Environment, Resource and Ecology Journal (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/erej.2025.090212
ISSN 2616-3756 Vol. 9 Num. 2

Analysis of Ecological and Environmental Change Trends and Influencing Factors in the Middle Yangtze River Urban Agglomeration

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Keywords: Ecological Environment, Trend, Optimal Parameter Geographic Detector

Abstract: With China's rapid economic development, human activities have encroached upon ecological spaces, subjecting regional ecosystems to increasing pressures. To advance the United Nations Sustainable Development Goals for ecological conservation, it has become imperative to strengthen environmental protection in critical regions. This paper uses the Middle Yangtze River Urban Agglomeration (MYRUA) as a case study. It employs the upgraded Remote Sensing Ecological Index (RSEI-new) to assess the quality of the regional ecological environment quality (EEQ) and analyzes its spatial and temporal trends. To further reveal the key drivers of ecological improvement or degradation, an Optimal Parameter Geographic Detector is utilized to systematically investigate the factors influencing EEQ and their interactions. The findings indicate that the regional ecological environment exhibits a general pattern of “low values in urban areas and high values in forested areas,” with low-value zones primarily concentrated in densely urbanized belts along the Yangtze River. Temporally, the ecological environment in the study area shows an overall positive trend, with approximately 54% of the region demonstrating significant improvement. Net primary productivity (NPP) of vegetation emerges as the key single-factor driver of ecological and environmental change, while the interaction effect between NPP and population density is most pronounced ($q = 0.413$), making it the primary composite driver of ecological and environmental change. Overall, identifying the trends and dominant factors of ecological and environmental change in the MYRUA provides vital statistical insights and scientific support for regional environmental management, ecological restoration, and policy optimization.

1. Introduction

To advance sustainable development in human society, the United Nations Sustainable Development Goals (SDGs) propose “Promoting the sustainable use of terrestrial ecosystems” (SDG 15). This objective arises from the deeply interdependent relationship between human systems and ecosystems. Human economic production and construction activities not only alter land use patterns but also continually erode space for vegetation growth, leading to ongoing disturbances in the ecological environment[1]. A healthy ecological environment is essential as a regional carbon sink and a foundation for green resources. When damaged, it exacerbates environmental pollution, reduces residents' quality of life, and may trigger more frequent extreme weather events and natural disasters[2]. Therefore, scientifically assessing regional ecological and environmental quality and accurately identifying the core drivers of ecological and environmental change are critically important for optimizing management strategies and ensuring the sustainable development of human society.

In the field of ecological environment status assessment, scholars have proposed various evaluation methods from different research perspectives. The most widely applied methods include the Pressure-State-Response (PSR) model[3], the Ecological Environment Index (EI)[4], and the Remote Sensing Ecological Index (RSEI)[5]. It is important to note that the PSR model and EI index may be affected by subjective weighting or biases in indicator selection during metric design. In contrast, the RSEI derives evaluation metrics from remote sensing data inversion and employs principal component analysis (PCA) for integrated computation, effectively reducing human interference. As a result, it has been extensively applied in ecological and environmental assessment research[6]. To further enhance the RSEI's adaptability and accuracy while accommodating diverse regional ecological characteristics, researchers have strategically supplemented it with specialized indicators. For example, factors such as soil erosion and air quality conditions were included to address the specific characteristics of mining cities[7], while the Air Quality Index was added to consider both urban and industrial development contexts[8].

To advance regional ecological restoration and improvement, accurately identifying the key drivers of ecological change and formulating targeted conservation policies based on these findings have become central issues in contemporary ecological governance. As a method for identifying influencing factors, optimal parameter geographic detector (OPGD) model[9] not only quantify the contribution of individual factors to ecological and environmental changes but also analyze the interactive effects among variables, thereby characterizing the nonlinear relationships between factors. Consequently, they have gradually become a commonly used method for identifying ecological and environmental impact factors.

As a pivotal hub connecting the upper and lower reaches of the Yangtze River, the Middle Yangtze River Urban Agglomeration (MYRUA) References has experienced intensified land development, driven by its role in receiving industrial transfers from downstream regions and promoting regional economic growth. However, this growth has led to challenges such as deteriorating air quality and impaired ecological functions. To accurately reflect the ecological and environmental quality of the region, this study incorporates air quality factors into the traditional RSEI framework to construct an upgraded Remote Sensing Ecological Index (RSEI-new) for a more comprehensive assessment of regional ecological and environmental quality. Concurrently, the SLOPE analysis method and the optimal parameter geographic detector model are employed to analyze trends and influencing factors of regional ecological and environmental changes. Ultimately, this research provides scientific basis and policy references for the sustainable ecological and environmental development of the MYRUA.

