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Original Research

Green Development Levels of Central and Eastern China: Assessment, Spatiotemporal Evolution, and Comparisons of Classifications

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Abstract

This study aims to assess the green development levels of central and eastern China, explore the spatiotemporal evolution in green development in these regions, and compare their characteristics of green development patterns. Central and eastern China are the nation's most economically dynamic and densely populated areas. These regions' status of green development is highly critical for the country's overall "green transformation". In this paper, we first constructed a green development assessment index system and then utilized IFAHP to calculate the weights of indicators. After the data for these indicators was collected, GRA-TOPSIS was employed to measure the green development levels. We then analyzed the spatiotemporal evolution of green development levels in these areas and made a comparative analysis. Results reveal that the values of green development levels in all these regions range between 0.4 and 0.6 and that the levels of green development between the central and eastern regions show significant disparities. It was also found that the overall green development levels exhibited a trend of fluctuation with an upward trajectory. Additionally, we observed that the proportion of high-level regions remained consistently below 50%, and a spatial agglomeration pattern exists in these regions. This study can not only provide insights for governments in central and eastern China to formulate green development policies but also provide inspiration for other countries with similar conditions to design green development strategies.

Keywords: greed development levels, central and eastern China, spatiotemporal evolution, comparisons of classifications

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Introduction

Since the reform and opening up, China's economy has maintained high-speed growth for over 30 years. Its GDP has ranked second in the world since 2010, and Chinese people have experienced a substantial increase in their quality of life [1]. However, during the rapid development process, the growth model characterized by high growth, high energy consumption, and high emissions has imposed significant pressure on the resources and environment [2-4]. China's overall energy consumption grew by an average annual rate of 7.5% from 2001 to 2015, reaching 4.30 billion tce in 2015 [5], which indicates that China's economic growth is accompanied by elevated levels of energy consumption and environmental pollution [6]. In order to solve the problem, the Chinese central government initiated the "green transformation" strategy in March 2015, which aimed to "promote new modes of industrialization, urbanization, and greenization of social and economic development". In October 2015, the "Outline of the 13th Five-Year Plan for National Economic and Social Development" enacted by the central government officially formulated specific tasks for the green transformation of society, economy, and environment in the next five years (2016-2020).

Currently, it is widely acknowledged in China that green development is an inherent necessity in responding effectively to the pressing challenges posed by resource and environmental issues. Green development represents the inevitable choice and fundamental path for achieving sustainable development in China's economy and society [3, 7]. However, the presence of strong externalities associated with environmental pollution impedes the spontaneous resolution of ecological protection issues through market mechanisms [8]. Furthermore, local government behavior is often influenced by opportunistic tendencies, posing substantial challenges and difficulties to the practical implementation of green development strategies. After the implementation of the aforementioned policies, it is of significance to investigate the current state of green development in China and the spatiotemporal characteristics exhibited among different regions in terms of their green development.

In the context of ongoing global climate change and the emergence of various environmental issues, green development has drawn extensive attention from scholars worldwide. One of the highly researched themes is the concept and connotation of green development. The term "green economy" was first introduced in 1989 by Pearce et al. in the book titled Blueprint for a Green Economy [9]. Hu and Zhou regarded green development as an approach to a developmental paradigm that involves the harmonization of economic progress and environmental protection [7]. Huang et al. believed that green development is a process of achieving economic and ecological harmony within the constraints of resource capacity and environmental limits [10]. Despite efforts by some researchers to define green development, the academic community has not reached a consensus, primarily due to the multifaceted nature of green development. Another widely studied topic is the influencing factors of green development. For instance, Huang et al. believed that government and market dynamics were pivotal factors in green development [11]. Li et al. proposed that enhancing scientific and technological prowess serves as a primary catalyst for advancing green development [12]. Yang et al. put forward the idea that the percentage of green coverage in built-up areas, GDP growth rate, unemployment rate, share of tertiary industry in GDP, and industrial so_2 emission intensity per unit of GDP are factors that significantly influence the level of green development [13]. Cheng and Ge believed that the level of green development in regions would be affected by educational expenditure, SO_2 emissions, wastewater treatment, etc. [14]. Yang et al. and Lu et al. suggested that the utilization efficiency of resources, such as energy, water, and land, in economic development and air quality play vital roles [2, 15]. Zhu et al. investigated the influence of optimizing industrial structure on green development and found that both rationalization and advancement of industrial structure yield positive impacts on green development levels [16]. The topic of green development evaluation systems has also garnered the attention of some scholars. Existing literature has two main approaches to measuring green development. One perspective emphasizes that the evaluation framework for green development should primarily focus on the environmental efficiency of production and consumption. In other words, while economic and social green development is important, natural resources and the environment should receive more attention [17]. The other perspective suggests that the core of green development lies in achieving sustainable development while simultaneously improving environmental quality and social welfare [18].

