **2022**, *814*, 152595. [[CrossRef](#)] [[PubMed](#)]
63. Shan, W.; Jin, X.; Meng, X.; Yang, X.; Xu, Z.; Gu, Z.; Zhou, Y. Dynamical monitoring of ecological environment quality of land consolidation based on multi-source remote sensing data. *Trans. Chin. Soc. Agric. Eng.* **2019**, *35*, 234–242. [[CrossRef](#)]
64. Lin, L.; Hao, Z.; Post, C.J.; Mikhailova, E.A. Monitoring Ecological Changes on a Rapidly Urbanizing Island Using a Remote Sensing-Based Ecological Index Produced Time Series. *Remote Sens.* **2022**, *14*, 5773. [[CrossRef](#)]
65. Gao, Y.G.; Li, Y.H.; Xu, H.Q. Assessing Ecological Quality Based on Remote Sensing Images in Wugong Mountain. *Earth Space Sci.* **2022**, *9*, e2021EA001918. [[CrossRef](#)]
66. Zhang, Y.; Jiang, F. Developing a remote sensing-based ecological index based on improved biophysical features. *J. Appl. Remote Sens.* **2021**, *16*, 012008. [[CrossRef](#)]
67. Sun, C.; Li, J.; Liu, Y.; Cao, L.; Zheng, J.; Yang, Z.; Ye, J.; Li, Y. Ecological quality assessment and monitoring using a time-series remote sensing-based ecological index (ts-RSEI). *GIScience Remote Sens.* **2022**, *59*, 1793–1816. [[CrossRef](#)]
68. Ning, L.; Jiayao, W.; Fen, Q. The improvement of ecological environment index model RSEI. *Arab. J. Geosci.* **2020**, *13*, 403. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.