2. Data Sources

The construction of RSEI-new utilizes MODIS product data and employs google earth engine (GEE) for modeling. Due to variations in resolution stemming from different raster data sources, the resolution was uniformly standardized to 1km during the data preprocessing stage. Data sources are listed in Table 1.

Table 1: Data sources.

Data function	Data name	Time	Source
RSEI-new	MOD11A2-LST	2003-2021	GEE (https://developers.google.com)
	MOD13Q1-KNDVI		
	MOD09A1-WET, NDBSI and MNDVI		
	MCD19A2-AOD		
Driving factor	Methane (CH_4)		European Commission (https://edgar.jrc.ec.europa.eu/)
	Population density (POP)		Oak Ridge National Laboratory(https://landscan.ornl.gov/)
	LUCC		Paper (https://doi.org/10.5281/zenodo.8176941)
	Precipitation (PRE)		GEE (https://developers.google.com)
	NPP		
	The share of secondary and tertiary industries in GDP（SIG）		CHINA CITY STATISTICAL YEARBOOK (https://www.stats.gov.cn/sj/ndsj/)
	Total Population (TP)		
	GDP		

3. Method

3.1 RSEI-new Model

Since traditional RSEI neglects air quality factors, it struggles to assess the negative impacts of industrial and urban development on air quality within MYRUA regions. Therefore, this paper introduces air quality indicators to construct a novel RSEI model. The RSEI-new$_0$ model employs the first principal component to circumvent biases arising from subjective weighting. Its expression is as follows:

$$RSEI - new_0 = PCA_1[f(NDVI, WET, LST, NDBSI, AOD)] \tag{1}$$

Among these, NDVI, WET, and NDBSI are calculated using MOD09A1 products; LST is constructed using MOD11A2; and AOD, representing the air quality factor, is calculated using the MCD19A2 Product-Optical_Depth_047 Band. Since areas with higher ecological quality usually have higher RSEI-new$_0$ values, and areas with lower ecological quality have lower RSEI$_0$ values. However, if RSEI-new$_0$ yields lower values in areas with good ecological quality, we calculate the final RSEI-new by subtracting RSEI-new$_0$ from 1. The inverse processing equation for RSEI-new is:

$$RSEI - new = 1 - PCA_1[f(NDVI, WET, LST, NDBSI, AOD)] \tag{2}$$

The RSEI-new is further normalized to ensure that its values ranging from 0 to 1, where 0 indicates severely poor ecological quality and 1 indicates signifies excellent ecological quality. The RSEI-new values were subsequently classified into five categories, each spanning an interval of 0.2: very poor (0–0.2), poor (0.2–0.4), moderate (0.4–0.6), good (0.6–0.8), and excellent (0.8–1).

3.2 Trend Analysis

To further analyze trends in ecological environment changes, SLOPE analysis was employed to examine ecological change trends in RSEI-new from 2003 to 2021. An F-test was applied to determine the significance of these trends. The formula is as follows:

$$\theta_{slope} = \frac{n \times \sum_{i=1}^{n} (i \times X_i) - \sum_{i=1}^{n} i \times \sum_{i=1}^{n} X_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \tag{3}$$

Where θ_{slope} denotes the regression slope; n represents the total number of study years; i indicates the time variable; X_i signifies the RSEI-new value. Combining the final trend analysis results with significance test outcomes allows categorizing RSEI-new trends as: extremely significant increase ($\theta_{slope} > 0$, $P < 0.01$), significant increase ($\theta_{slope} > 0$, $0.01 < P < 0.05$), stable ($P > 0.05$), significant decline ($\theta_{slope} < 0$, $0.01 < P < 0.05$), extremely significant decline ($\theta_{slope} < 0$, $P < 0.01$).

