

Article

Exploration of Eco-Environment and Urbanization Changes Based on Multi-Source Remote Sensing Data—A Case Study of Yangtze River Delta Urban Agglomeration

Yuhua Li ^{1,2,3} and Shihang Wang ^{1,2,3,*}

¹ School of Geomatics, Anhui University of Science and Technology, Huainan 232001, China; lyh15749@163.com

² Key Laboratory of Aviation-Aerospace-Ground Cooperative Monitoring and Early Warning of Coal Mining-Induced Disasters of Anhui Higher Education Institutes, Anhui University of Science and Technology, Huainan 232001, China

³ Coal Industry Engineering Research Center of Mining Area Environmental and Disaster Cooperative Monitoring, Anhui University of Science and Technology, Huainan 232001, China

* Correspondence: wangshihang122@sina.com

Abstract: Rapid urbanization inevitably exerts pressure on the surrounding ecological environment, and balancing the relationship between the ecological environment and urbanization is crucial for sustainable urban development. Taking the Yangtze River Delta urban agglomeration (YRDUA) as a case study, this paper utilizes MODIS data and nighttime light data to construct the MODIS Remote Sensing Ecological Index (MRSEI) and Comprehensive Nighttime Light Index (CNLI) distributions to depict ecological environment quality and urbanization levels. Based on this, the Coupled Coordination Degree (CCD) model is employed to calculate the coupling coordination level between the two, and the Geodetector is used to analyze the underlying causes affecting the CCD. The results indicate the following: (1) the overall ecological environment of the YRDUA tends to be stable, but there are significant differences between regions. Areas with deteriorating ecological conditions are concentrated in cities with higher rates of urbanization changes. (2) All cities are developing towards coordination, but there are imbalances in development among different regions. (3) The key factors affecting the CCD are derived from socioeconomic elements rather than natural elements, with the interaction between GDP and DEM having the strongest explanatory power for the CCD. (4) The CNLI is positively correlated with the CCD, the MRSEI is negatively correlated with the CCD, and the level of urbanization is the decisive factor for CCD changes. The research findings can provide theoretical guidance for promoting sustainable urban development.

Keywords: CNLI; CCD; ecological environment; Geodetector; MRSEI; urbanization; YRDUA



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1. Introduction

Currently, a massive urbanization movement is spreading across the globe, with developing countries serving as the primary driving force behind this trend [1]. As the world's largest developing country and the second-largest economy, since the reform and opening-up, China has undergone an unprecedented urbanization process in human history. The urbanization rate skyrocketed from 17.92% in 1978 to 64.72% in 2021 [2]. Particularly since the beginning of this century, China's rate of urbanization has been three times the global average [3]. While rapid urbanization has promoted swift economic growth, it has also brought about a series of detrimental effects, including air pollution [4], soil contamination [5], ecological degradation [6], and water pollution [7]. These issues pose significant challenges to achieving sustainable urban development goals and highlight the imprudence of neglecting ecological considerations in the pursuit of urbanization. Consequently, there is an urgent need to employ scientific methods to clarify the interaction between the ecological environment and urbanization, providing a theoretical basis for relevant departments to formulate urban development strategies.

Currently, many scholars have explored methods for quantifying ecological environment and urbanization levels [8–10]. However, most of these studies are based on panel statistical data, which limits detailed spatial analysis. Moreover, these data often suffer from inconsistent standards and slow updates, resulting in poor availability [11]. Nevertheless, the rapid development of remote sensing technology provides a new and crucial means for monitoring regional ecological quality [12]. With its real-time capabilities, comprehensive coverage, and objectivity, remote sensing technology is playing an increasingly important role in urban ecology studies [13]. It has promoted the adoption of methods that characterize the quality of the ecological environment and levels of urbanization.

In the field of ecological environment assessment, various remote sensing-based indices have been utilized to describe the conditions of specific areas. Vegetation indices are widely used for studying vegetation changes [14], surface temperature indices for assessing urban heat island effects [15], and water body indices for depicting changes in coastlines [16]. Although these single indices are practical, the complexity and diversity of factors affecting ecosystems mean that relying on a single ecological indicator for a comprehensive assessment is insufficient. The introduction of the Remote Sensing Ecological Index (RSEI) addresses this issue by integrating indicators such as greenness, dryness, wetness, and heat [17]. Compared to single indices, the RSEI provides a more robust assessment of ecological status [18]. It has been extensively applied in areas such as urban ecological quality monitoring [19], ecological evaluations of mining areas [20], and assessments of ecological quality in natural ecological zones [21].

In urbanization assessment, the emergence of nighttime light detection sensors, represented with the Operational Linescan System (OLS) and Visible Infrared Imaging Radiometer Suite (VIIRS), has provided a crucial technical means for studying the intensity of human activities. Nighttime light data, with its capability for broad-range and long-term Earth observation, along with its openness, effectively supports research on human activities at the surface level and the urbanization process. Many scholars have confirmed that nighttime light data have certain advantages in measuring urbanization levels [22–24]. Currently, research on nighttime light data mainly focuses on urban expansion [25,26], assessments of socioeconomic dynamics [27], and estimations of electricity consumption and carbon emissions [28,29], yielding rich results in these fields.

The concept of coupling originates from the notion of capacitive coupling in physics, which refers to the phenomenon where two or more elements interact and influence each other [30,31]. This concept has been expanded into fields like ecology and geography to study the “human–land” coupling relationships [32,33]. In the domain of urban sustainable development, the coupling of the ecological environment with urbanization is a focal area of research among many scholars [34]. Existing methods for studying the coupling between the ecological environment and urbanization include the Environmental Kuznets Curve (EKC) model [35], the coupling coordination degree (CCD) model [36], urban metabolism theories [37], and planetary boundary theories [38]. Among these, the CCD model utilizes coupling degree to explain the interrelations among subsystems and further employs coordination degree to conduct comprehensive assessments and research of the entire system. This model effectively measures the interaction between ecological environment and urbanization. Additionally, its simplicity, ease of calculation, and clear results have led to its wide recognition and use by numerous scholars [39].

As one of China’s most economically developed and socioeconomically advanced regions, the Yangtze River Delta urban agglomeration (YRDUA) holds a crucial strategic position in China’s modernization and reform and opening-up processes [40]. However, the rapid urbanization has been accompanied by increasing pressures on the regional ecological environment [41]. Thus, exploring the interaction between ecological environment and urbanization in the YRDUA serves as a valuable reference for other urban agglomerations in China. This research aims to address the following questions:

1. Is there a negative correlation between the quality of the urban ecological environment and the level of urbanization?

2. In the coupling and coordination relationship between the ecological environment and urbanization, which factor plays a decisive role?

The primary hypothesis of this research is that against the backdrop of urban expansion, the ecological environment is gradually deteriorating, and the coupling and coordination relationship between the ecological environment and urbanization is increasingly becoming unbalanced.

The primary objectives of this study have been established as follows: (1) Ecological and urbanization indices are to be constructed to measure the quality of the ecological environment and the level of urbanization within the YRDUA. The changing trends of these indices are to be analyzed using trend analysis methods, providing insights into their temporal dynamics. (2) The CCD model is to be employed to calculate the degree of coupling and coordination between the ecological environment and urbanization. The key factors influencing the CCD are to be explored using a geographical detector, which will help identify the drivers and constraints within these interactions.

2. Materials and Methods

2.1. Study Area

The YRDUA is strategically located in the lower reaches of the Yangtze River, bordered by the East China Sea and the Yellow Sea (Figure 1). This prime geographical location, at the confluence of river and sea, is home to numerous coastal ports. The region encompasses one municipality directly under the central government (Shanghai) and three provinces (Jiangsu, Zhejiang, and Anhui), covering 41 prefecture-level cities with a total area of 358,000 square kilometers. The topography of the Yangtze River Delta is varied and complex. The northern part of the region is predominantly flat plains, while the southern part features higher elevations with many mountains and hills. The climate is characterized by a subtropical monsoon, positioned in a transitional zone between northern and southern weather patterns. By the end of 2021, the Yangtze River Delta's GDP totaled 27.6 trillion yuan, accounting for 24.1% of China's total GDP, and its permanent population reached 235 million people, representing 16.6% of the national total [42–45]. The YRDUA is one of the most economically vibrant, open, and innovative regions in China, possessing unique advantages and tremendous development potential. Since the economic reforms, the urbanization rate in this cluster has rapidly increased to over 70%, exerting considerable pressure on the regional eco-environment due to rapid urban expansion. Consequently, this study uses the YRDUA as a case to explore the coupling mechanisms between eco-environment and urbanization.

2.2. Data

This study selected MOD13A1, MOD11A2, and MOD09A1 from the MODIS product database as data sources to calculate the MODIS Remote Sensing Ecological Index (MRSEI). The EVI is extracted from MOD13A1 with a spatial resolution of 500 m; the LST is sourced from MOD11A2 with a resolution of 1 km; and both the Surface Water Content Index (SWCI) and the MODIS-based Normalized Difference Built-up and Soil Index (NDSI_M) are derived from MOD09A1, also at a 500 m resolution. Given that the MRSEI is suitable primarily for terrestrial regions and not for extensive aquatic areas, this study applied the MNDWI to exclude water bodies [46]. All data acquisition, preprocessing, and calculations were performed on the Google Earth Engine. The CNLI, reflecting the level of urbanization, was calculated using the corrected nighttime light data by Li et al. [47].

Several factors including altitude, climate, vegetation, population, and economic factors were selected to explore the reasons behind the CCD. The sources of the above data are listed below: DEM, GDP, and population density (POD) were sourced from the Resource and Environmental Science Data Platform (<https://www.resdc.cn/Default.aspx> (accessed on 19 June 2024)) with a spatial resolution of 1 km. Fraction of vegetation coverage (FVC) and air quality (AQ, PM2.5) were obtained from the National Tibetan Plateau Data Center (<http://data.tpdc.ac.cn> (accessed on 19 June 2024)) with spatial resolutions of 250 m and

1 km [48,49], respectively; and temperature (TEM) and precipitation (PRE) were sourced from the National Earth System Science Data Center (<https://www.geodata.cn> (accessed on 19 June 2024)), with a spatial resolution of 1 km for each.

