

# Spatiotemporal Evolution and Associated Factors of Ecological Quality in the Poyang Lake Basin from 2000 to 2024 Based on Remote Sensing

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**Abstract:** Based on the Google Earth Engine (GEE) platform, this study constructed a Remote Sensing Ecological Index (RSEI) time series for the Poyang Lake Basin from 2000 to 2024. The analysis integrated Theil-Sen median trend estimation, the Mann-Kendall test, the Hurst exponent, and an interpretable machine-learning framework combining extreme gradient boosting (XGBoost) with Shapley additive explanations (SHAP) to examine the spatiotemporal evolution of ecological quality and the factors associated with its spatial heterogeneity. The basin-average RSEI increased slightly from 0.693 in 2000 to 0.710 in 2024, indicating that the basin generally remained at a good ecological level, although interannual fluctuations were evident. Spatially, the RSEI showed a stable pattern of high values in the surrounding mountainous forest belts and lower values in the central plain, urbanized areas, and some lake and wetland zones. The ecological grade structure improved, with the proportion of areas classified as “excellent” increasing from 14.42% to 22.93%. Theil-Sen and Mann-Kendall results showed that areas with historical ecological improvement were more extensive than areas of degradation. However, the Hurst exponent indicated that many pixels exhibited anti-persistent characteristics ( $H < 0.5$ ), suggesting that future ecological trajectories may be uncertain rather than a simple continuation of historical improvement. XGBoost-SHAP analysis showed that land surface temperature (LST) and NDVI (Normalized Difference Vegetation Index) made the largest contributions to RSEI prediction. Because both variables are components of the RSEI, these results should be interpreted as index sensitivity to heat and vegetation conditions rather than independent causal effects. External variables, including GDP, population density, nighttime light intensity, elevation, and slope, showed additional predictive associations with spatial heterogeneity, conditional on the fitted model. These findings not only support differentiated watershed management but also provide a remote sensing perspective on long-term ecological quality changes associated with climate variability and human activities.



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**Keywords:** ecological quality; spatiotemporal evolution; association analysis; Poyang Lake Basin

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## 1. Introduction

Under the combined effects of ongoing global climate change and the increasing intensity of human activities, regional ecosystems are subjected to multiple pressures, resulting in a trend of accelerated structural adjustments and simultaneous functional decline [1]. To more accurately depict this process of change and its feedback effects on human society, ecological quality, represented here by the remote-sensing-derived RSEI, can be used to reflect the ecosystem's response to fluctuations in climate factors and human disturbances, as well as its evolution direction at specific spatiotemporal scales [2]. Climate change often alters water and thermal conditions and the probability of extreme events, while human activities continuously reshape ecological processes through land-use transformation, resource development, and spatial expansion [3]. The overlap of these two factors causes ecological degradation to manifest in a multidimensional manner across different levels and elements, further triggering increased ecological risks and enhanced spillover effects. For example, issues such as rising drought frequency, greater risk of snow and glacier disasters, loss of biodiversity, and pressure on the habitats of rare species are becoming increasingly prominent [4]. Against this backdrop, monitoring the spatiotemporal changes in ecological quality over large areas and long time series can not only identify critical stages and hotspots of ecological degradation and recovery but also systematically analyze their associated factors [5]. This provides a scientific basis for understanding ecological evolution patterns, supporting zonal and categorized governance, and developing more targeted restoration and management strategies [6]. More importantly, it offers a theoretical entry point for revealing how regional ecological systems respond to the long-term coupling of climate variability and human disturbance across space and time.

In recent years, the rapid development of remote sensing technology has provided a stable data foundation for large-scale and long-term ecological and environmental monitoring [7]. Among these technologies, the Remote Sensing Ecological Index (RSEI) integrates core factors such as vegetation greenness (NDVI), wetness (WET), temperature (LST), and dryness (represented by NDBSI through IBI and SI) to efficiently and relatively objectively evaluate regional ecological quality, revealing spatiotemporal differences in environmental conditions from a multi-scale perspective [8]. Methodologically, RSEI often employs Principal Component Analysis (PCA) for index construction and weight allocation, thereby highlighting dominant information and reducing biases caused by individual indicator characteristics [9]. Currently, RSEI has been widely used to characterize the spatiotemporal evolution of regional ecological quality and has played an important role in the refined assessment of complex ecological regions. Hanqiu Xu and others combined RSEI time series with change vector analysis based on remote sensing imagery, extracting NDVI, LST, WET, and built-up indices, unified under the RSEI, and enhanced evaluation efficiency and operability through visualization, modeling, and change detection [8]. Basin-scale applications have examined ecological changes and associated human pressures [5,6]. Julio Novoa and others evaluated riparian zone efficiency in agricultural landscapes using high-resolution remote sensing imagery to develop the Riparian Strip Efficiency Index, which shares the acronym RSEI but differs from the Remote Sensing Ecological Index [10]. Xiong assessed the spatial distribution and spatiotemporal evolution characteristics of ecological quality using the RSEI, pushing research toward long time series studies [2]. Since then, RSEI has been applied in various research areas, basins, administrative scales, urban agglomerations, and across different spatial and temporal dimensions. Liu et al. incorporated an air quality indicator into the RSEI to develop a modified remote sensing ecological index (MRSEI), which was better suited to assessing ecological quality in Beijing [11]. Subsequently, numerous studies have fused the RSEI with air quality indicators, soil salinity, PM2.5, and other metrics. Overall, RSEI, with its high automation, strong spatial expression capability, and comparability of results, has been widely applied in ecological monitoring research in various regions such as urban agglomerations, basins, and mountainous areas [5,6]. However, existing studies have mainly focused on three aspects. First, numerous studies have evaluated ecological quality using remote sensing ecological indices to reveal spatiotemporal evolution patterns. Second, several studies have employed trend analysis or Hurst exponent methods to assess the persistence and future tendency of ecological changes. Third, recent studies have increasingly applied machine learning algorithms to identify the nonlinear effects of natural and anthropogenic drivers on ecosystem dynamics. Recent work has extended RSEI construction through deep learning [12] and integrated modified indices with XGBoost-SHAP [13,14], including the multi-vegetation-index assessment of the Jinsha River Basin [14]. These advances motivate a basin-specific synthesis of ecological status, trend persistence, and model associations for Poyang Lake through 2024.

The Poyang Lake Basin, located mainly in Jiangxi Province, is a critical region for water security, biodiversity conservation, and regional strategies in China [15]. Its ecological health is directly linked to the stability of the ecological security pattern in the middle and lower Yangtze River. The basin is characterized by a connected river–lake–wetland system and diverse habitats shaped by seasonal hydrological fluctuations, while regional land-use activities and socioeconomic development are closely linked to the river–lake environment. Human activities such as rapid land use transformation, urban expansion, and adjustments in transportation and industrial layout, combined with climate factors like changes in precipitation distribution, rising temperatures, and drought fluctuations, have resulted in stronger spatiotemporal heterogeneity and regional differences in ecological quality [16]. As a result, its protection and management must adopt a systematic perspective, considering multiple objectives such as water resource allocation, biodiversity habitat maintenance, and regional sustainable development [17]. Flood management and ecological protection also involve social concerns; research in China's Yellow River floodplain has examined the relationship between resettlement and farmers' livelihood resilience [18]. This broader perspective connects environmental management with the needs of local communities. However, with the acceleration of urbanization and the intensification of economic activities, human disturbances have become more frequent, bringing new pressures and challenges to ecological protection. Furthermore, the intensity, methods, and expansion pace of human activities in different regions are inconsistent, leading to more pronounced regional variations in driving factors. Therefore, systematically identifying these influencing factors is essential for understanding the evolution of habitat quality. In recent years, scholars have conducted research on ecological risks, habitat quality, and the impacts of human activities and climate change in the Poyang Lake Basin [19,20]. However, in practice, issues such as limited data availability, complex processing workflows, and low computational efficiency persist, highlighting the urgent need to establish a method for quickly and stably monitoring and assessing long-term ecological quality in the Poyang Lake Basin. The humid subtropical basin combines forested uplands with cultivated plains and seasonal wetlands; agricultural livelihoods and urban development make land and water management central to the relationship between local communities and ecological protection [21].