3.3 Optimal Parameters-based Geographical Detectors Model

The OPGD addresses the issue of variable discretization by building upon traditional geographic detectors. It automatically classifies continuous variables using equal breaks, natural breaks, quantile breaks, geometric breaks, and standard deviation breaks, thereby reducing human interference. Therefore, this study selects the OPGD and utilizes its R package (https://www.geodetector.org/) to analyze the driving forces of the ecological environment in the MYRUA. Its formula is as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{4}$$

In the formula: q denote the explanatory power of the factor, with a value range of [0, 1]. A higher value indicates more pronounced spatial heterogeneity in Y and greater explanatory power. h represents the stratum (Strata) of the dependent variable X. N_h and N denote the number of units in stratum h and the entire area, respectively. σ_h^2 and σ^2 represent the variance of Y values within stratum h and the entire area, respectively; SSW and SST denote the sum of variance within strata and the total variance across the entire area, respectively. First, the study determines the optimal q-value and classification method by applying different classification approaches to continuous variables. This helps identify the individual explanatory power of various influencing factors on spatial variations in ecological environment quality. Subsequently, we employ interaction detection analysis to examine the combined effects of different factors on the ecological environment.

4. Results

4.1 Spatiotemporal Variations of RSEI-new

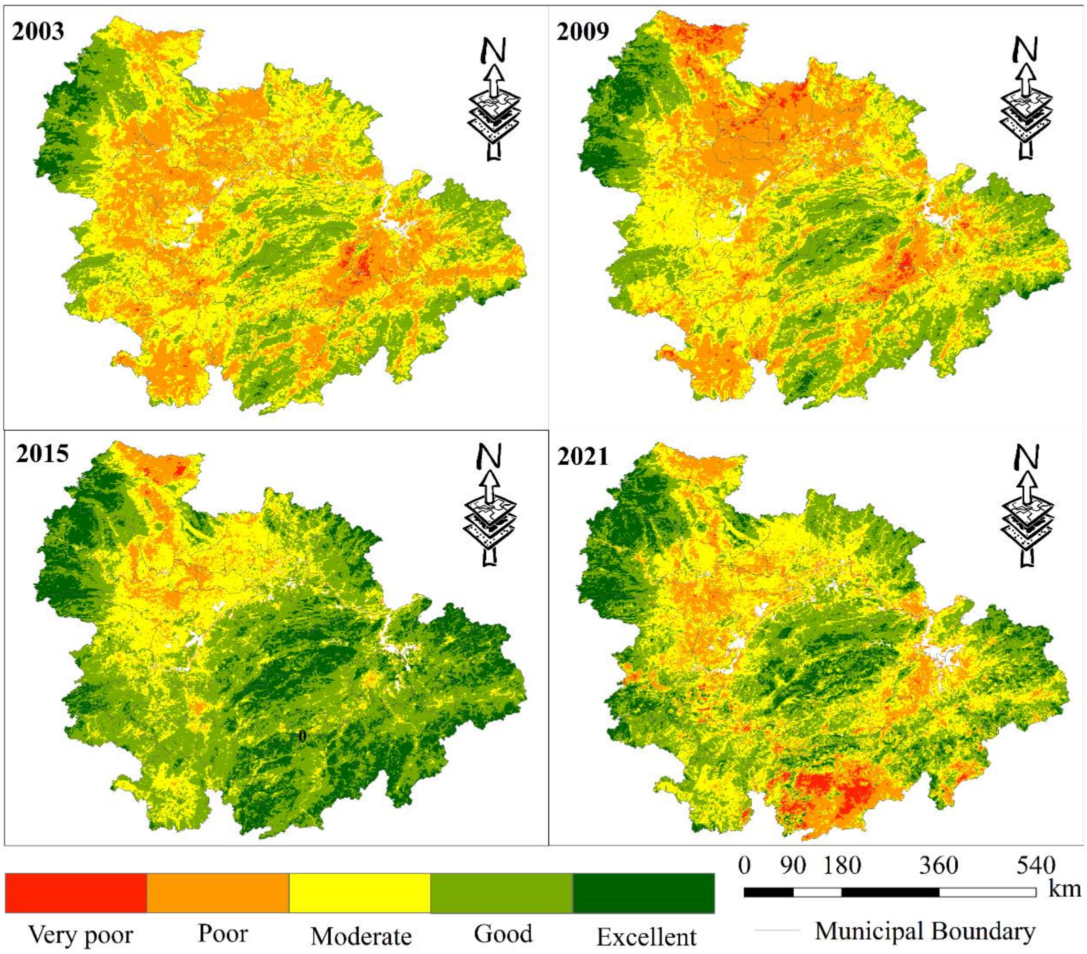

Figure 1: Spatio-temporal distribution of RSEI-new.