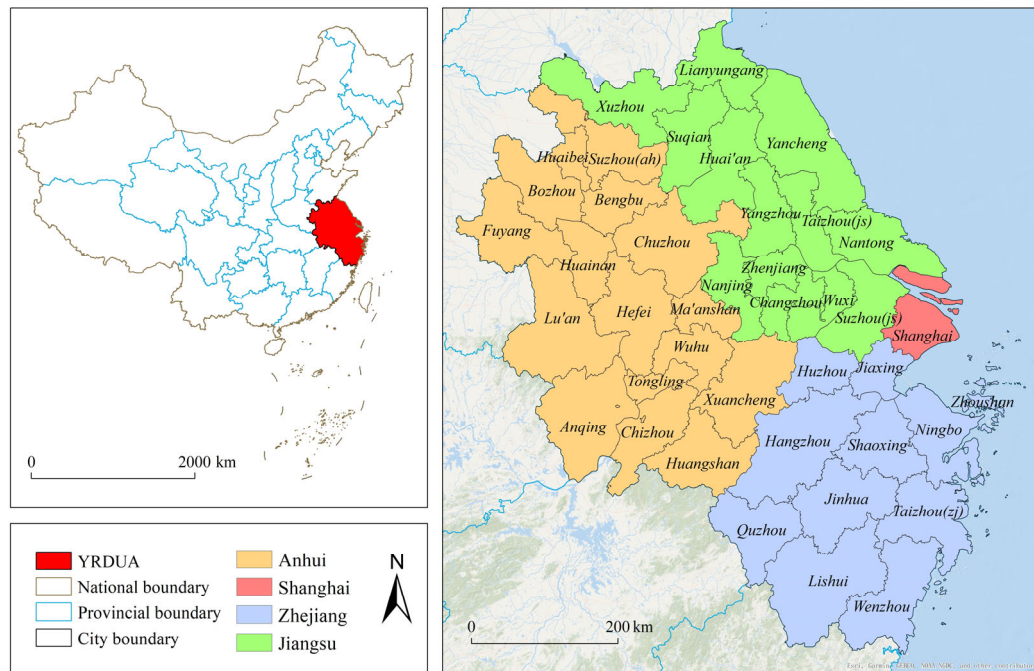


Figure 1. Location of the YRDUA.

2.3. Methods

2.3.1. Research Framework

The core theme of this study is to explore the relationship between the ecological environment quality and urbanization levels within the YRDUA. The research design of this paper, as illustrated in Figure 2, is divided into three main components: ecological environment quality, urbanization level, and coupling coordination degree.

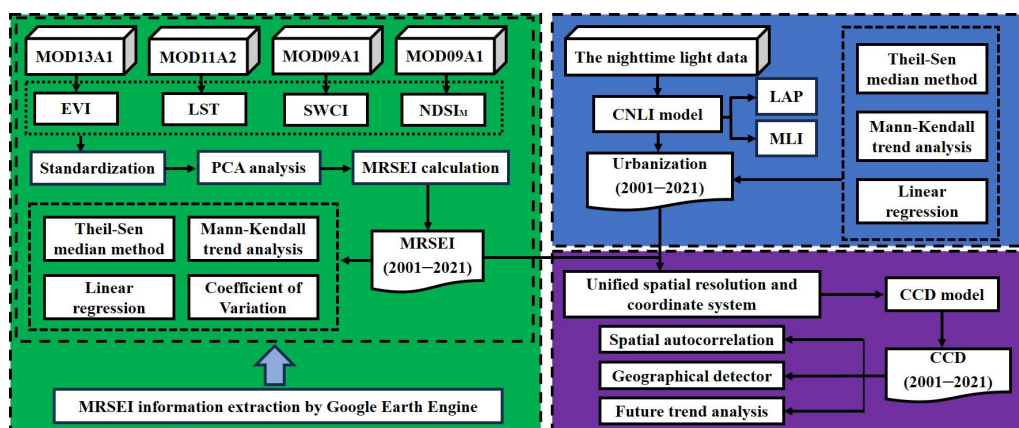


Figure 2. Research framework diagram.

The first step involves constructing the MRSEI model and CNLI model. These models will be used to calculate the annual MRSEI and CNLI values for cities in the YRDUA, thereby quantifying the quality of the ecological environment and the level of urbanization. Against the backdrop of rapid urbanization, this study aims to determine whether the ecological environments in various regions are deteriorating. To achieve this, trend analysis

methods such as the Theil–Sen median method, Mann–Kendall trend analysis, and linear regression are employed to calculate the change rates of the MRSEI and CNLI for different cities in the YRDUA. The CNLI change rate reflects the urban expansion speed of the cities. If the MRSEI change rate is greater than 0, it indicates that the ecological environment is improving; conversely, a negative rate suggests a deterioration of the ecological environment. In the final part of this paper, the CCD model is introduced. By incorporating the results from the MRSEI and CNLI, we are able to calculate the CCD values for different cities, thus assessing whether the coupling coordination relationships in these cities are progressing towards harmony or disarray. Using spatial autocorrelation analysis, we evaluate whether development across different regions is balanced. To determine whether the quality of the ecological environment or the level of urbanization plays a decisive role in the coupling coordination relationship, this study employs a geographical detector to select natural and socioeconomic factors for exploring the key factors influencing the CCD. Finally, this paper predicts the future development of the YRDUA by combining the Hurst exponent with the CCD trend analysis. This approach provides insights into long-term sustainability trends and potential challenges or opportunities in urban and ecological planning within the region.

From the content described, to address the research questions posed earlier and to test the hypotheses, this study employs methods such as analysis, synthesis, and comparison. These methods play a crucial role in numerous studies [50,51]. In this study, their importance is reflected in the following aspects. Synthesis: ecological environment and urbanization are two complex systems and quantifying them through the integration of multiple indices achieves a more effective result. Therefore, the MRSEI integrates four indices: EVI, SWCI, NDSI_M, and LST, while the CNLI incorporates two indices: lighted area proportion (LAP) and the mean light intensity (MLI). Analysis: the research is divided into three parts, focusing on the quality of the urban ecological environment, the level of urbanization, and the coupling coordination degree, respectively. The results from each part will be synthesized to compile MRSEI and CNLI values for cities in the YRDUA. This compilation allows us to discern the relationship between the ecological environment quality and urbanization levels. Comparison: by comparing the change rates of the CNLI across different cities, we examine the impact of urban expansion speed on the ecological environment by analyzing the MRSEI change rates. Additionally, we compare the explanatory power of natural factors versus socioeconomic factors on the CCD to determine the decisive factors influencing the CCD. These comparative analyses help verify the impacts and interrelationships between these key elements. The subsequent chapters provide individual introductions to each method.

2.3.2. Calculation of the MRSEI

The traditional RSEI is built from the following four parts: NDVI, WET, LST, and NDBSI [17]. Existing RSEI constructions typically use NDVI as the greenness component. Considering the saturation problem of NDVI in areas of high vegetation coverage, EVI is used as the greenness component instead. EVI is derived directly from MOD13A1; hence, it does not require calculation using a formula. The LST is sourced from MOD11A2:

$$LST = 0.02 \times DN - 273.15 \quad (1)$$

here DN represents the grayscale value of the image from MOD11A2.

Wetness is obtained through Tasseled Cap Transformation applied to Landsat imagery, which is commonly used with Landsat and IKONOS data. This transformation is not directly comparable to MODIS data [52]. In this study, SWCI serves as the wetness indicator. This index is calculated from the 6th and 7th bands of MODIS, which are sensitive to changes in water reflectance, allowing for effective extraction of water content in vegetation

canopies and the ground surface. It is widely used in studies of surface aridity [53]. The formula is as follows:

$$SWCI = \frac{\rho_{swir1} - \rho_{swir2}}{\rho_{swir1} + \rho_{swir2}} \quad (2)$$

MODIS, due to differences in sensors and band configurations, is characterized by lower reflectance rates in green and red bands for constructed land, and higher reflectance rates for other land classes. Based on this, a new MODIS building index called $NDSI_M$ was proposed. The $NDSI_M$ consists of the Normalized Difference Building Index ($NDBI_M$) and the Bare Soil Index (BSI_M) [54]:

$$NDBI_M = \frac{\rho_{red} - \rho_{green}}{\rho_{red} + \rho_{green}} \quad (3)$$

$$BSI_M = \frac{(\rho_{swir1} + \rho_{red}) - (\rho_{nir} + \rho_{blue})}{(\rho_{swir1} + \rho_{red}) + (\rho_{nir} + \rho_{blue})} \quad (4)$$

$$NDSI_M = \frac{NDBI_M + BSI_M}{2} \quad (5)$$

here ρ_{swir1} , ρ_{swir2} , ρ_{red} , ρ_{green} , ρ_{swir1} , ρ_{nir} , and ρ_{blue} are the reflectance values of the corresponding bands in MOD09A1.

To compress multidimensional variable information and reduce variable count, Principal Component Analysis (PCA) is employed to synthesize multiple indicators, thereby minimizing biases introduced through subjective weighting. Given that the four components discussed are not uniformly scaled, direct PCA computation could skew the weighting of these indicators. Consequently, normalizing these indicators prior to PCA computation is essential:

$$MRSEI_0 = \begin{cases} PC1(EVI, SWCI, LST, NDSI_M) V_{EVI}, V_{SWCI} > 0 \\ 1 - PC1(EVI, SWCI, LST, NDSI_M) V_{EVI}, V_{SWCI} < 0 \end{cases} \quad (6)$$

$$MRSEI = \frac{MRSEI_0 - MRSEI_{0_min}}{MRSEI_{0_max} - MRSEI_{0_min}} \quad (7)$$

here $PC1$ denotes the first principal component derived from the four indicators; $MRSEI_0$ is the initial ecological index; $MRSEI_{0_min}$ and $MRSEI_{0_max}$ represent the minimum and maximum values of the $MRSEI_0$, respectively; $MRSEI$ is defined as the normalized version of the $MRSEI_0$.

2.3.3. Calculation of the CNLI

This study developed the CNLI to reflect the level of urbanization in regions. This index has been extensively validated and shows a significant correlation with the composite indicators of urbanization in China [55], enabling the extraction of urbanization information over large areas and multiple years. The CNLI is obtained by multiplying the LAP and MLI:

$$CNLI = LAP \times MLI \quad (8)$$

$$LAP = \frac{Area_{light}}{Area} \quad (9)$$

$$MLI = \frac{\sum_{i=1}^{DN_M} DN_i \times n_i}{N_L \times DN_M} \quad (10)$$

here $Area_{light}$ is the area of a lighted pixel, $Area$ is the area of the region, DN_i is the grayscale value of the i th level pixel, n_i is the number of pixels at the i th level, N_L is the total number of pixels, and DN_M is the maximum possible grayscale value.

2.3.4. Trend Analysis

The Sen's slope estimate is a robust non-parametric statistical method for trend calculation [56]. It is based on median estimates and is resistant to outliers and measurement errors, offering high computational efficiency [57]. The equation is as follows:

$$\beta = \text{Median}\left(\frac{x_i - x_j}{i - j}\right), 1 \leq j < i \leq N \quad (11)$$

where x_i and x_j , respectively, represent the i th and j th year's x -values; N is the sample size; the Median denotes the median function; and β represents the median of slopes between two data points.