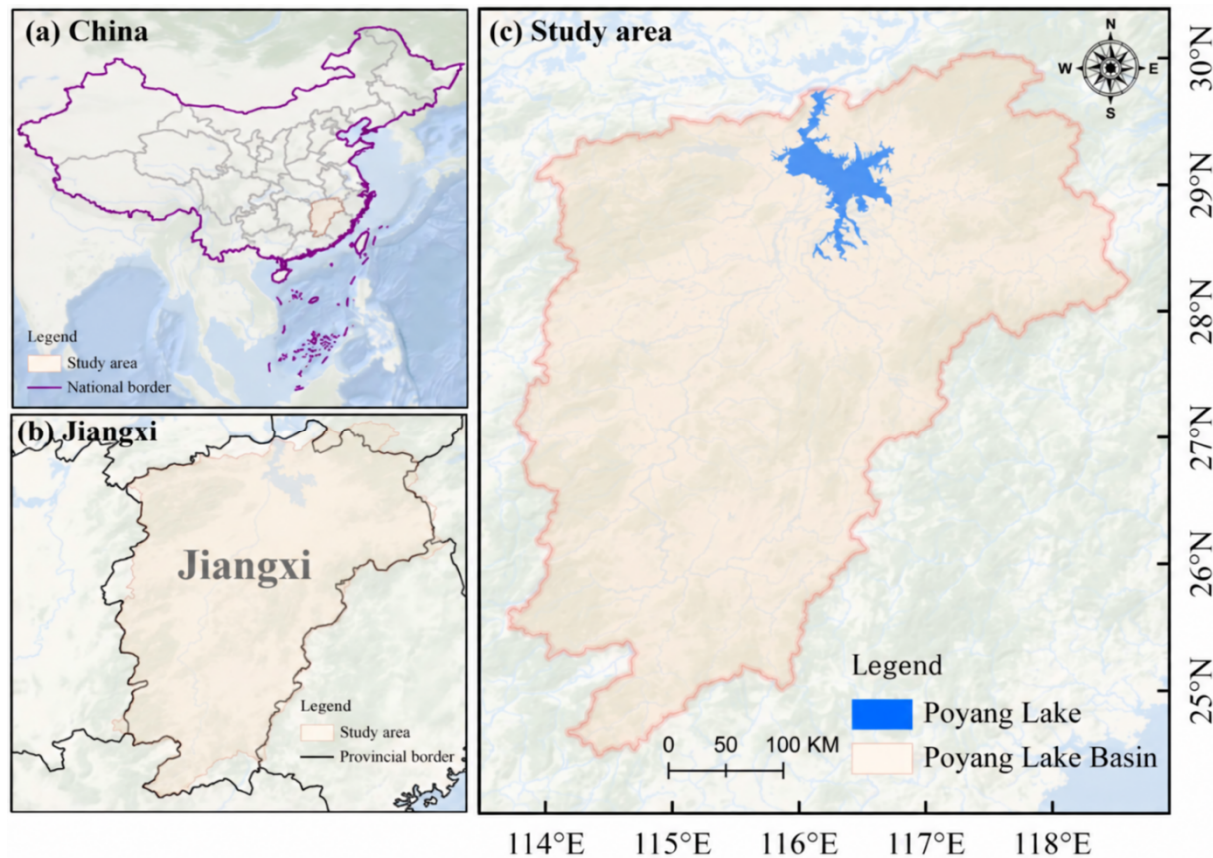
In summary, under the backdrop of global population growth, climate warming, environmental degradation, and resource scarcity, this study focuses on the Poyang Lake Basin. The scientific questions are how RSEI changed across the basin during 2000–2024, where historical improvement coincides with low persistence, and which external variables are associated with the basin's spatial heterogeneity in ecological quality. Addressing these questions helps connect ecological status assessment, evolutionary trend diagnosis, and interpretable model associations within a unified analytical framework. Relying on the data management and parallel computing capabilities of the Google Earth Engine platform, long-time series remote sensing images are selected as the data foundation [22]. Key indicators, such as vegetation greenness, surface wetness, surface temperature, and surface dryness, are extracted, and the Remote Sensing Ecological Index (RSEI) is constructed through Principal Component Analysis (PCA) for rapid, objective, and comparable evaluation of ecological quality in the basin. Based on this, a long-term spatiotemporal analysis is conducted from both interannual variation and spatial differentiation perspectives. This analysis characterizes the evolution of ecological quality across different landforms and functional areas, identifying hotspots of improvement and degradation and their directional changes. Furthermore, the XGBoost method is introduced to establish a quantitative relationship between ecological quality and potential driving factors [23]. The predictive contributions of climate factors and human activity indicators are assessed, key variables are identified, and their nonlinear response characteristics are analyzed. This provides scientific support for ecological protection and restoration, zoned management and control, and the promotion of green and high-quality development in the Poyang Lake Basin.

## 2. Study Area and Data

### 2.1. Study Area

The Poyang Lake Basin is geographically located between 24°29'17" and 30°03'01" N and between 113°42'21" and 118°35'45" E, covering an area of approximately 162,200 square kilometers, with over 90% of the area within Jiangxi Province (Figure 1). The basin consists of six sub-basins: the Raohe River, Xinjiang River, Xiushui River, Fuhe River, Ganjiang River, and the Poyang Lake area, forming a typical pattern of river-lake connectivity and convergence of multiple water systems [24]. As an important barrier for water and ecological security in the middle and lower reaches of the Yangtze River, the basin's wetland and river-lake systems play a crucial role in water source conservation, flood regulation, habitat maintenance, and carbon sequestration. Changes in its ecological quality not only impact regional water resource allocation and flood disaster prevention but also directly affect the stability of migratory bird habitats and biodiversity conservation, further limiting the region's

sustainable socioeconomic development [25]. However, in recent years, urban expansion and rapid land-use transformation have significantly intensified human disturbances, while the ongoing changes in precipitation distribution and the increase in extreme climate events have compounded climate factors, leading to the basin's ecosystems bearing compounded pressures [21]. This has resulted in localized ecological degradation and the accumulation of ecological risks. Therefore, establishing an ecological quality monitoring and assessment system that covers a large area and long time series, and systematically identifying its dominant associated factors, is of significant importance for conducting zoned governance, determining priority areas for ecological restoration, and optimizing basin management policies.



**Figure 1.** Location and topography.

## 2.2. Data

This study fully leverages the high-performance parallel computing advantages of the Google Earth Engine (GEE) cloud platform, selecting Landsat series surface reflectance products from 2000 to 2024. The images were filtered by the study area and time period, and cloud and cloud-shadow pixels were masked using quality assessment information before annual compositing. By integrating the four components of vegetation greenness, wetness, temperature, and dryness, a long-term Remote Sensing Ecological Index (RSEI) dataset for the Poyang Lake Basin was constructed, effectively overcoming the computational bottleneck of traditional single-machine models in large-scale ecological monitoring. Based on this, additional multidimensional driving factor data were integrated, including natural geographical factors (land use, SRTM DEM elevation and slope) and Socio-economic factors (basic road geographic information and nighttime light data) in Table 1. To eliminate spatial discrepancies in the multi-source heterogeneous data, all datasets underwent strict standardization preprocessing in ArcGIS 10.8. Specifically, the datasets were unified in terms of spatial projection, boundary extent, and analytical grid before further analysis. Continuous variables were resampled to the target analytical scale using appropriate interpolation methods, while categorical variables, such as land-use data, were processed using nearest-neighbor resampling to preserve class attributes. Remote sensing indicators cover the study period, whereas the temporal coverage of ancillary data is limited by the available source products. These preprocessing steps provided a consistent data basis for revealing the evolution of ecological quality in the basin and its associated factors [26]. The 2020 land-use layer in Table 1 is a static spatial reference and does not represent land-use changes throughout 2000–2024.