As shown in Figure 1, the regional ecological environment is predominantly rated “medium” and “good,” with these categories collectively accounting for over 60% of the total area. Areas rated ‘poor’ and “very poor” are primarily concentrated in urban zones, particularly in cities like Wuhan and Nanchang, where concentrated human activities and construction land use have adversely affected vegetation growth. Moderate and good grades are predominantly distributed along the Yangtze River, in valley areas, and in regions where forested and cultivated lands intermingle, exhibiting continuous block-like spatial clustering. Areas rated excellent are primarily located in mountainous regions, such as the Jiuling Mountains in the central part, Wudang Mountain and Wushan in the northwest, and the Wuyi Mountains in the south. Temporal trends reveal overall ecological improvement from 2003 to 2008, with an average increase of 0.234. From 2008 to 2016, the average declined by approximately 0.298 amid fluctuating conditions. and rebounded again from 2016 to 2021, with the average value increasing by 0.152. This ecological recovery trend aligns with the ecological restoration requirements outlined in the Yangtze River Economic Belt Development Plan and the symposium on the development of the Yangtze River Economic Belt, indicating that the effectiveness of regional ecological governance is gradually becoming apparent.

4.2 Trend Analysis of Ecological and Environmental Changes

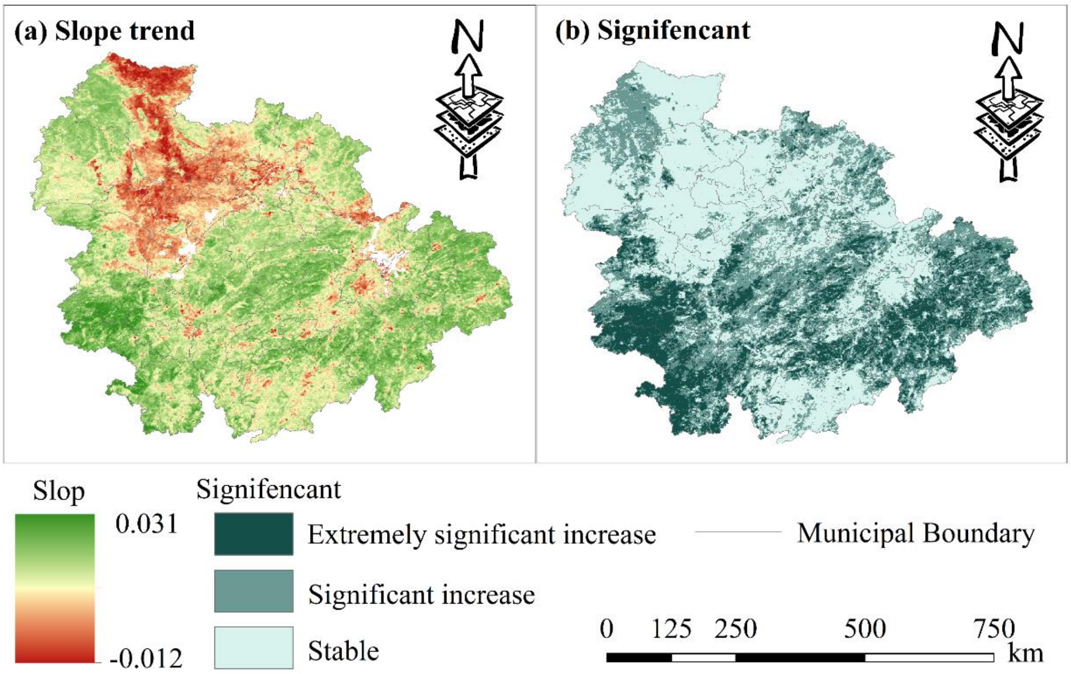

Figure 2: Spatial-temporal trends of RSEI-new.

As shown in Figure 2, the slope values in the study area ranged from 0.017 to 0.031, indicating overall minimal ecological fluctuations and a generally positive trend. Only 1.063% of the area exhibited slope values below 0, primarily concentrated in the northern part of Xiangyang and the Hanjiang River basin spanning Jingmen and Tianmen. The remaining 98.557% of areas had slope values >0, with Loudi and Yiyang showing the most significant improvements. Combined with the RSEI-new significance results, 18.628% and 35.375% of the study area exhibited extremely significant and significant improvements, respectively, while 45.997% remained stable, indicating a pronounced overall ecological improvement trend.