In summary, previous research on green development has made some progress in exploring the theoretical foundations, influencing factors, and measuring green development levels. Nevertheless, there remain several areas warranting further exploration. Firstly, a lack of consensus on the connotation of green development has led to the inevitable issue of constructing indicator systems that are incomplete or unscientific, significantly impeding the theoretical development and practical evaluation of green development. The green development evaluation system is a complex system comprised of various dimensions, and its content will evolve with the development of the economy and society. Given the inherent requirements of transitioning to a new era of economic and social development, it is necessary to construct a green development assessment index system that is in line with the current economic and social development situation. Secondly, most existing research on the determination of indicator weights fails to consider the diversity, complexity, and comprehensiveness of the green development assessment index system, as well as the incomplete information of experts and the hesitation of experts during the rating process. Therefore, it is necessary to employ a more scientifically and logically sound method to address the problems in determining the weights of green development indicators.

The purpose of this paper is to establish a sound green development assessment system, evaluate the current status of green development in central and eastern China after the implementation of the "green transformation" strategy by the Chinese central government, investigate the spatial and temporal relationship of green development levels in these regions, and identify their unique characteristics of green development patterns. By doing so, we hope to offer implications for governments to enhance regional green development levels and reduce regional disparities.

The contributions of this paper may lie in the following areas: (1) We constructed a comprehensive assessment index system that is in line with the current situation of the green development of central and eastern China. (2) To accurately assess the green development levels of the central and eastern regions of China, we have combined IFAHP (Intuitionistic Fuzzy Analytic Hierarchy Process) and the GRA-TOPSIS method to construct a comprehensive evaluation system, which contributes to the development of research methodologies for green development evaluation. By considering the inherent fuzziness of the indicators for green development evaluation, we believe that IFAHP can better account for the hesitancy of experts when assessing indicator weights. By combining the method of GRA with TOPSIS, we can take advantage of both the flexible measurement of Gra and the straightforward calculation of Euclidean distance, which, we believe, can achieve better results that can balance rigidity and flexibility. (3) We utilized kernel density estimation to present the overall distribution of green development levels in the target areas and used the method of Moran's Index to conduct a global spatial autocorrelation analysis, so as to clearly reveal the spatial clustering pattern of green development levels in these regions. (4) The results of our study could provide insights for governments in central and eastern China to formulate green development policies and provide inspiration for other countries with similar conditions in designing green development strategies.

Materials and Method

Research Area

The research areas include six provinces in the central regions of China, which are Shanxi, Henan, Anhui, Hubei, Jiangxi, and Hunan, as well as seven provinces and three municipalities in the eastern region of China, namely Hebei, Shandong, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Beijing, Tianjin, and Shanghai (Fig. 1). Our motivations for exploring these regions are as follows: (1) Central and eastern China occupy an important strategic position in China. These areas of China are the most economically dynamic and densely populated areas of the nation. In 2021, the GDP of the eastern and central regions of China accounted for 73.65% of the national total, while the proportion of the population in these regions was 65.76% of the national total. Meanwhile, there exist substantial conflicts between environmental resources

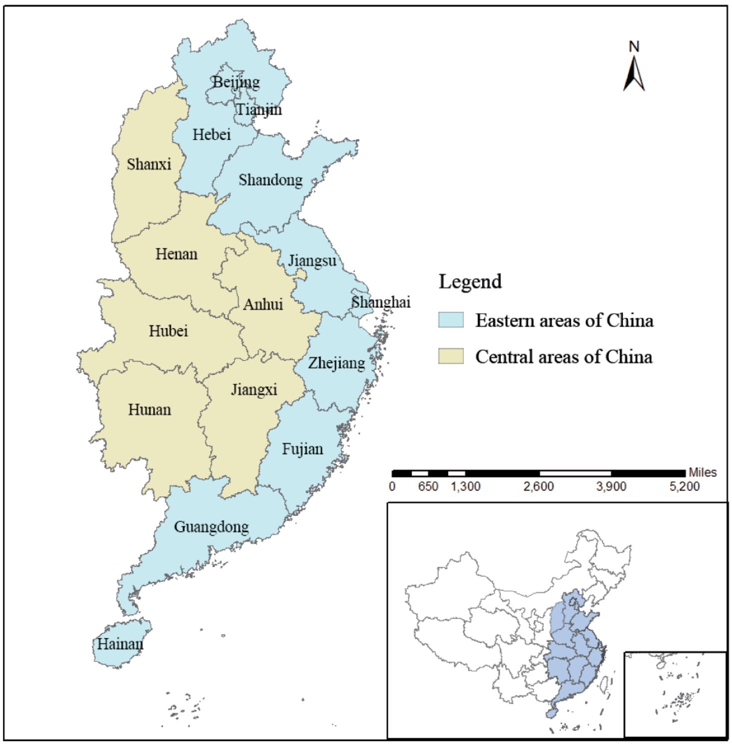

Fig. 1. Research subjects. Note: This map is based on the standard map with approval number