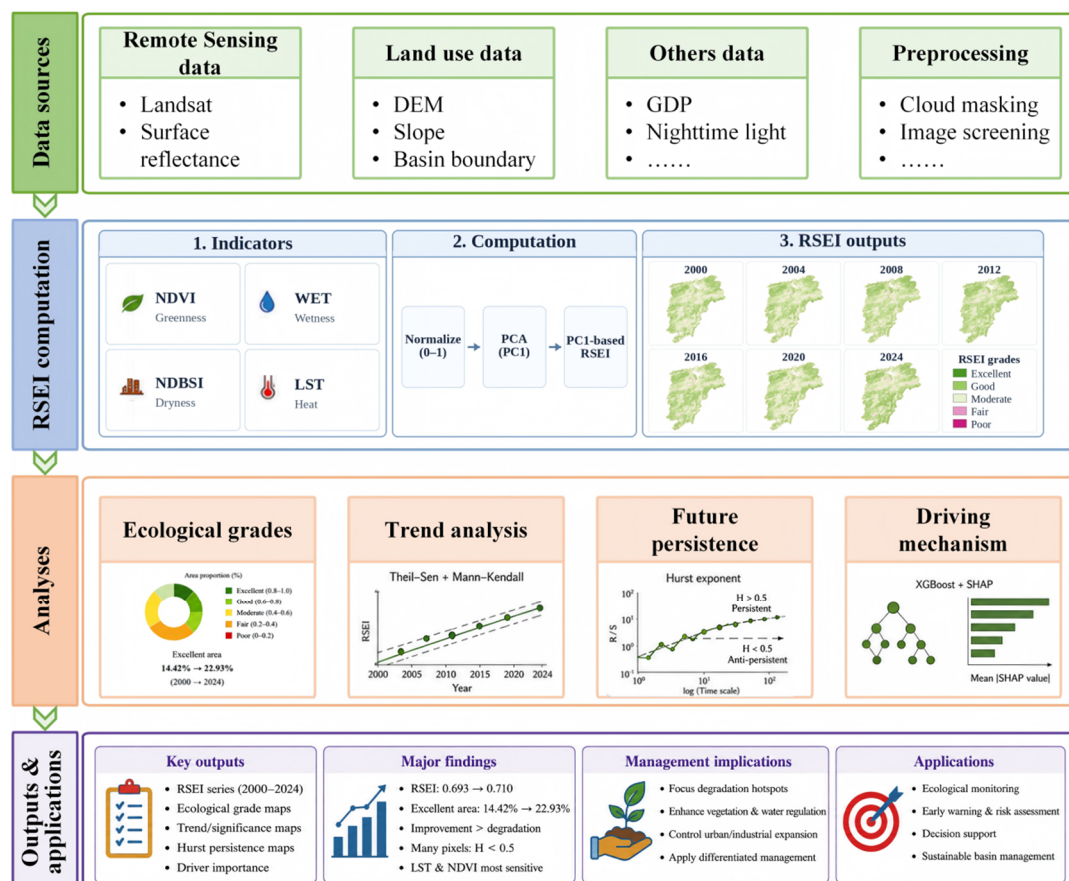


**Table 1.** Main data used in this study.

| Type                   | Properties                        | Time | Data Type       | Data Source                                                                                                                                                                                                                             |
|------------------------|-----------------------------------|------|-----------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Land Use Data          | CLCD30                            | 2020 | Raster (30 m)   | <a href="https://zenodo.org/records/5816591">https://zenodo.org/records/5816591</a> , accessed on 26 January 2026                                                                                                                       |
| Natural Factors        | Elevation                         | 2020 | Raster (30 m)   | gee                                                                                                                                                                                                                                     |
|                        | Slope                             |      |                 | gee                                                                                                                                                                                                                                     |
|                        | NDVI                              |      |                 | gee                                                                                                                                                                                                                                     |
|                        | Water system data                 | 2020 | Vector          | Tianditu                                                                                                                                                                                                                                |
|                        | River system data                 |      |                 |                                                                                                                                                                                                                                         |
|                        | Soil thickness and Soil texture   |      |                 |                                                                                                                                                                                                                                         |
|                        | The potential evapotranspiration  |      |                 |                                                                                                                                                                                                                                         |
| Socio-economic Factors | Precipitation                     | 2020 | Raster (1000 m) | <a href="http://www.geodata.cn">http://www.geodata.cn</a> , accessed on 26 January 2026                                                                                                                                                 |
|                        | The administrative boundary       |      |                 |                                                                                                                                                                                                                                         |
|                        | Basic road geographic information |      |                 |                                                                                                                                                                                                                                         |
| Socio-economic Factors | Nighttime light data              | 2020 | Raster (1 km)   | <a href="https://www.geodata.cn/main/face_science_detail?typeName=face_science&amp;guid=38493429288227">https://www.geodata.cn/main/face_science_detail?typeName=face_science&amp;guid=38493429288227</a> , accessed on 26 January 2026 |

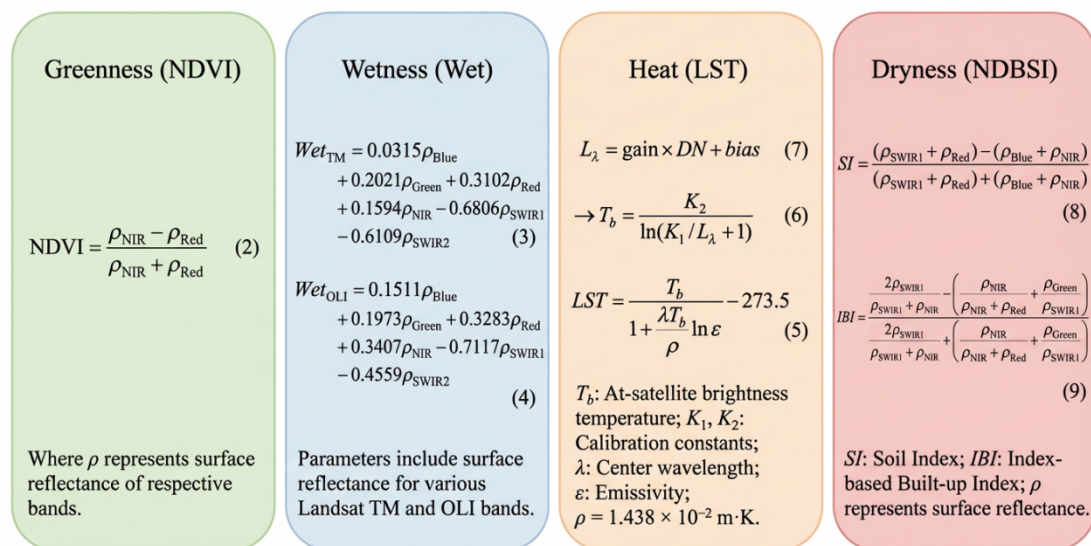
### 3. Research Methods

Based on the above datasets and research objectives, the overall research framework is presented in Figure 2. Multi-source data were integrated to construct the long-term RSEI series, characterize its spatiotemporal evolution and future persistence, and interpret the natural and anthropogenic factors associated with its spatial variation using the XGBoost–SHAP framework. The resulting evidence was further synthesized to provide a scientific basis for differentiated ecological management in the Poyang Lake Basin. Specifically, RSEI describes ecological status, Theil–Sen and Mann–Kendall identifies historical changes, the Hurst exponent diagnoses persistence, and SHAP describes model associations rather than causal mechanisms. The persistence diagnosis is a monitoring aid, not a forecast of a specified future year.