The Mann–Kendall test is a non-parametric statistical method that offers distinct advantages, including the ability to analyze data without requiring the independent variables to adhere to a normal distribution or exhibit a linear trend [58]. In ecological environment quality trend research, the Theil–Sen median and the Mann–Kendall test are effectively combined to examine the significance of trend changes in long-time-series data [59]. The equations are as follows:

$$\text{sign}(x_i - x_j) = \begin{cases} 1, & x_i - x_j > 0 \\ 0, & x_i - x_j = 0 \\ -1, & x_i - x_j < 0 \end{cases} \quad (12)$$

$$S = \sum_{j=1}^{m-1} \sum_{i=j+1}^m \text{sign}(x_i - x_j) \quad (13)$$

$$\text{Var}(S) = \frac{m(m-1)(2m+5)}{18} \quad (14)$$

$$Z = \begin{cases} \frac{S+1}{\sqrt{\text{Var}(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S-1}{\sqrt{\text{Var}(S)}}, & S < 0 \end{cases} \quad (15)$$

here m represents the number of time series, x_i and x_j denote the x values for the i th and j th years, respectively, and VAR stands for variance. When the absolute Z -value surpasses 1.65, 1.96, or 2.58, the observed trend is statistically significant at the 90%, 95%, and 99% confidence levels, respectively. Trends are categorized as shown in Table 1.

Table 1. Trend classification.

Theme	Sen	Z	Trend
1	≥ 0.0005	> 1.96	Significant improvement
2	≥ 0.0005	-1.96 – 1.96	Slight improvement
3	-0.0005 – 0.0005	-1.96 – 1.96	Stable
4	≤ 0.0005	-1.96 – 1.96	Slight degradation
5	≤ 0.0005	< -1.96	Serious degradation

Notes: Given that the quantity of pixels with $Z > 1.96$ or $Z < -1.96$ falls within the range of -0.0005 to 0.0005 , these pixels are classified as stable and unchanged types.

This paper also introduces univariate linear regression trend analysis, with the calculation method as follows:

$$L = \frac{n \times \sum_{i=1}^n (i \times Y_i) - \sum_{i=1}^n i \sum_{i=1}^n Y_i}{n \times \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2} \quad (16)$$

where L is the changes rate, n is the total number of years: 21, and Y_i represents the index value of the i th year.

The coefficient of variation (CV) is employed to indicate the stability of the eco-environment [60]. A higher CV value indicates lower stability in the eco-environment of

the area, while a lower CV value suggests greater stability. According to the natural breaks method, CV values are categorized into different levels.

The Hurst exponent, derived from R/S analysis, is utilized to investigate the persistence characteristics of watershed ecological quality [61]. The range of the Hurst exponent is [0, 1], with values closer to 0 indicating stronger anti-persistence and those closer to 1 indicating stronger persistence. The Hurst exponent exhibits persistence when it is greater than 0.5, anti-persistence when it is less than 0.5, and randomness when it is equal to 0.5.

2.3.5. CCD Model

To study the coupling relationship between the ecological environment and urbanization in the YRDUA using the CCD model, and to analyze its spatiotemporal coupling characteristics, the calculation process of CCD is as follows:

$$C = 2 \times \sqrt{\frac{E \times U}{(E + U)^2}} \quad (17)$$

$$T = \alpha E + \beta U \quad (18)$$

$$CCD = \sqrt{C \times T} \quad (19)$$

here C represents the coupling degree, E represents the MRSEI, U represents the CNLI, T represents the integrated level of ecological environment and urbanization, α and β represent the contribution degree of ecological environment and urbanization, respectively, and $\alpha + \beta = 1$, because the level of ecological environment and urbanization are equally important for the development of a region [62,63], so take $\alpha = \beta = 0.5$. CCD represents the level of coordination between the ecological environment and urbanization, where a higher value indicates greater coordination. The CCD is divided into five categories [31,64], as detailed in Table 2.

Table 2. The categories of the CCD levels.

CCD Value	Levels	Degree of Coordination
$0 < CCD \leq 0.3$	I	Seriously unbalanced
$0.3 < CCD \leq 0.4$	II	Moderately unbalanced
$0.4 < CCD \leq 0.5$	III	Basically balanced
$0.5 < CCD \leq 0.6$	IV	Moderately balanced
$0.6 < CCD \leq 1$	V	Highly balanced

2.3.6. Geodetector

The Geodetector is capable of investigating the underlying reasons affecting CCD, including single-factor detection and interaction detection [65]. A higher q -value from the detection results indicates a greater influence of that driving factor on CCD. Interaction detection can be used to determine whether the interaction between two factors enhances or weakens their explanatory power regarding CCD. Five distinct patterns of influence are delineated in Table 3. The mathematical representation of this method is as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_{h^2}}{N \sigma^2} \quad (20)$$

here h ($1 \dots L$) denotes the number of layers of the independent variable, N_h and N represent the total sample size of the h th stratum and the entire study area, σ_{h^2} and σ^2 are the sample variances of the h th stratum and the entire study area, respectively. The explanatory power increases with the increase in the q value, which ranges from 0 to 1.

Table 3. Interaction types and each description.

Interaction Criterion	Interaction Type
$q(x_1 \cap x_2) = q(x_1) + q(x_2)$	Independent
$q(x_1 \cap x_2) > q(x_1) + q(x_2)$	Nonlinear enhancement
$q(x_1 \cap x_2) > \text{Max}(q(x_1), q(x_2))$	Two-factor enhancement
$q(x_1 \cap x_2) < \text{Min}(q(x_1), q(x_2))$	Nonlinear weakening
$\text{Min}(q(x_1), q(x_2)) < q(x_1 \cap x_2) < \text{Max}(q(x_1), q(x_2))$	Single-factor nonlinear weakening

3. Results

3.1. Analysis of Spatiotemporal Variations and Trends in the MRSEI within the YRDUA

The spatial distribution pattern of the MRSEI for the YRDUA is shown in Figure 3. For the respective years 2001, 2006, 2011, 2016, and 2021, the mean values of the MRSEI were recorded at 0.556, 0.551, 0.577, 0.571, and 0.570, illustrating minimal fluctuations on a general scale yet considerable diversity in spatial distribution. The MRSEI was classified into five categories using the equal interval method: worst, poor, moderate, good, and excellent. The proportion of different MRSEI levels and their transitions are presented in Figure 4. The transitions among MRSEI levels are primarily concentrated between adjacent categories, with few shifts between non-adjacent categories, indicating that transitioning from poor to excellent is a prolonged process. Thus, the impact of ecological degradation on the local environment is enduring. The moderate and good categories account for approximately 80% of the total area, with the poorest categories fluctuating between 2% and 3%. Spatially, at the beginning of this study, the worst areas were mainly concentrated in the northern part of Anhui Province and within the built-up areas of various cities. Over time, the ecological environment in the northern part of Anhui Province improved. However, with rapid urban expansion, the area of low MRSEI patches caused by impervious surfaces gradually increased. The proportion of the area classified as excellent steadily increased from 2.21% in 2001 to 6.51% in 2021. The improved areas mainly came from the non-urbanized southwestern part of the urban agglomeration, encompassing most of the mountainous regions such as the Dabie Mountains and Jiuhua Mountain in Anhui Province, and Tianmu Mountain in Zhejiang Province. These areas are elevated and experience less human disturbance. Additionally, their rich vegetation consolidates the soil's water retention capabilities and suppresses the increase in surface temperatures, playing a significant role in promoting regional ecological improvement.

The 21-year statistical analysis of the MRSEI across the 41 cities of the YRDUA, as shown in Figure 5a, highlights significant spatial disparities in ecological quality. Cities with high MRSEI values such as Lishui, Huangshan, and Chizhou are located in mountainous and hilly regions, benefitting from rich forest coverage and natural reserves. The abundant vegetation improves air quality, mitigates urban heat island effects, and prevents soil erosion. Additionally, lower population density and minimal human disturbance have enabled these cities to maintain high ecological quality over time. In contrast, cities like Shanghai, Suzhou, and Wuxi, with MRSEI values consistently below 0.4, are situated in plains conducive to large-scale industrialization and urban development, which places immense pressure on their ecological environment. Coupled with high local population density and weak ecological recovery capabilities, these factors exacerbate the ecological degradation in these cities. A descending order ranking of the MRSEI for each prefecture-level city shows Shanghai with the lowest MRSEI value, and over 90% of the cities in Jiangsu Province ranking in the bottom 50%, indicating that ecological pressures within the YRDUA are predominantly concentrated in Shanghai and Jiangsu Province. The average annual MRSEI for the 41 cities was visualized using the natural breaks classification method, as displayed in Figure 5b. The distribution of MRSEI values shows a clear clustering effect, with high MRSEI cities concentrated in the southwest of the YRDUA and low MRSEI cities in the north, presenting a “low in the north, high in the south” pattern.

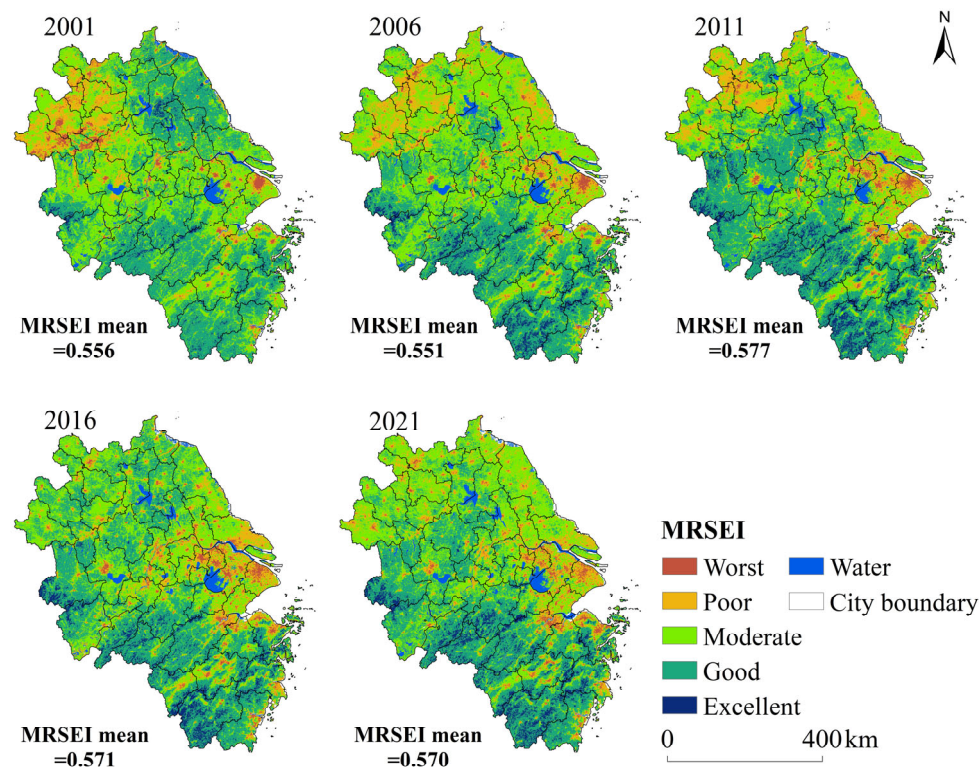


Figure 3. The MRSEI map of the YRDUA from 2001 to 2021.