Spatially, areas with stable ecological conditions encompass both regions with solid ecological foundations like Ji'an and Yichang, as well as highly urbanized cities such as Wuhan, Xiantao, Qianjiang, and Nanchang, suggesting ecological pressures in these urban centers have gradually stabilized. Regions showing ecological improvement or significant improvement are predominantly distributed across forested and cultivated land areas. Notably, the study area exhibits a transitional trend from stable to significantly increased to extremely significantly increased ecological conditions, reflecting a progressive pattern of ecological change.

4.3 Drivers of Ecological and Environmental Change

To avoid model bias caused by sample data overlapping with target data, this study selected the multi-year average values of influencing factors across prefecture-level cities from 2003 to 2021 as input variables. Due to significant data gaps in Tianmen, Xiantao, and Qianjiang, these locations were excluded, resulting in 532 sample points. All factors yielded p-values below 0.05, indicating statistical significance.

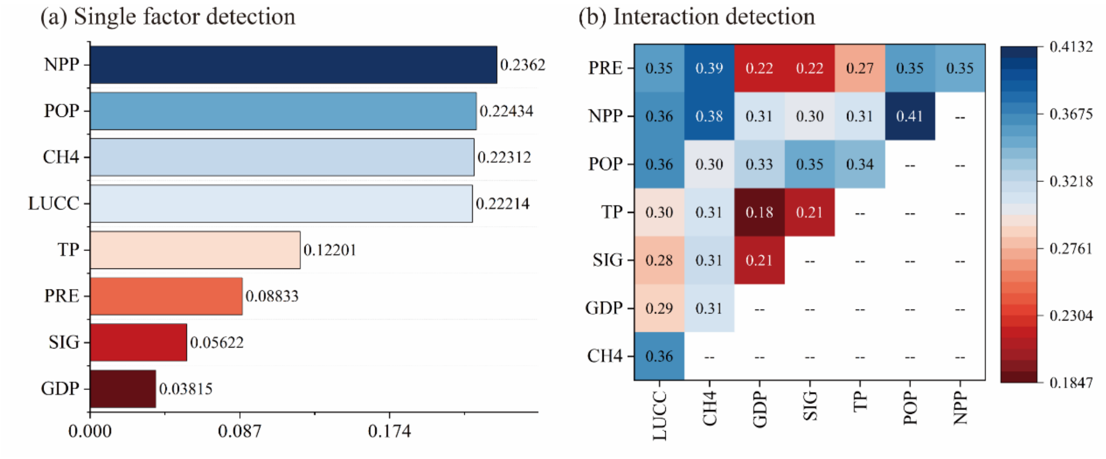

Figure 3: Analysis of Influencing Factors of RSEI-new.

The results of single-factor and interaction factor detection are shown in Figure 3. Single-factor detection revealed that NPP is the primary factor influencing ecological environment changes (q = 0.238), followed by PD, CH_4, and LUCC. The q values for PRE, SIG, and GDP were all below 0.1, indicating relatively weak explanatory power for ecological environment changes. Interaction detection results indicate that NPP∩PD exhibits the strongest explanatory power (q = 0.413), followed by PRE∩CH_4 and NPP∩CH_4 (q values of 0.385 and 0.384, respectively). TP∩GDP exhibited the weakest effect (q = 0.185). Overall, the q-values for interaction factors were generally higher than those for single factors, indicating that the combined action of multiple factors significantly enhances the explanatory power for ecological changes.

5. Conclusion

The SDGs underscore the urgency of strengthening terrestrial ecological conservation. This study employs the RSEI-new index to evaluate regional ecological conditions and analyzes their trends and key influencing factors. Key findings are as follows:

(1) The overall ecological environment across the region remains at a relatively high level. Areas with poorer ecological conditions are primarily urban regions, particularly in cities like Nanchang and Wuhan. Conversely, areas with better ecological conditions are mainly mountainous regions distant from urban centers.

(2) The overall ecological environment of the Middle Yangtze River Urban Agglomeration shows a positive trend. Areas with extremely significant and significant improvements account for 18.628% and 35.375% of the total area, respectively.

(3) NPP, PD, and CH_4 are the primary single factors influencing the ecological environment. All factors are enhanced through interactions, indicating that interactions between social and ecological factors can exert more significant impacts on the ecological environment.

The factor analysis indicates that enhancing regional ecological environments requires strengthening vegetation conservation to increase NPP values. Additionally, attention must be paid to the impact of interactions between regional vegetation and population density on ecological environment quality. Coordinating population development with vegetation conservation objectives is essential to advance the sustainable development of ecological environments.

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