**Figure 2.** Overall research framework.

### 3.1. Remote Sensing Ecological Index

This study constructed the Remote Sensing Ecological Index (RSEI) by integrating four ecological components—greenness, wetness, heat, and dryness—using Principal Component Analysis (PCA). The calculation process included the following steps. First, Landsat surface reflectance images were filtered by study area and year, and cloud and cloud-shadow pixels were removed before annual compositing. Second, four component indicators were calculated from the annual composites: NDVI was used to represent vegetation greenness, WET was derived from the tasseled cap transformation to represent surface wetness, LST was used to describe the thermal environment, and NDBSI was used to represent surface dryness caused by bare soil and built-up land. Third, all four indicators were normalized to a range of 0–1 to remove dimensional differences. Fourth, PCA was applied to the normalized indicators, and the first principal component was used to construct the initial RSEI because it contained the main ecological information. Finally, the direction of the first principal component was adjusted so that higher values represented better ecological quality, and the final RSEI was normalized to 0–1. The RSEI values were then divided into five ecological quality grades—Excellent, Good, Moderate, Fair, and Poor—using equal intervals of 0.2 [12]. Due to its high degree of automation, strong ability to integrate multi-source information, and suitability for comparative analysis across different scales and types of regions, this index has been widely applied in ecological quality monitoring and spatiotemporal evolution studies in cities, watersheds, wetland lakes, and mountainous regions. Following commonly used RSEI indicator-selection criteria, vegetation greenness, wetness, heat, and dryness were selected to represent vegetation condition, surface moisture, thermal environment, and built-up/bare-soil stress, respectively. Specifically, vegetation greenness is represented by the Normalized Difference Vegetation Index (NDVI); wetness is represented by the WET component obtained through the tasseled cap transformation; heat is represented by land surface temperature (LST); and dryness is represented by the normalized difference bare soil and built-up land index (NDBSI), which is calculated from the bare soil index and the normalized difference built-up index. These four indicators were calculated from the preprocessed Landsat annual composites. The formulas and parameter settings for these four indicators are shown in Figure 3. To further check the reliability of the RSEI time-series, the annual RSEI results were compared with vegetation indicators, including NDVI and vegetation coverage, as well as relevant published studies on ecological changes in the Poyang Lake Basin. This consistency check does not constitute independent validation.



**Figure 3.** Calculation framework for RSEI component indicators using Landsat data.

### 3.2. Trend Analysis of Variation Characteristics

The combination of the Sen slope estimation and Mann–Kendall significance test is a classic non-parametric trend analysis framework commonly used for estimating the rate of change and determining the significance of trends in long time series data. Due to its low distribution assumption requirements, strong interpretability of results, and wide applicability, this method has been extensively applied in the temporal variation studies of ecological quality, vegetation cover, hydrology, climate, and other fields. It is well-suited for supporting trend comparison analysis across different regions and scales. Based on this, the Poyang Lake Basin was chosen as the research area. The combination of Sen slope estimation and Mann–Kendall significance test was used to perform

trend analysis on the Remote Sensing Ecological Index (RSEI) from 2000 to 2024. The analysis quantitatively characterizes the change direction, rate of change, and significance level of ecological quality in the basin, and classifies the trend types accordingly, revealing the spatiotemporal evolution characteristics of ecological quality in the basin. This analysis provides a critical bridge from ecological status identification to evolutionary process diagnosis, thereby supporting not only the subsequent identification of driving factors and zonal management and control, but also a more complete methodological understanding of regional ecological change from historical trend to future tendency. The formulas are as follows:

$$\beta = \text{Median}\left(\frac{x_j - x_i}{j - i}\right), \quad j > i \quad (1)$$

In this context,  $x_i$  and  $x_j$  represent the indicator values in the  $i$ -th and  $j$ -th years, respectively, and  $\beta$  is the Sen slope. When  $\beta > 0$ , it indicates that the indicator shows an upward trend; when  $\beta < 0$ , it indicates a downward trend. The absolute value of  $\beta$  reflects the rate of change.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (2)$$

In this case,  $\text{sgn}(\cdot)$  represents the sign function. When the sample size is large, the statistic  $S$  approximates a normal distribution, and its standardized statistic  $Z$  is calculated using the following formula:

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

By comparing the  $Z$  with the critical value at a given significance level, the significance of the trend can be determined. If the absolute value of  $Z$  exceeds the critical value  $Z$ , the trend is considered statistically significant. This means that the observed trend is unlikely to have occurred by chance, subject to the test assumptions; it does not identify the cause of the change.

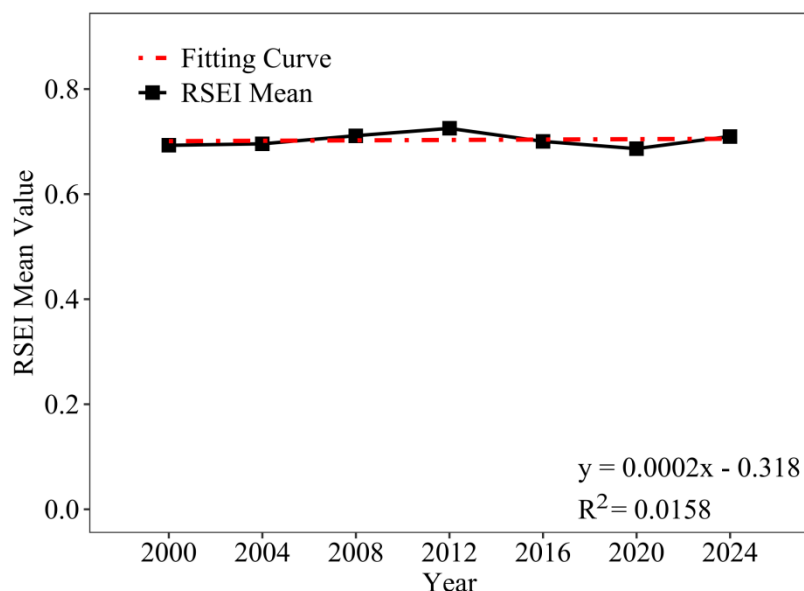
### 3.3. Driver Analysis

To further examine the variables associated with the spatial variation of ecological quality in the Poyang Lake Basin, this study uses the Extreme Gradient Boosting (XGBoost) algorithm for quantitative analysis. It should be noted that NDVI and LST are also components of the RSEI calculation. Therefore, their importance in the XGBoost–SHAP results mainly reflects the sensitivity of RSEI to its internal biophysical components, rather than independent causal effects. The SHAP analysis was used to identify statistical contributions to model prediction, while external variables such as GDP, population density, nighttime light, elevation, and slope were interpreted as background or human-activity factors associated with RSEI differences [13]. XGBoost is an efficient gradient boosting tree ensemble learning algorithm that generates multiple weak learners (usually regression trees) iteratively, and combines them through weighted summation to form a strong predictive model. In each training round, the model optimizes the objective function by fitting the residuals from the previous round of predictions, significantly enhancing its ability to fit complex nonlinear relationships. Due to its high computational efficiency, strong resistance to overfitting, and ability to handle multivariate interaction effects, XGBoost has been widely applied in ecological quality assessments, land use change driving analysis, and studies of the combined impacts of climate and human activities, particularly under multi-factor coupling conditions [14]. For result interpretation, this study further introduces the SHAP (Shapley Additive Explanations) model to provide interpretability analysis of the XGBoost predictions. SHAP calculates the average marginal contribution of each feature variable under different sample conditions, quantitatively measuring their direction and degree of impact on ecological quality predictions, thus revealing the relative influence of climate factors and human activity indicators and their nonlinear response characteristics. This component overlap introduces circularity; independent-driver assessment would require refitting and evaluating a model excluding RSEI components. Methodologically, this interpretable machine-learning strategy also offers a transferable analytical paradigm for examining complex nonlinear associations of ecological change in other large basin systems. Predictive accuracy does not, by itself, validate the ecological meaning of RSEI or an independent ranking of external drivers.

## 4. Results

### 4.1. Spatiotemporal Distribution Characteristics of Ecological Quality

Between 2000 and 2024, the average Remote Sensing Ecological Index (RSEI) of the Poyang Lake Basin showed an overall upward trend with fluctuations, with the endpoint values indicating that the ecological quality in the region generally improved during the study period (Figure 4). During this period, the RSEI values showed fluctuations before becoming relatively stable. The individual-year low values discussed for 2002, 2005, and 2014, which are not displayed in Figure 4, require further comparison with image quality, annual compositing results, and matched meteorological and hydrological records. These abnormal values may be related to the combined effects of seasonal image availability, cloud and cloud-shadow contamination, hydrological fluctuations, and the sensitivity of annual normalization, rather than indicating basin-wide ecological degradation alone. Therefore, the interpretation of these individual years should be treated with caution, and greater attention should be paid to the long-term trend and spatially consistent patterns. From 2015 to 2024, the region entered a relatively stable phase, with the average RSEI breaking free from the earlier volatility and maintaining a range of 0.68 to 0.71, stabilizing at 0.710 by 2024. Overall, except for extreme drought or disaster years, the RSEI in the Poyang Lake Basin mostly fluctuated within the high value range of 0.68 to 0.75, indicating a good ecological quality. The stable trend after 2015 may be associated with ecological protection, including the Yangtze River Ecological Protection and Basin Ecological Restoration projects.