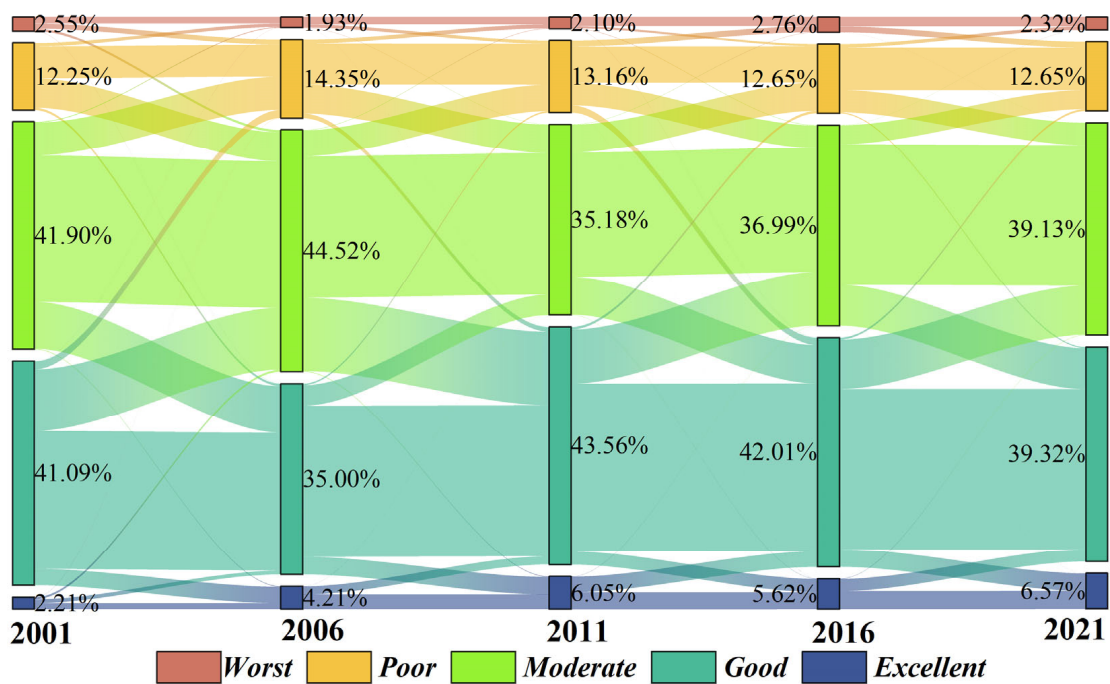


Figure 4. Sankey diagram of the changes in the MRSEI levels of the YRDUA from 2001 to 2021.

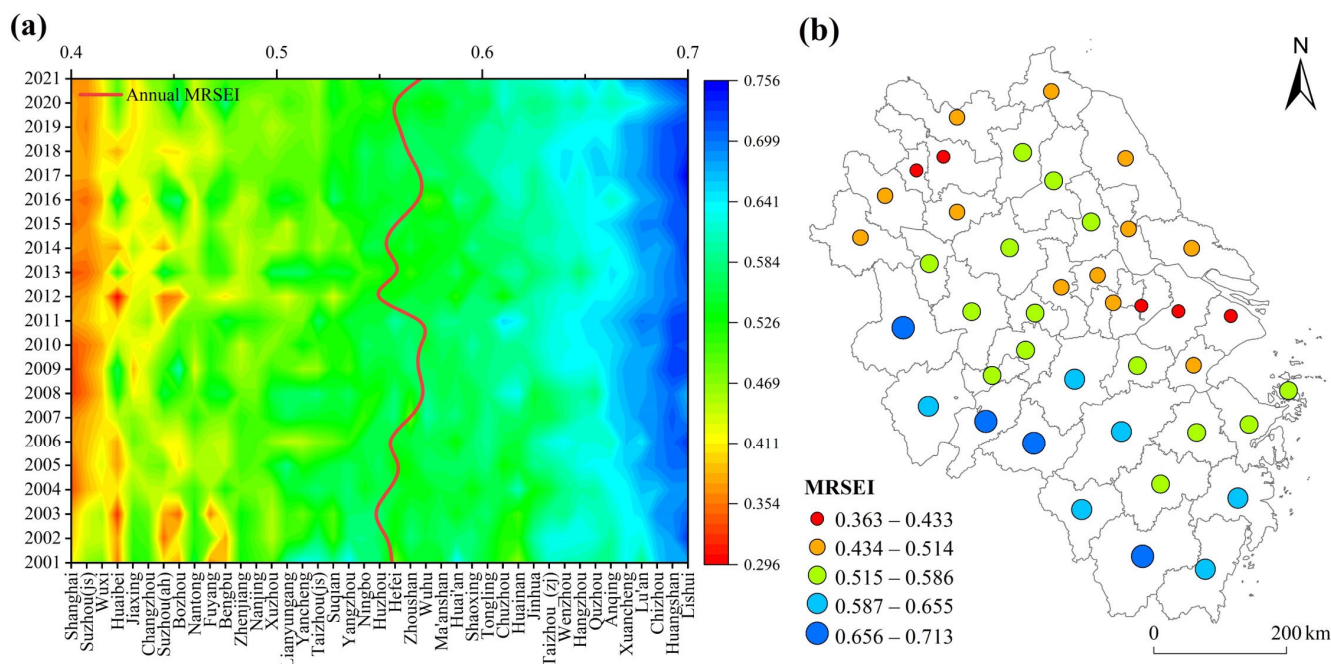


Figure 5. Spatiotemporal distributions of the MRSEI from 2001 to 2021. (a) represents the MRSEI's changing trend in each city, and (b) represents the MRSEI's average value in each city.

To quantify and analyze the ecological environment trends of cities within the YRDUA, the Sen's slope estimate combined with the Mann–Kendall test was used for visualization of changes in the MRSEI, and the CV was employed to assess the volatility of the ecological environment in the region. According to the results shown in Figure 6, the proportion of areas with a significant increase in the MRSEI is 22.8%, while those with a significant decrease account for 15.1%. Areas with slight increases account for 32.4%, and those with slight decreases make up 21.6%. The proportion of areas where the ecological environment remained unchanged is 8.1%, indicating that the regions where the ecological environment improved exceed those where it deteriorated. Areas with high variability constitute 1.5% of the region, whereas relatively high and moderate variability areas make up 8.4% and 17.4%, respectively, primarily located in northern Anhui Province and northern Jiangsu Province. The proportions of areas with relatively low and low variability are the highest, at 32.3% and 40.4%, respectively. Further statistical analysis using Theil–Sen and simple linear regression methods was conducted on the ecological environment change rates of the 41 cities in the YRDUA, as displayed in Table 4. The results show that 23 cities have a positive change rate, indicating an improvement in their ecological environment, while 18 cities have a negative change rate, signaling a deterioration. Cities such as Bozhou, HuaiBei, and Huainan are among those improving, with Bozhou having the highest positive change rate of 0.00557. Conversely, cities like Taizhou, Jiaxing, and Nantong are deteriorating, with Taizhou experiencing the highest negative change rate of -0.00589 . It is notable that 8 out of the 10 cities with the highest increase in ecological quality are located in northern Anhui Province. In contrast, 8 out of the 10 cities with the highest decline are in Jiangsu Province. Despite being one of the wealthiest provinces in the YRDUA, the eco-environment in Jiangsu Province is not promising, both in terms of current conditions and future trends.

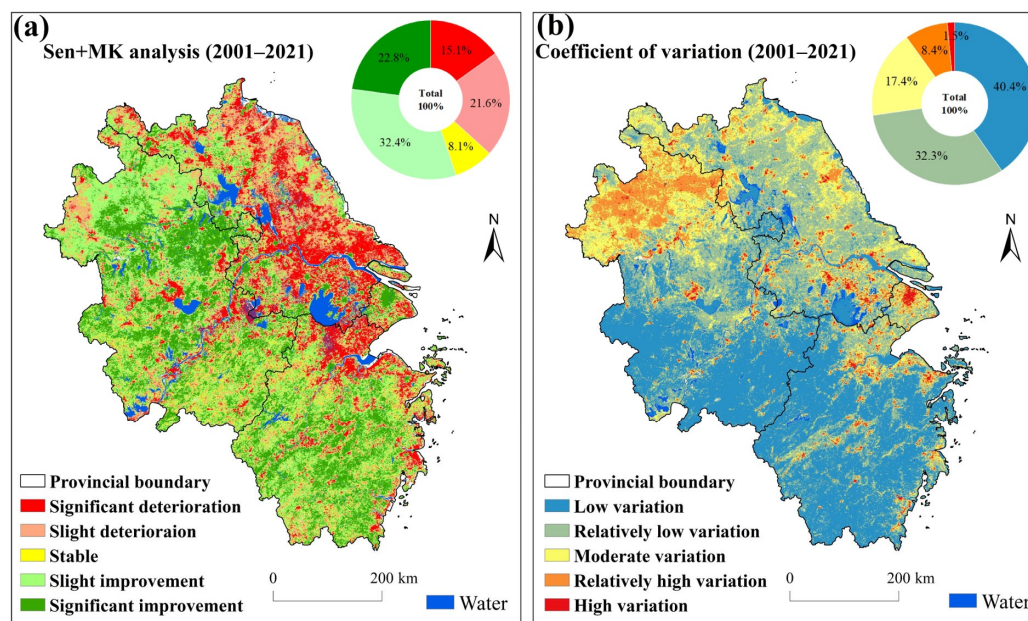


Figure 6. The results of trend analysis of the MRSEI: (a) Sen + MK test and (b) coefficient of variation.

Table 4. The MRSEI's changing rate in each city in the YRDUA.

Ranking	City	Sen	Line	Slope	Ranking	City	Sen	Line	Slope
1	Bozhou	0.00563	0.00552	0.00557	22	Hangzhou	0.00046	0.00034	0.00040
2	Huaibei	0.00561	0.00524	0.00542	23	Shanghai	0.00042 *	0.00010	0.00026
3	Huainan	0.00439 **	0.00469	0.00454	24	Ma'anshan	−0.00012 *	−0.00023	−0.00018
4	Bengbu	0.00435	0.00462	0.00449	25	Xuzhou	−0.00039	−0.00025	−0.00032
5	Chuzhou	0.00438 **	0.00435	0.00436	26	Suqian	−0.00040	−0.00039	−0.00040
6	Suzhou(ah)	0.00291	0.00289	0.00290	27	Wuhu	−0.00057 *	−0.00082	−0.00070
7	Fuyang	0.00215	0.00253	0.00234	28	Huai'an	−0.00080	−0.00098	−0.00089
8	Quzhou	0.00227 *	0.00226	0.00227	29	Ningbo	−0.00117	−0.00126	−0.00122
9	Lishui	0.00192	0.00192	0.00192	30	Nanjing	−0.00111 *	−0.00133	−0.00122
10	Lu'an	0.00183	0.00201	0.00192	31	Wuxi	−0.00175 *	−0.00210	−0.00192
11	Jinhua	0.00187	0.00188	0.00187	32	Huzhou	−0.00197	−0.00205	−0.00201
12	Wenzhou	0.00175	0.00170	0.00173	33	Zhenjiang	−0.00264 *	−0.00277	−0.00271
13	Hefei	0.00168 *	0.00163	0.00165	34	Changzhou	−0.00264 *	−0.00284	−0.00274
14	Chizhou	0.00126	0.00111	0.00118	35	Yancheng	−0.00302	−0.00328	−0.00315
15	Huangshan	0.00112	0.00109	0.00110	36	Suzhou(js)	−0.00331 *	−0.00372	−0.00352
16	Anqing	0.00108	0.00096	0.00102	37	Lianyungang	−0.00361	−0.00362	−0.00361
17	Xuancheng	0.00111	0.00087	0.00099	38	Yangzhou	−0.00443 *	−0.00460	−0.00451
18	Taizhou(zj)	0.00089 *	0.00089	0.00089	39	Jiaxing	−0.00479	−0.00492	−0.00485
19	Tongling	0.00089 *	0.00075	0.00082	40	Nantong	−0.00497 **	−0.00492	−0.00495
20	Shaoxing	0.00082	0.00074	0.00078	41	Taizhou(js)	−0.00591 **	−0.00588	−0.00589
21	Zhoushan	0.00074	0.00075	0.00074					

Notes: Sen represents Sen's slope, Line represents Linear slope, Slope represents the average value, * represents $1.65 \leq |Z| < 1.96$, ** represents $1.96 \leq |Z| < 2.58$, *** represents $|Z| \geq 2.58$.

3.2. Analysis of Spatiotemporal Variations and Trends in the CNLI within the YRDUA

The MLI and LAP for the YRDUA were calculated for the years 2001, 2006, 2011, 2016, and 2021, capturing the changes in nighttime light intensity and the extent of lighted areas, respectively. As shown in Figure 7, there has been a notable increase in both light intensity and light area over these years. Specifically, the MLI, which measures changes in the intensity of light, increased from 0.166 in 2001 to 0.343 in 2021, a growth of 107%. The LAP, which quantifies the percentage of the study area illuminated by artificial lights, rose from 54.2% in 2001 to 92.1% in 2021, marking a 70% increase. High-brightness light pixels are primarily concentrated in Shanghai, the southern part of Jiangsu Province, and the coastal cities of Zhejiang Province. Over time, these nighttime light pixels have gradually expanded inland. The increasing intensity of lights and the expanding illuminated areas

indicate intensified urban expansion, indirectly reflecting the rapid economic development of the YRDUA.

The overall CNLI of the YRDUA has shown a steady increase from 0.105 in 2001 to 0.356 in 2021 (Figure 8), demonstrating a consistent upward trend. Cities with high CNLI are primarily located around Shanghai, including Suzhou, Wuxi, and Changzhou. As China's economic hub and the core city of the YRDUA, Shanghai leads the development of its neighboring cities. In contrast, cities with low CNLI values are mainly found in the southwestern part of the urban agglomeration, such as Huangshan, Chizhou, and Lishui.

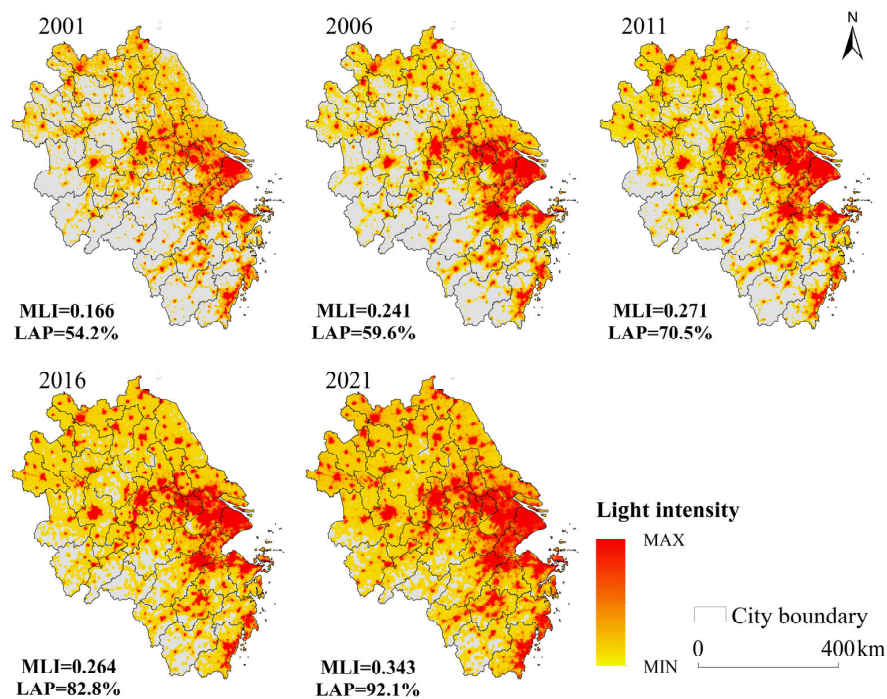


Figure 7. The light images of the YRDUA and their changes during 2001–2021.

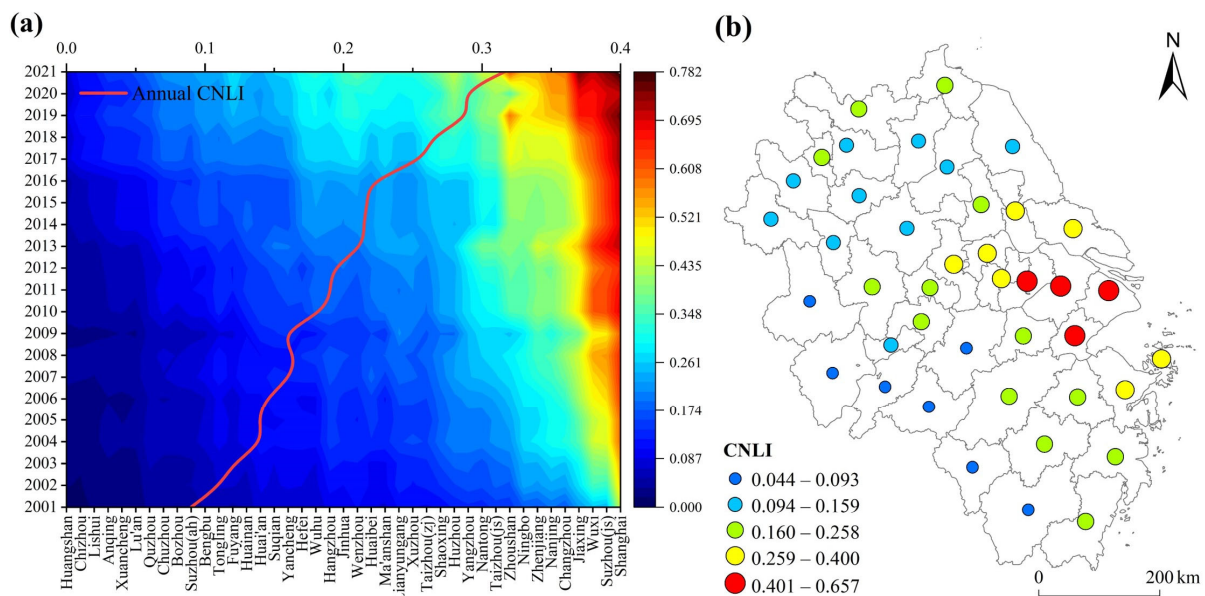


Figure 8. Spatiotemporal distributions of the CNLI from 2001 to 2021. (a) represents the CNLI's changing trend in each city, and (b) represents the CNLI's average value in each city.

The analysis of the CNLI for the cities within the YRDUA was conducted using the Theil–Sen estimator and linear regression methods, as presented in Table 5. The results indicate that urbanization levels have improved across all cities in the region. Among the 41 cities analyzed, 38 exhibited significant changes in their CNLI, with only three cities showing non-significant changes. Cities like Jiaxing, Zhoushan, Suzhou, Wuxi, and Changzhou experienced substantial urbanization rate changes, with Jiaxing having the highest rate of change at 0.01955. These cities are geographically proximate to Shanghai and benefit significantly from the economic influence of Shanghai, which, being China’s economic hub, had a high level of urbanization at this study’s outset and thus exhibited a lower change rate compared to its neighboring cities. Conversely, cities such as Chizhou, Lishui, Huangshan, Anqing, and Quzhou showed lower urbanization rate changes, with Huangshan recording the lowest at 0.00581. These cities face numerous challenges in economic development, such as a monolithic industrial structure heavily reliant on agriculture, forestry, and tourism. With a weak industrial foundation, these cities struggle to support high-quality urban development. Additionally, geographical constraints and stagnant transportation networks limit their attractiveness to populations. Consequently, these cities have not made significant urbanization progress over the years. On the other hand, the overall change rate of the CNLI was greater than that of the MRSEI.

Table 5. The CNLI’s changing rate in each city in the YRDUA.

Ranking	City	Sen	Line	Slope	Ranking	City	Sen	Line	Slope
1	Jiaxing	0.01915 ***	0.01994	0.01955	22	Bengbu	0.00850 ***	0.00968	0.00909
2	Zhoushan	0.01887 ***	0.01926	0.01907	23	Yangzhou	0.00865 ***	0.00903	0.00884
3	Suzhou(js)	0.01744 ***	0.01962	0.01853	24	Bozhou	0.00854 ***	0.00910	0.00882
4	Wuxi	0.01507 ***	0.01665	0.01586	25	Xuzhou	0.00855 ***	0.00901	0.00878
5	Changzhou	0.01453 ***	0.01598	0.01525	26	Lianyungang	0.00836 ***	0.00875	0.00856
6	Zhenjiang	0.01498 ***	0.01542	0.01520	27	Hangzhou	0.00765 ***	0.00926	0.00845
7	Nanjing	0.01409 ***	0.01555	0.01482	28	Huainan	0.00761 ***	0.00917	0.00839
8	Ningbo	0.01412 ***	0.01490	0.01451	29	Suzhou(ah)	0.00792 ***	0.00886	0.00839
9	Nantong	0.01255 ***	0.01288	0.01271	30	Yancheng	0.00802 ***	0.00870	0.00836
10	Taizhou(js)	0.01225 ***	0.01258	0.01241	31	Chuzhou	0.00746 ***	0.00907	0.00827
11	Wuhu	0.01157 ***	0.01248	0.01202	32	Suqian	0.00778 ***	0.00863	0.00820
12	Shanghai	0.01091 ***	0.01228	0.01159	33	Tongling	0.00650 ***	0.00793	0.00722
13	Huzhou	0.01082 ***	0.01184	0.01133	34	Huai’an	0.00648 ***	0.00743	0.00696
14	Ma’anshan	0.01087 ***	0.01147	0.01117	35	Lu’an	0.00517 ***	0.00719	0.00618
15	Wenzhou	0.01028 ***	0.01182	0.01105	36	Xuancheng	0.00493 ***	0.00669	0.00581
16	Hefei	0.01020 ***	0.01173	0.01097	37	Quzhou	0.00496 ***	0.00663	0.00579
17	Jinhua	0.01003 ***	0.01157	0.01080	38	Anqing	0.00379 ***	0.00610	0.00494
18	Shaoxing	0.01027 ***	0.01122	0.01074	39	Chizhou	0.00337 **	0.00528	0.00432
19	Taizhou(zj)	0.00979 ***	0.01103	0.01041	40	Lishui	0.00337 **	0.00519	0.00428
20	Fuyang	0.00952 ***	0.01053	0.01002	41	Huangshan	0.00147 *	0.00297	0.00222
21	Huaibei	0.00957 ***	0.01046	0.01001					

Notes: Sen represents Sen’s slope, Line represents Linear slope, Slope represents the average value, * represents $1.65 \leq |Z| < 1.96$, ** represents $1.96 \leq |Z| < 2.58$, *** represents $|Z| \geq 2.58$.