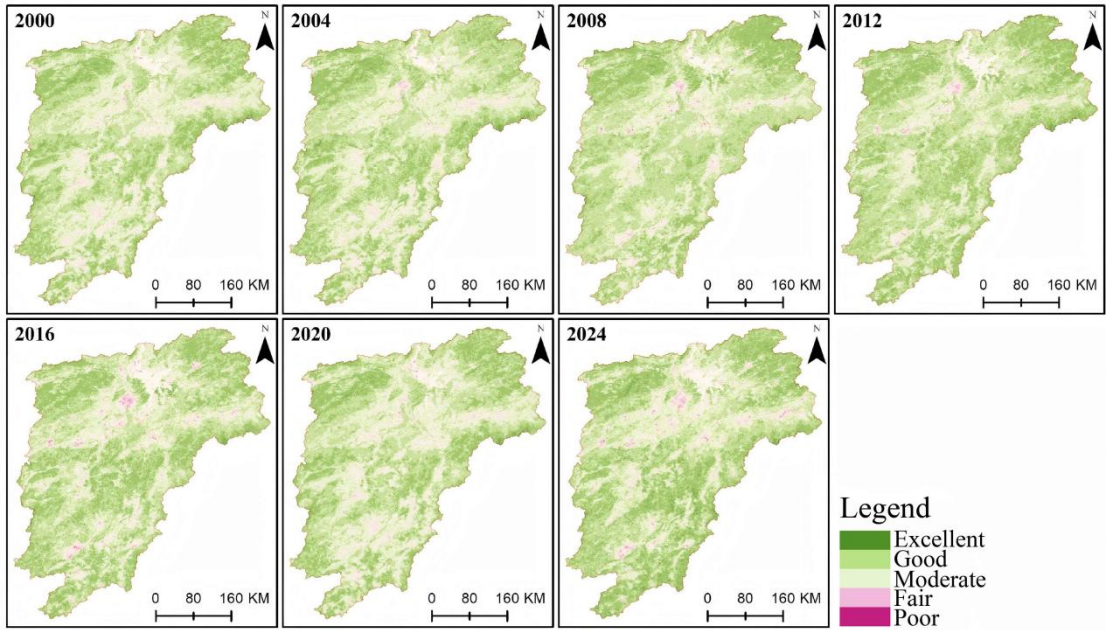


**Figure 4.** The average RSEI of the Poyang Lake Basin at seven representative years.

To further analyze the spatiotemporal evolution patterns of ecological quality in the Poyang Lake Basin, the normalized RSEI values were divided into five categories (Excellent, Good, Moderate, Fair, and Poor) with intervals of 0.2 (Figure 5 and Table 2). The area and proportion of each category were calculated every four years between 2000 and 2024. The results show that the ecological quality of the Poyang Lake Basin remained at a good level overall, with a slight increase with interannual fluctuations. The average RSEI value increased from 0.693 in 2000 to 0.710 in 2024. In terms of grade structure, the ecological quality of the basin has long been dominated by the “Good” category, with its area proportion consistently stable at over 61%. The most notable change was the increased proportion of the highest grade; the area summaries do not identify individual-pixel transitions. The proportion of “Excellent” areas increased from 14.42% in 2000 to 22.93% in 2024 (an increase of 8.51 percentage points), reflecting a significant improvement in the quality of core ecological barrier zones. In terms of spatial distribution, the basin as a whole exhibits a “high surrounding, low middle” circular pattern. High-value areas are mainly distributed in the mountainous forest belts of the five river upstream regions, while low-value areas are concentrated in the urbanized regions of the Poyang Lake Plain and the river valley areas. Despite noticeable ecological quality fluctuations in years such as 2002 and 2014, which may relate to water-level fluctuations or climate events but require independent verification, after 2015, the RSEI values stabilized within a high-value range. This pattern may be associated with the ongoing implementation of ecological restoration projects such as the “Yangtze River Ecological Protection”. Figure 4 presents the basin mean, whereas Figure 5 and Table 2 present the five grades: Poor, Fair, Moderate, Good, and Excellent in ascending RSEI order.

**Table 2.** Area and proportion of different RSEI ecological quality grades in the Poyang Lake Basin from 2000 to 2024.

| RSEI Level | 2000                 |                | 2004                 |                | 2008                 |                | 2012                 |                | 2016                 |                | 2020                 |                | 2024                 |                |
|------------|----------------------|----------------|----------------------|----------------|----------------------|----------------|----------------------|----------------|----------------------|----------------|----------------------|----------------|----------------------|----------------|
|            | Area km <sup>2</sup> | Proportion (%) | Area km <sup>2</sup> | Proportion (%) | Area km <sup>2</sup> | Proportion (%) | Area km <sup>2</sup> | Proportion (%) | Area km <sup>2</sup> | Proportion (%) | Area km <sup>2</sup> | Proportion (%) | Area km <sup>2</sup> | Proportion (%) |
| [0, 0.2]   | 20                   | 0.01           | 40                   | 0.02           | 81                   | 0.04           | 32                   | 0.02           | 155                  | 0.09           | 426                  | 0.23           | 116                  | 0.06           |
| [0.2, 0.4] | 971                  | 0.53           | 1325                 | 0.72           | 1658                 | 0.9            | 1462                 | 0.80           | 3017                 | 1.65           | 4364                 | 2.39           | 3262                 | 1.79           |
| [0.4, 0.6] | 32,472               | 17.75          | 29,642               | 16.16          | 24,462               | 13.33          | 18,080               | 9.93           | 28,317               | 15.53          | 34,731               | 18.98          | 25,413               | 13.92          |
| [0.6, 0.8] | 123,127              | 67.29          | 126,554              | 69.00          | 130,301              | 70.99          | 128,910              | 70.78          | 119,306              | 65.44          | 114,272              | 62.46          | 111,961              | 61.31          |
| [0.8, 1]   | 26,386               | 14.42          | 25,863               | 14.1           | 27,056               | 14.74          | 33,637               | 18.47          | 31,525               | 17.29          | 29,162               | 15.94          | 41,872               | 22.93          |