3.3. Analysis of Spatiotemporal Variations and Statistics for the CCD in the YRDUA

3.3.1. Temporal Evolution of the CCD Levels

The introduction of a coupling coordination model, which integrates the MRSEI and CNLI metrics, enabled the calculation of the CCD for cities within the YRDUA. The statistical results of the CCD values for these cities are illustrated in Figure 9. Throughout the study period, all cities demonstrated a trend towards improved coordination. Initially, approximately half of the cities were in a state of severe disharmony. By the end of the study period, cities in severe disharmony had nearly vanished, with the vast majority achieving at least a basic level of coordination. The cities were categorized into three types based on the trend in their CCD levels: (1) Cities that started at a basic or moderate level of coordination and rapidly advanced to a high level of coordination. This category includes cities like Shanghai, Suzhou, Jiaxing, and Wuxi, which have well-developed industrial bases and a history of early development. These advantages, coupled with substantial policy support and resource allocation, allowed these cities to swiftly improve

their ecological environment and urbanization processes. (2) Cities that began in severe or moderate imbalance but transitioned quickly, reaching moderate and then high levels of coordination. Cities such as Xuzhou, Ma'anshan, Huaibei, and Hefei fall into this category. These cities made the most significant progress, overcoming initial developmental hurdles and effectively improving their ecological and urban metrics. (3) Cities that started in a state of severe imbalance and changed more slowly, remaining in severe or moderate imbalance by the end of the study. Cities like Chizhou, Lishui, and Huangshan belong to this category. Located in mountainous or hilly areas, these cities face complex terrain and strict environmental protection regulations that hinder large-scale industrial and residential development, impeding further urbanization. These three types highlight the diversity of urban development trajectories in the YRDUA. Urban and ecological planning should be tailored to the specific conditions and challenges of each city to promote balanced development, thereby enhancing the region's overall sustainability and livability.

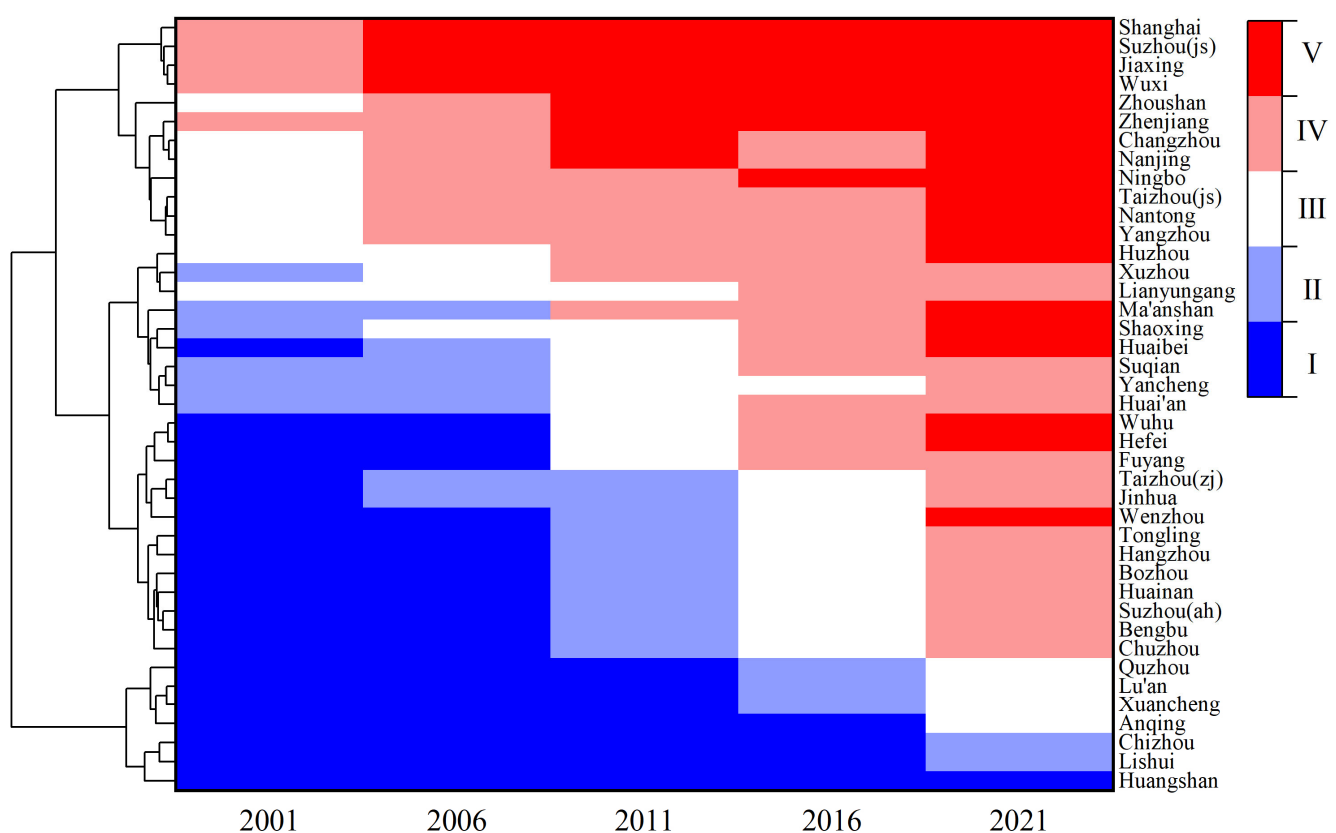


Figure 9. Level and clustering of the CCD in the YRDUA from 2001 to 2021.

3.3.2. Spatial Dependency of the CCD

Based on a county-level perspective, we analyzed the distribution pattern of the CCD in the YRDUA for the years 2001, 2011, and 2021 through local spatial autocorrelation analysis (Figure 10). The Moran's I values for 2001, 2011, and 2021 were 0.656, 0.672, and 0.589, respectively, indicating a significant spatial positive correlation in the CCD distribution over the years. The distribution was most clustered in the "HH" (high-high) and "LL" (low-low) scatter plots, suggesting that cities with high (or low) CCD are more likely to cluster together spatially. High CCD counties are primarily clustered around Shanghai, southern Jiangsu Province, and northern Zhejiang Province—regions that are economically advanced and have higher levels of urbanization. Conversely, low CCD counties are mostly found in southwestern Anhui Province and western Zhejiang Province. This distribution reflects the uneven development in the YRDUA, highlighting that development benefits

and ecological coordination are concentrated in economically developed areas, while less developed areas remain relatively backward.

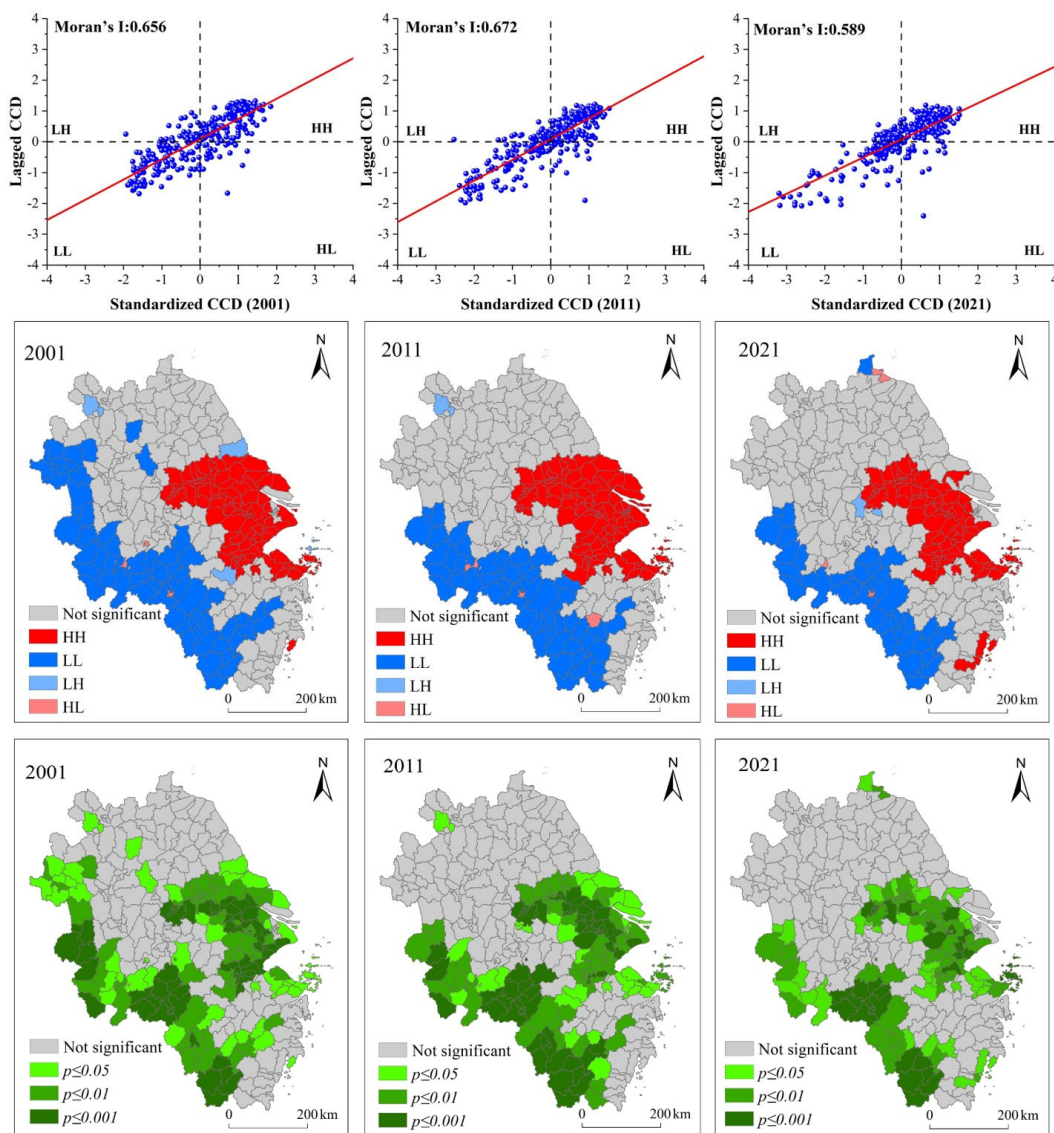


Figure 10. Scatter diagram of Local Moran (**top**), clustering diagram of local autocorrelation (**center**), and significance distribution diagram of the CCD (**bottom**) at the county scale for the years 2001, 2011, and 2021.

3.3.3. Factors Affecting the CCD Based on Geodetector

This research utilized the Geodetector to explore the impact of seven factors—GDP, POD, FVC, DEM, AQ, TEM, and PRE—on the CCD of the YRDUA. To ensure a good match among all factors, we resampled all data to a resolution of 1000 m. Simultaneously, we created a 6 km × 6 km grid to correspond with these data. The single-factor detection results, as shown in Table 6, indicate that all factors passed the significance test at the 0.01 level, demonstrating a significant influence on the CCD of the YRDUA. From 2001 to 2021, the average q-values ranked as follows: GDP ($q = 0.502$), POD ($q = 0.477$), DEM ($q = 0.373$), PRE ($q = 0.240$), FVC ($q = 0.218$), AQ ($q = 0.169$), and TEM ($q = 0.049$). GDP and POD were identified as key factors influencing the CCD, with natural factors having a less pronounced impact compared to socioeconomic factors. Further analysis using an interaction detector showed that the explanatory power of these factors was enhanced when their interactions were considered (Figure 11). All interactions demonstrated an enhancing effect compared

to single-factor detections, with dual-factor enhancement accounting for 80.71% of the interactions and nonlinear enhancements making up 19.29%. Among all interactions, the combination of GDP and DEM (GDP $\cap$ DEM) provided the strongest explanatory power for the CCD.

Table 6. Results of single-factor detection of the YRDUA during 2001–2021.

Influencing Factors	q-Value					
	2001	2006	2011	2016	2021	Average
GDP	0.478 ***	0.570 ***	0.597 ***	0.427 ***	0.438 ***	0.502 ***
POD	0.477 ***	0.427 ***	0.595 ***	0.449 ***	0.438 ***	0.477 ***
FVC	0.088 ***	0.219 ***	0.244 ***	0.250 ***	0.286 ***	0.218 ***
DEM	0.375 ***	0.332 ***	0.443 ***	0.366 ***	0.350 ***	0.373 ***
AQ	0.177 ***	0.143 ***	0.218 ***	0.186 ***	0.121 ***	0.169 ***
TEM	0.025 ***	0.024 ***	0.033 ***	0.069 ***	0.096 ***	0.049 ***
PRE	0.122 ***	0.176 ***	0.343 ***	0.345 ***	0.214 ***	0.240 ***

Notes: *** represents $|Z| \geq 2.58$.

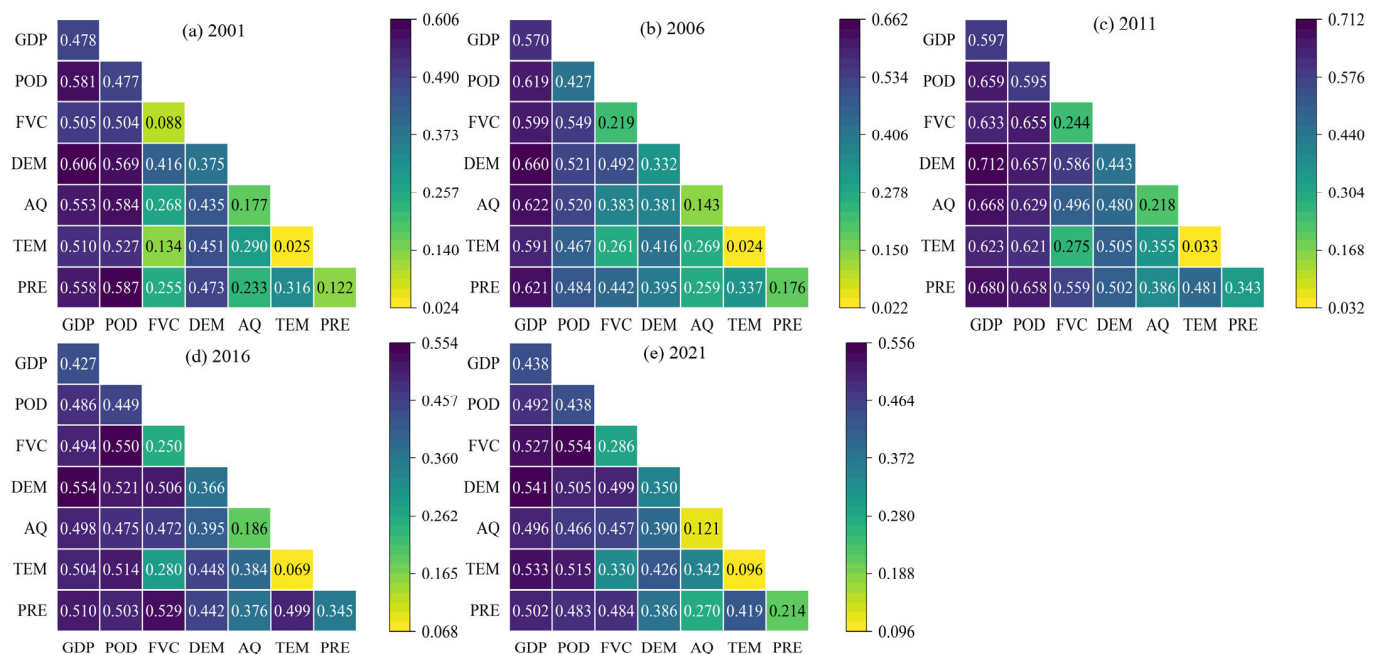


Figure 11. Interaction detection results in the YRDUA during 2001–2021.

3.3.4. Prediction of Future CCD

Currently, most studies focus on discussing the current state of the CCD, with a lack of consideration for future trends [66–68]. Researching the future development of the CCD is crucial for achieving sustainable development goals [69]. Therefore, by using the Hurst exponent to predict future trends of the CCD in the YRDUA (Figure 12), the results indicate that 44.7% of the areas show a persistent trend, while 55.3% of the areas display an anti-persistent trend. The proportions of the CCD continuously increasing and decreasing are 41.7% and 2.6%, respectively. Meanwhile, 50.7% of the areas will transition from improvement to deterioration, and 2.6% will change from deterioration to improvement. Additionally, 2.4% of the areas show randomness. From these results, it is evident that the overall future of the CCD in the YRDUA is at risk of decline, with Jiangsu Province experiencing the most significant decrease. Anhui Province, having smaller patch sizes compared to the other two provinces, indicates that it has consistently lagged in the integrated development process of the YRDUA, lacking in potential for catching up. Based on these findings, this paper offers the following suggestions: (1) As the wealthiest province in the

YRDUA, Jiangsu Province faces threats to sustainable development due to environmental degradation. It is essential to focus on developing a green economy, promoting industrial and technological innovation, and fostering the coordinated development of economic construction and ecological civilization. (2) To address the current imbalance in regional development, it is advisable to encourage the central cities within the urban cluster to drive the development of surrounding cities, enhance inter-city communication and cooperation, and promote harmonious development across the region.

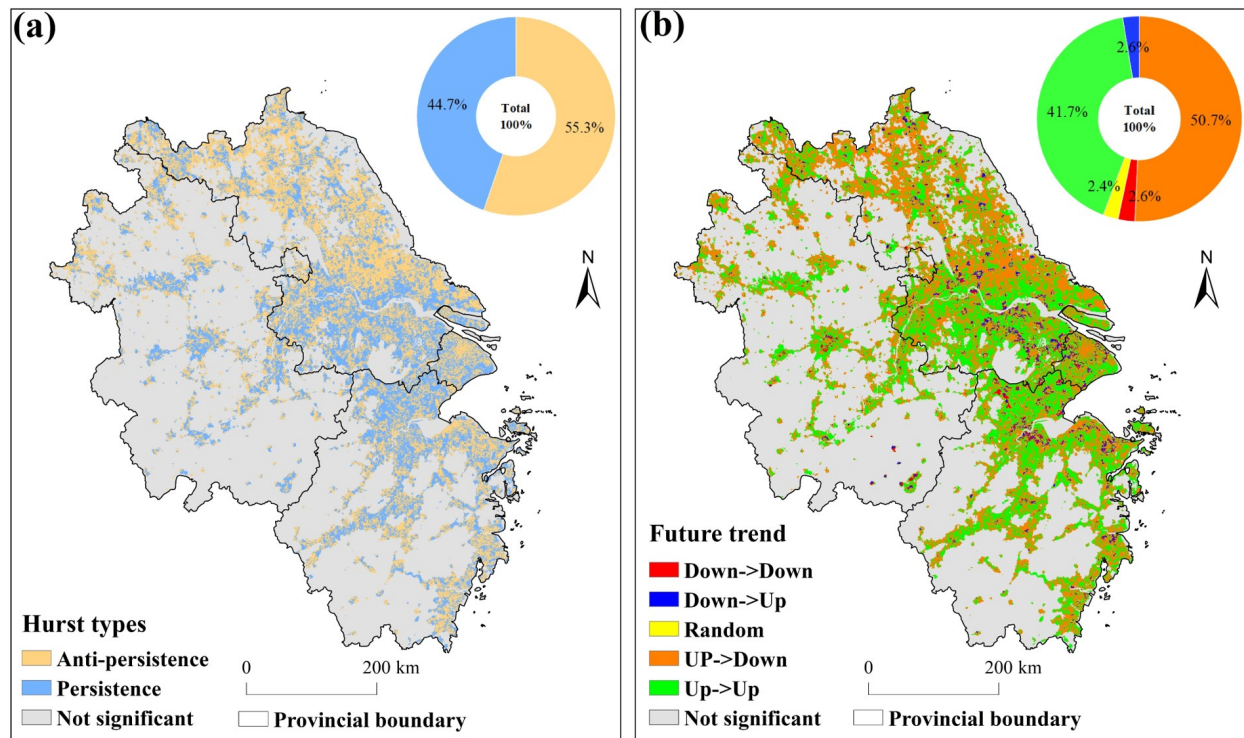


Figure 12. The CCD's (a) hurst types and (b) future trend in the YRDUA.