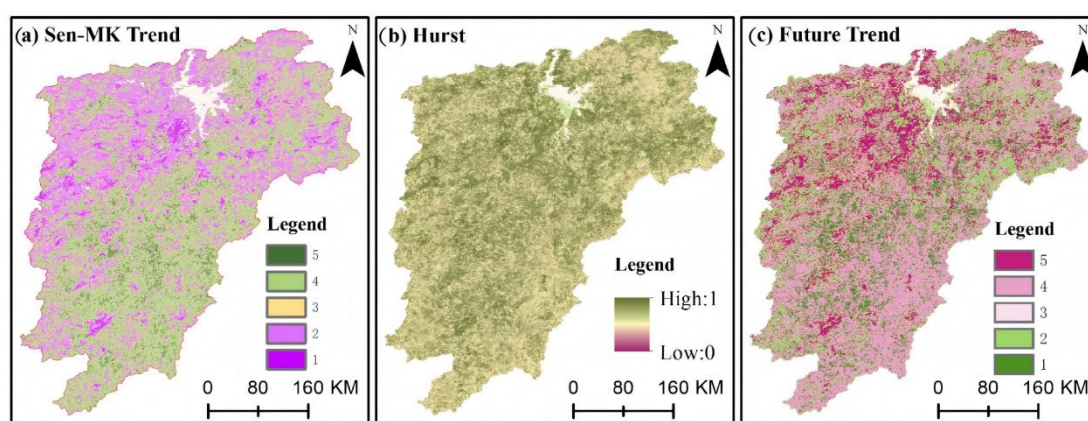


**Figure 5.** Spatial distribution of the five RSEI ecological quality grades of the Poyang Lake Basin.



#### 4.2. Evolution and Future Trends of Ecological Quality

To systematically characterize the temporal evolution features of ecological quality in the Poyang Lake Basin from 2000 to 2024 and its possible future change tendencies, a comprehensive evaluation was conducted using Theil–Sen median trend analysis and the Hurst exponent method (Figure 6). Figure 6 shows the historical trend, significance level, persistence characteristics, and possible future tendency of ecological quality. The results indicate that, during the study period, the overall trend in the Poyang Lake Basin was a pattern of improvement in ecological quality. The Theil–Sen trend analysis revealed that areas of ecological improvement dominated spatially, mainly located in the upper and middle reaches of the basin’s mountainous regions and the surrounding ecological areas of the lake, presenting a contiguous distribution pattern. In contrast, areas of ecological degradation were more scattered, primarily concentrated in urbanized areas, regions with high traffic disturbance, and some lakeshore areas, exhibiting point-like or patchy distributions. Overall, the area of improvement was significantly larger than the area of degradation, reflecting that over the past two decades, the ecological quality of the Poyang Lake Basin has generally been in a stage of recovery and optimization. The Hurst exponent analysis further revealed the persistence characteristics of ecological changes. The overall Hurst exponent in the study area was predominantly less than 0.5, indicating that most areas exhibited anti-persistent characteristics. This indicates anti-persistence in the observed series and motivates caution about extrapolating historical trends. Therefore, although the Theil–Sen results show that ecological improvement dominated during the historical period, this improvement should not be directly interpreted as a stable future trend. Areas with  $H < 0.5$  and a historical improvement trend may face potential fluctuation or reversal, while areas with  $H > 0.5$  are more likely to maintain their previous trend. Based on the combined analysis of Theil–Sen trends and the Hurst exponent, future ecological quality in the Poyang Lake Basin should be interpreted as uncertain and spatially differentiated, with the coexistence of sustained improvement, potential improvement, potential degradation, and sustained degradation. Areas of sustained improvement and potential future improvement may be spatially extensive, while areas of future degradation and sustained degradation may primarily be concentrated in regions with high human activity intensity or high ecosystem sensitivity. Overall, the historical ecological quality of the Poyang Lake Basin showed a dominant improvement trend. However, because most areas exhibited anti-persistent characteristics, future ecological quality should be interpreted with caution. The basin may not experience a simple continuation of historical improvement; instead, some historically improved areas may face reversal risk or unstable fluctuations. Therefore, future management should pay particular attention to areas with anti-persistent characteristics and potential degradation risks. This combined evidence suggests that regional ecological change in the basin is not a simple linear continuation of the past, but a dynamic process characterized by the coexistence of recovery dominance, local vulnerability, and future uncertainty. Strengthening ecological protection and reasonably regulating human activities will be crucial for enhancing the stability and resilience of the basin’s ecosystem. The Hurst exponent alone does not specify the timing or probability of a future reversal.

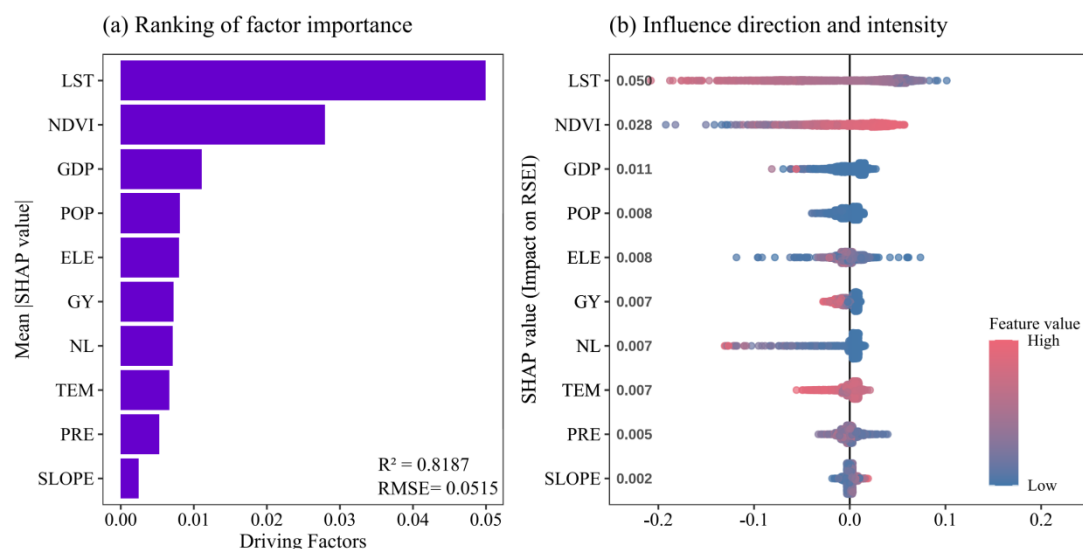


**Figure 6.** Spatial patterns of (a) ecological trends identified using Theil–Sen estimation and the Mann–Kendall test, (b) the Hurst exponent, and (c) potential future ecological trends in the Poyang Lake Basin.

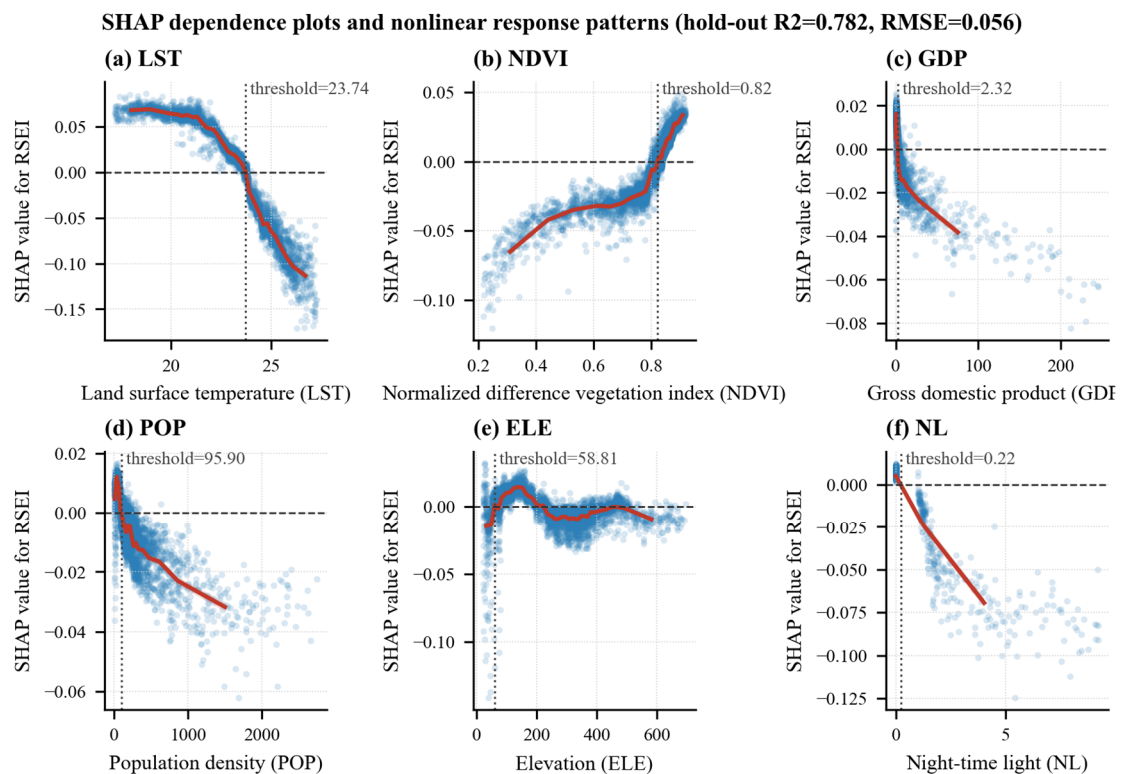
#### 4.3. Ecological Quality Association Analysis

Based on the Extreme Gradient Boosting (XGBoost) and Shapley Additive Explanations (SHAP) models, the nonlinear response relationships and influence strengths of various natural and human activity driving factors on the Remote Sensing Ecological Index (RSEI) in the Poyang Lake Basin were systematically analyzed (Figure 7).