4. Discussion

4.1. Exploring the Relationship among the MRSEI, CNLI, and CCD

From the research results, we can see that the urbanization level in the YRDUA has been increasing year by year, while the ecological environment quality has remained relatively stable. Therefore, the relationship between ecological environment quality and urbanization level is not simply a negative correlation. This indicates that there is a complex interaction under human intervention. On one hand, the expansion of urban areas leads to an increase in impermeable surfaces, resulting in a continuous increase in areas with low MRSEI values. On the other hand, the concept of ecological civilization has gradually taken root, and the implementation of policies such as returning farmland to forests has improved the ecological environment in non-urbanized areas. As a result, the overall MRSEI value has not shown significant fluctuations. To further investigate the relationship among ecological environment, urbanization, and the degree of coupling coordination, we ranked 41 cities in the YRDUA based on their MRSEI, CNLI, and CCD values from largest to smallest. Our observations revealed a negative correlation between the MRSEI and CCD (Figure 13a) and a positive correlation between the CNLI and CCD (Figure 13b). This indicates that the development of urbanization contributes to improving the level of coupling coordination, with urbanization levels being the dominant factor influencing the CCD [67]. Given the pronounced issue of uncoordinated regional development in the YRDUA, there is a need to optimize urban spatial layout and fully leverage the leading role of central cities. Focusing on central cities as the core, it is essential to promote the collaborative development of surrounding small- and medium-sized cities to ensure long-term stable urban development.

Additionally, we found a negative correlation between the MRSEI and CNLI (Figure 13c). The advancement of urbanization inevitably causes damage to the ecological environment, which, in turn, can constrain the development of urbanization [63,70]. Therefore, balancing the relationship between the eco-environment and urbanization is crucial for achieving sustainable urban development. To explore the distribution patterns of the CCD change rates under different MRSEI and CNLI backgrounds, we used bubbles to represent cities, with larger bubbles indicating higher CCD change rates. The maximum CCD change rate was 0.0165, and the minimum was 0.0050. Notably, smaller bubbles were mostly found in areas with higher CNLI values, indicating that urban development does not have a sustained positive impact on CCD [71]. Once urbanization reaches a certain level, its contribution to the CCD diminishes, highlighting the importance of ecological restoration to further enhance the CCD.

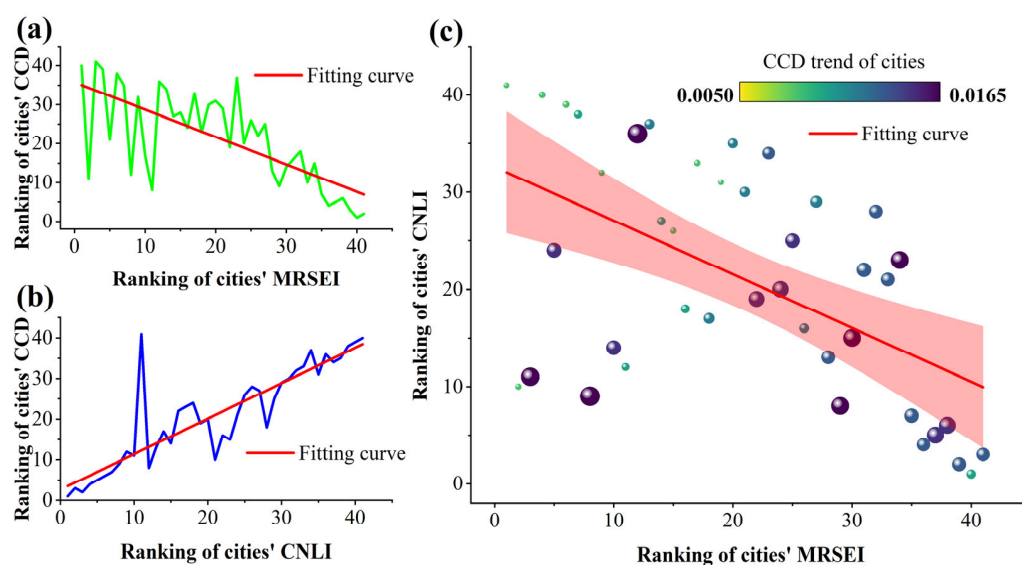


Figure 13. The relationship between the (a) MRSEI and CCD, (b) CNLI and CCD, (c) MRSEI and CNLI.

4.2. Analysis of the Factors Influencing the CCD

To explore the underlying factors affecting the CCD, this paper introduces the geographical detector model. This model not only quantifies the explanatory power of different factors on the CCD but also considers how interactions between these factors can either enhance or mitigate their impact on the CCD [65,72]. Single-factor detection results show that GDP and POD have the highest explanatory power, as they are closely related to urban development, which is the key driver of the CCD. On one hand, economic development acts as a major catalyst for urbanization [70], and considering the long-standing urban–rural disparities in China, cities remain the core engines for GDP growth. On the other hand, the concentration effect of urban resources continuously attracts populations and industries to urban areas. Under the influence of the interaction detector, the explanatory power of all factors is enhanced. The interaction of GDP with DEM ($GDP \cap DEM$) shows the strongest explanatory power for the CCD. Existing studies suggest that elevation significantly impacts urban distribution, as terrain elevations can influence the direction and spatial expansion of cities. High-altitude areas are less suitable for large-scale urban construction, while low-altitude areas are more conducive to urban expansion, leading to the predominance of megalopolises in regions with elevations under 500 m [73]. Considering the topographical distribution of the YRDUA, economically developed cities are mostly located in the lower plain areas. Overall, the natural geographical advantages indeed play a significant role in a city's development. Therefore, government departments should tailor strategic planning to the local conditions, pursuing a path of sustainable development that aligns with local characteristics.

4.3. Suggestions

In Section 3.3.1 of this paper, based on the trends of the CCD, all cities in the YRDUA are categorized into three types. In brief, the first type includes cities with a solid urbanization foundation, developed industrial bases, and high levels of economic openness, represented by Shanghai, Suzhou, and Wuxi. The second type includes cities with significant urban development potential, represented by Hefei, Wuhu, and Wenzhou. The third type consists of cities located in mountainous or hilly areas, where the complex terrain hampers further urbanization, including cities like Huangshan, Chizhou, and Lishui. These three types highlight the diversity of urban development trajectories in the YRDUA. For these cities, this paper proposes the following recommendations: For the first type of cities, (1) promote the application of green buildings, green transportation, and green energy to reduce urban carbon emissions [71]. (2) Utilize big data and artificial intelligence technologies to optimize urban resource distribution and enhance city management efficiency. (3) Strengthen the protection and restoration of urban ecosystems and increase urban green space [67]. For the second type of cities, (1) during rapid urban development, reasonably plan urban spatial layouts to prevent disordered urban expansion. (2) Integrate ecological environment protection into urban development strategies to promote the coordinated development of economy, society, and environment. (3) Raise public awareness of ecological and environmental protection and encourage public participation in urban environmental protection and governance. For the third type of cities, (1) fully utilize local natural and cultural resources to develop eco-tourism, promoting a win-win situation for economic development and environmental protection [66]. (2) Improve infrastructure and enhance the level of public services to increase the city's livability and attractiveness. (3) Support and develop ecological agriculture to reduce the negative environmental impact of agriculture and enhance the sustainability of agricultural production.

4.4. Limitations and Prospects

Despite preprocessing and correction of the MODIS data and nighttime light data in calculating the ecological and urbanization indicators, this study inevitably remains influenced by the limitations of the data sources themselves [18]. The MRSEI and CNLI are comprehensive indicators reflecting ecological environment quality and urbanization level, respectively. The MRSEI currently includes only four components, whereas ecosystems are extremely complex. For example, in the context of increasing urban expansion, air quality (PM_{2.5}) has become a significant concern for urban residents [59]. Including an air quality component in addition to the traditional four factors would provide a more comprehensive depiction of the ecological environment. Moreover, when calculating the proportion of regional urban light area, larger areas may lead to an underestimation of urbanization levels for regions with the same urban scale. Due to topographical limitations, many regions consist of mountains, forests, and lakes that are unsuitable for urbanization. To more accurately depict urbanization levels, it would be better to exclude these areas when defining the total area of a region. Additionally, describing urbanization levels solely from the perspective of nighttime lighting may not fully capture the comprehensive strength of a city. Considering that urbanization is characterized by economic development, population growth, and urban area expansion [74], future studies could include GDP density and population density as components. These could be synthesized into a comprehensive indicator using the entropy weight method to reflect urbanization levels more accurately, thus avoiding the biases caused by relying on a single data source and making the experimental conclusions more reliable. In summary, the refinement and supplementation of ecological and urbanization indicators is one of the main directions for future research.

5. Conclusions

This study constructed the MRSEI and CNLI to evaluate the eco-environment and urbanization level of the YRDUA, respectively. It also conducted a spatio-temporal analysis to elucidate the distribution patterns and dynamic trends of both the ecological environ-

ment and urbanization. Employing a coupling coordination degree model, we quantified the interplay between eco-environment and urbanization processes. Furthermore, we employed the Geodetector to investigate the influence of various factors on the CCD. The principal findings are as follows:

- (1) During the study period, the MRSEI fluctuations within the YRDUA were relatively minor, indicating a stable ecological environment, yet regional disparities were pronounced. Cities with high MRSEI values were predominantly located in the south-western part of the YRDUA, while cities with low MRSEI values were mainly situated around Shanghai and within Jiangsu Province. Areas experiencing ecological degradation were primarily concentrated in cities with higher CNLI change rates, whereas regions showing ecological improvement were mostly found in cities with lower CNLI change rates;
- (2) All cities progressed towards greater coordination, and in the end, cities with severe imbalances had virtually disappeared, with the majority reaching at least a basic level of coordination. Cities with high (low) CCD values exhibit spatial clustering, indicating significant regional imbalances in development. Given the diverse urban development trajectories in the YRDUA, urban and ecological planning should be tailored to the specific conditions and challenges of each city to promote balanced development and improve the region's overall sustainability and quality of life;
- (3) In the single-factor analysis, GDP and POD had the highest explanatory power for the CCD, indicating that socioeconomic factors more substantially influence CCD than natural factors do. Under interaction, the combined effect of GDP and DEM further amplified the explanatory power, making it the most influential interaction for understanding CCD dynamics;
- (4) The CCD was found to be positively correlated with the CNLI and negatively correlated with the MRSEI. Urbanization is a critical factor in enhancing the CCD, thus optimizing urban spatial layout and forms, particularly within urban agglomerations and metropolitan areas, is crucial for fostering coordinated development among cities and towns of various sizes, thereby ensuring sustainable urbanization. The MRSEI and CNLI were negatively correlated, indicating that urban expansion inevitably damages the ecological environment. Therefore, during urban development, it is vital to prioritize ecological preservation and green development, focusing on ecosystem restoration and protection.

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