In Figure 7, higher mean absolute SHAP values indicate stronger factor importance, and positive or negative SHAP values represent contributions that raise or lower the model prediction relative to its baseline. Figure 7 reports  $R^2 = 0.8187$  and  $RMSE = 0.0515$ ; Figure 8 separately reports the hold-out values given below. These prediction metrics do not establish causal validity. Among all variables included in the model, land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI) showed high average SHAP values. Since both variables are components of the RSEI calculation, their high importance mainly reflects the internal sensitivity of RSEI to thermal and vegetation conditions. The SHAP distribution indicates that higher LST is generally associated with lower RSEI predictions, while higher NDVI is associated with higher RSEI predictions. Therefore, these results should be interpreted as component-level explanatory relationships rather than independent causal effects. In contrast, variables such as GDP, population density, nighttime light, elevation, and slope provide additional information on the external socioeconomic and natural background conditions related to RSEI variation. Figure 8 further shows the nonlinear response patterns of selected variables. The hold-out model performance was acceptable, with an  $R^2$  of 0.782 and an RMSE of 0.056. LST showed a clear negative threshold effect: when LST exceeded approximately 23.74, its SHAP value declined rapidly, describing the fitted response of RSEI to its thermal component. NDVI showed the opposite pattern, with a stronger positive contribution when NDVI approached 0.82. For socioeconomic variables, GDP, POP, and NL generally exhibited negative SHAP responses after their threshold values, suggesting that intensified human activities may suppress ecological quality. Elevation showed a relatively weak and fluctuating effect, indicating that terrain mainly acts as a background constraint. Since LST and NDVI are components of RSEI, their responses should be interpreted as index sensitivity rather than independent causal effects. In contrast, the average SHAP values for economic development level (GDP) and population density (POP) were moderate, with overall negative effects, suggesting that enhanced economic activities and population concentration have, to some extent, increased pressure on the ecosystem. Nighttime light intensity (NL) also showed a negative contribution, reflecting the potential adverse impacts of urban expansion and increased human activity intensity on ecological quality. Regarding topographic factors, elevation (ELE) and slope (SLOPE) had relatively low overall contributions, but their SHAP distributions indicated that, within certain ranges, they had a stable moderating effect on RSEI. Areas with higher elevation and steeper slopes generally corresponded to better ecological quality. In terms of climate factors, temperature (TEM) and precipitation (PRE) had relatively low contributions to the fitted RSEI predictions. TEM showed a generally weak negative effect, while the positive and negative impacts of PRE were not entirely consistent, indicating that precipitation's influence on ecological quality has some nonlinear characteristics. Among agricultural-related factors, grain yield (GY) had a small average SHAP value and only influenced RSEI locally. Overall, the model explanation of RSEI variation in the Poyang Lake Basin exhibited associations with multiple factors, with land surface thermal environment and vegetation cover making the largest component contributions. Natural background factors provided basic constraints, while the influence of socioeconomic activity factors gradually became apparent, collectively shaping the spatial differentiation and evolutionary characteristics of ecological quality at the basin scale. These fitted response thresholds are not independently established ecological thresholds.



**Figure 7.** XGBoost-SHAP analysis of factors associated with RSEI variation in the Poyang Lake Basin. LST and NDVI are RSEI components; their SHAP importance is not independent evidence of ecological drivers.



**Figure 8.** SHAP dependence plots and nonlinear response patterns of selected variables associated with RSEI in the Poyang Lake Basin. Thresholds describe the fitted model responses and are not validated ecological limits.

## 5. Discussion

### 5.1. Spatiotemporal Evolution Characteristics of Ecological Quality

Ecological quality is a comprehensive reflection of the regional ecosystem's status and its change process, with its spatiotemporal evolution characteristics reflecting the overall level of ecological conditions at different stages and their spatial differentiation patterns [27]. On a long-term scale, ecological quality is influenced by both natural environmental background differences and regional development processes, exhibiting significant temporal trends and spatial heterogeneity [28]. Therefore, systematically analyzing ecological quality from both temporal and spatial perspectives is a key approach to revealing the regional ecological evolution laws. By comparing ecological quality at different periods, it is possible to identify the spatial distribution features and evolution paths of areas of ecological improvement, stability, and degradation, as well as to depict the overall trend of ecological quality changes at the basin scale. Additionally, combining the analysis of spatial distribution features and evolutionary directions helps uncover the continuity and stage-specific characteristics of ecological environmental changes, providing foundational insights into understanding the regional ecological evolution process and its future development trends, while also offering scientific support for subsequent ecological protection and management from a spatiotemporal perspective. The observed spatial pattern is generally consistent with previous studies on the Poyang Lake Basin, which have emphasized the combined influence of hydrological variation, land-use change, wetland evolution, and human activities on regional ecological conditions. The “high surrounding, low middle” structure is consistent with the following plausible ecological processes. The mountainous forest belts around the basin have higher vegetation coverage, steeper terrain, and lower development intensity, which help maintain soil conservation, water retention, and habitat stability. In contrast, the central plain and urbanized areas are more strongly affected by built-up land expansion, impervious surface increase, transportation construction, and industrial activities. These processes weaken vegetation regulation, increase land surface temperature, and fragment ecological space. In lakeshore and wetland areas, seasonal water-level fluctuations and wetland disturbance may also affect the RSEI components, especially greenness, wetness, and heat. Therefore, the spatial differentiation of ecological quality in the basin can be understood as the result of the interaction between natural terrain constraints, hydrological processes, land-use transformation, and human disturbance intensity. Temporally, RSEI has shifted from stronger fluctuations to relative stability, although this does not establish a restoration mechanism. Prior to 2014, the index exhibited marked fluctuations potentially associated with wet and dry conditions, but after 2015, RSEI was relatively stable within the high value range of

0.68 to 0.71. This spatiotemporal evolution pattern is generally consistent with the known ecological background, land-use pattern, and existing regional studies/reports of the Poyang Lake Basin. The improvement in mountainous and lakeshore ecological areas may be related to ecological restoration and protection measures, while the relatively low ecological quality in urbanized areas is consistent with stronger human disturbance and land development. This contextual consistency aids interpretation of the RSEI results, although it does not provide independent ground validation. It also provides important scientific evidence for future differentiated “mountain-water-forest-farmland-lake-grass” zoned management strategies and for coordinating urban development with ecological security boundaries. More importantly, by integrating ecological status assessment, historical trend diagnosis, future tendency analysis, and interpretable nonlinear model associations, this study provides a unified analytical framework for addressing how regional ecological quality evolves under coupled natural and anthropogenic influences. For comparison, Zeng et al. [21] reported basin ecosystem service values of 510.20 and 504.24 billion yuan in 2000 and 2020, respectively, whereas our RSEI increased from 0.693 to 0.710 during 2000–2024. The different indicators and periods preclude direct equivalence and show why RSEI improvement alone cannot establish the effects of vegetation or wetland restoration. Xu et al. [8] reported an RSEI increase from 0.794 to 0.852 in Fujian during 2002–2017, alongside a forest-area increase of 7078 km<sup>2</sup>. This provides a quantitative vegetation-related comparison, but differences in region, period, and index processing prevent direct attribution of the Poyang Lake change to restoration.

## 5.2. Ecological Quality Driver Analysis

The spatial differentiation and evolution of ecological quality in the Poyang Lake Basin are essentially the result of the complex nonlinear coupling between natural geographical background and human activity disturbances at multiple spatiotemporal scales [29]. Compared with conventional linear attribution approaches, the XGBoost–SHAP framework used in this study makes it possible to identify not only factor importance but also the directional and threshold-like responses of ecological quality to different drivers, thereby deepening the methodological understanding of regional ecological change. The XGBoost–SHAP results are consistent with the general interpretation in previous studies in the Poyang Lake Basin: ecological quality is shaped by both natural background constraints and human disturbance. Previous studies have examined land-use change and related ecological conditions in the Poyang Lake Basin [21]. In this context, our results revealed a fluctuating upward trend in RSEI during the study period, suggesting a possible association between regional ecological restoration measures and the long-term improvement of ecological quality. The relationship between land surface temperature and vegetation condition indicates that ecological quality is highly sensitive to the balance between thermal stress and vegetation regulation. In forested mountainous areas, vegetation cover can reduce surface heat, stabilize soil moisture, and support ecological functions. In contrast, in urbanized plains, the expansion of impervious surfaces enhances heat accumulation and reduces vegetation cover, thereby lowering ecological quality. This proposed process may help explain why ecological degradation is more likely to appear in areas with intensive urban expansion, transportation development, and industrial activities. The model results show that land surface temperature (LST) has the largest negative component contribution to RSEI prediction. The close linkage between LST and the Normalized Difference Vegetation Index (NDVI) in the SHAP importance ranking is consistent with the contrast between “thermal environmental stress” and “vegetation regulation function” in the subtropical humid ecosystem. In highly urbanized areas like Nanchang, the expansion of impervious surfaces leads to a significant increase in sensible heat flux, triggering a pronounced urban heat island effect. This heat stress accelerates soil moisture evaporation and suppresses plant physiological metabolism, directly causing the degradation of ecosystem services. In contrast, vegetation may play a compensatory role in maintaining ecological microcirculation stability through transpiration cooling and photosynthetic carbon fixation. At the same time, socio-economic factors such as GDP, population density, and nighttime light intensity exhibit negative threshold-like patterns in the fitted model, suggesting an association between human activity and pressure on natural ecological space. Particularly in the densely urbanized plains, high-intensity land development fragments landscape connectivity, exacerbating habitat fragmentation risks, making these areas ecological “low-value traps” in the basin. In contrast, natural background factors primarily play a fundamental constraint role. Topographic factors (elevation and slope) contribute to the formation of a natural “development shield” in the upper reaches of the five rivers by increasing development costs and difficulties. This effectively preserves the original forest land and biodiversity, constructing a solid ecological barrier on the basin’s periphery. Precipitation has relatively low SHAP importance, which may depend on the predictor set and the spatial and temporal aggregation used. In the Poyang Lake Basin’s water-rich, humid context, the model gives precipitation relatively low importance, without excluding seasonal water limitation; instead, variations in energy conditions (temperature) show a stronger

sensitivity to ecological quality. In conclusion, the evolution of ecological quality in the Poyang Lake Basin is not a simple linear combination of individual factors, but rather a complex process reshaped by land surface thermal environment as the stressor and vegetation cover as the regulator, influenced by the passive protection of topographic background and the active disturbance of urbanization. This interpretation suggests that future ecological governance should shift from a single focus on “greening” to a dual emphasis on “cooling and greening”. For watershed management, these findings can be translated into differentiated zoning control strategies. In mountainous forest areas with high RSEI values, local authorities should maintain strict ecological protection, restrict intensive construction, and strengthen soil and water conservation. In urbanized low-RSEI areas, management should focus on controlling impervious surface expansion, increasing urban green-blue spaces, and reducing land surface thermal stress. In lakeshore and wetland areas, ecological water-level regulation, wetland restoration, riparian buffer protection, and seasonal monitoring should be strengthened. These measures provide management options for local evaluation while coordinating ecological protection with urban and industrial development. The processes discussed here are ecological hypotheses; SHAP values, especially for components already included in RSEI, do not independently validate them.

### 5.3. Limitations and Future Prospects

This study, based on the powerful data processing capabilities of the GEE cloud platform, overcomes the limitations of traditional methods in large-scale, long-term time series computations, successfully constructing a spatiotemporal dataset of ecological quality in the Poyang Lake Basin from 2000 to 2024 and systematically revealing its associated factors. This provides an important quantitative basis for long-term monitoring and scientific regulation of the basin’s ecosystem. However, there is still room for further development in this study. (1) Some driving factors used in this study, such as land-use data and road network data, were derived from a single year and were treated as static or quasi-static variables. This may introduce uncertainty when explaining long-term ecological changes from 2000 to 2024. Therefore, the attribution results should be interpreted mainly as the influence of spatial background conditions and dominant human disturbance patterns, rather than as a complete explanation of annual ecological changes. In future research, long-term land-use, road expansion, population, and socioeconomic time-series data should be incorporated to improve dynamic attribution. In the future, additional dimensions such as air quality, water environment, and biodiversity could be integrated into the RSEI framework to enhance the comprehensiveness of the assessment results. (2) The timeliness of monitoring can be improved. Given the significant seasonal hydrological characteristics of Poyang Lake, future monitoring should refine the temporal resolution from interannual to seasonal or monthly intervals to capture intra-annual fluctuations in ecological quality. In addition, abnormal values in individual years require independent meteorological, hydrological, and field evidence; vegetation indicators can provide supplementary consistency checks to reduce uncertainty in long-term RSEI interpretation. (3) Further refinement of the deep mechanism analysis and predictive capabilities is needed. Future research should further combine multi-source heterogeneous data, especially ground-truth measurements, with artificial intelligence algorithms. Meteorological records, hydrological observations, water quality monitoring, ecological station data, and field survey data should be incorporated to validate the RSEI trends more directly. This will help reduce the uncertainty of remote-sensing-based assessment and provide stronger support for regional ecological safety early warning. No component-excluded model or additional land-use years are included in the present analysis, so independent-driver rankings and dynamic land-use attribution remain unresolved. RSEI represents land-surface greenness, wetness, heat, and dryness; low values over open water or seasonally exposed wetlands should not be equated directly with poor aquatic habitat quality. Annual compositing and normalization may also affect interannual comparability.

## 6. Conclusions

This study focuses on the Poyang Lake Basin, constructing a long-term ecological monitoring framework based on the GEE platform and using the XGBoost-SHAP model to deeply analyze the spatiotemporal evolution characteristics of regional ecological quality and its associated factors. The main conclusions are as follows:

- (1) Between 2000 and 2024, the average RSEI in the Poyang Lake Basin increased from 0.693 to 0.710, remaining at a good level. Temporally, there was an observed transition from “severe fluctuations” (2000–2014) to “relative stability” (2015–2024), suggesting greater stability in the index. Spatially, the basin exhibits a “high surrounding, low middle” pattern, with high-value areas in the upstream mountainous regions of the five rivers and low-value areas in the Poyang Lake Plain urban areas. The ecological grade structure improved overall, with the proportion of “excellent” areas rising from 14.42% to 22.93%, indicating notable improvement in core ecological function areas.



- (2) Historical evolution was dominated by improvement, but future changes remain uncertain with localized degradation risks. Trend analysis shows that the area of ecological improvement in the basin is larger than the area of degradation, indicating that the basin is in a recovery phase. However, the Hurst exponent reveals strong anti-persistent characteristics, suggesting that the ecological recovery process still exhibits volatility. The Theil–Sen results indicate that ecological improvement dominated during the historical period. However, the Hurst exponent shows that many areas have anti-persistent characteristics, suggesting that historical improvement may not necessarily continue in the future. Therefore, future ecological change in the basin should be understood as uncertain and spatially differentiated. Dynamic monitoring and early warning should be strengthened, especially in areas with anti-persistent characteristics, urbanized areas, and ecologically sensitive lakeshore zones.

The fitted model reflects “heat–green” component sensitivity and associations with natural and human factors. XGBoost-SHAP attribution analysis shows that land surface temperature (LST) and vegetation cover (NDVI) are the largest component contributors to RSEI predictions, without establishing an independent “thermal stress–vegetation regulation” mechanism. Topographic associations are consistent with lower development intensity in mountainous areas, while GDP and nighttime light show negative predictive contributions at the local scale. This suggests that ecological governance in the Poyang Lake Basin should shift from purely vegetation restoration to a dual focus on “cooling and greening” and should implement differentiated spatial management strategies based on topography and human activity intensity.

### Author Contributions

D.G.: conceptualization, methodology, software, writing—original draft preparation; S.L.: conceptualization, supervision, writing—reviewing and editing; L.Y.: data curation, formal analysis, validation; X.H.: investigation, visualization, writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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### Institutional Review Board Statement

Not applicable. The study did not involve humans or animals.

### Informed Consent Statement

Not applicable. The study did not involve humans or animals.

### Data Availability Statement

Data will be made available on request.

### Conflicts of Interest

The authors declare no conflict of interest.

### Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used AI tools solely for language editing. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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