and economic growth. Clearing up the current situation in these conflicts plays a crucial role in addressing the challenges hindering China's progress toward sustainable development. (2) Geographically, the central and eastern regions of China are adjacent (Fig.1), and they are intricately interconnected in terms of industrial structure. The central and eastern areas of China both have their own unique advantages and disadvantages for green development. In comparison to the central regions, the eastern regions boast a more developed economy and higher levels of education and technology. The central regions also have their own distinct strengths, including abundant natural resources, huge stocks of human capital, etc. Assessing the level of green development in these regions and identifying their temporal evolution patterns and spatial clustering relationships are crucial for adjusting their industrial structures and promoting regional coordination between these two areas to achieve higher levels of green development in both regions. (3) Evaluating the green development levels of the central and eastern regions since the release of the "green transformation" strategy can help clarify the impact of green development policies on the development paths of regions with different resource endowments and developmental advantages.

Sources of Data

The data utilized in this paper is derived from various authoritative sources, including the China Statistical Yearbook (2016-2021), the China Statistical Yearbook on the Environment (2016-2021), statistical yearbooks of the provinces or municipalities, and bulletins of the provinces or municipalities. For some data that are not available due to either the lack of updates in the yearbook data or changes in the yearbook indicators, we obtain them through calculations using the mean filling method. The scope of our research data spans from 2016 to 2021. The year 2016 is the first year after the Chinese central government introduced the concept of "green transformation". One of the purposes of this study is to assess the current state of green development in central and eastern China after the "green transformation" strategy was introduced by the central government. The data from 2021 is the most recent available data to date.

Methods

IFAHP

The assessment of green development levels presents significant challenges since the green development index system is a complex system that encompasses ecology, culture, society, and other interconnected aspects. The intricate nature, hierarchical structure, and diverse elements of the system contribute to its inherent fuzziness and uncertainty. Additionally, due to the diverse fields of expertise involved in specific indicators, experts evaluating the indicators for green development levels may not be familiar with all the indicators. This lack of complete information can lead to hesitation. The IFAHP is an extension of the Fuzzy Analytic Hierarchy Process (FAHP) that better handles uncertain situations, such as hesitations or the reluctance of experts to express their opinions during the definition process [19]. Therefore, in this study, IFAHP was used to determine the weights of specific indicators in the evaluation system for green development levels in the central and eastern regions of China.

Intuitionistic fuzzy sets are an extension of fuzzy set theory, which includes three distinct states: membership, non-membership, and hesitancy. These states represent experts' attitudes of support, opposition, and neutrality in their decision-making, allowing for a more detailed description of the vagueness and uncertainty associated with indicators. Compared with traditional fuzzy sets, intuitionistic fuzzy sets provide a more powerful means of expression because they can simultaneously account for all three states. This approach aligns better with human logic in the judgment process and, consequently, can improve the accuracy of subjective assessments.

The specific explanation and steps of the IFAHP are as follows:

Set X is a nonempty set, also referred to as an intuitionistic fuzzy set. $t_A(x)$ 与 $f_A(x)$ respectively represent the degrees of membership and non-membership of the element x in the subset A of set X and satisfy:

$$A=\left\{\left\langle x,t_A(x),f_A(x)\right\rangle \mid x\in X\right\},\ 0\leq t_A(x)\leq 1,\ 0\leq f_A(x)\leq 1,\ \text{and } 0\leq t_A+f_A\leq 1.$$

Furthermore, $\pi_A=1-t_A(x)-f_A(x)$, where $x\in X$ represents the degree of hesitation of x belonging to set A.

Step 1: To construct an intuitionistic fuzzy judgment matrix: $R=\left(r_{pq}\right)_{n\times n}=\left(t_{pq},f_{pq}\right)_{n\times n}$ Here, p represents the row and q represents the column of the judgment matrix. n represents the number of indicators in the corresponding indicator layer.

Step 2: Test the consistency of the judgment matrix. To ensure a reliable solution, it is important to verify the consistency of the judgment matrix so as to guarantee the effectiveness of decision-making. If the intuitionistic fuzzy judgment matrix does not meet the acceptable consistency criteria, it becomes necessary to correct the preference relations until the new preference relations meet the consistency requirements. This paper adopts the method developed by Szmid and Kacprzyk [20] to measure the distance. By utilizing the derived distance formula (1), the consistency of the intuitionistic fuzzy judgment matrix can be evaluated effectively.

$$d(R,\overline{R})=\frac{1}{2(n-1)(n-1)}\sum_{p=1}^{n}\sum_{q=1}^{n}\left(\left|\overline{t}_{pq}-t_{pq}\right|+\left|\overline{f}_{pq}-f_{pq}\right|+\left|\overline{\pi}_{pq}-\pi_{pq}\right|\right) \tag{1}$$

Here, $R=\left(r_{pq}\right)_{n\times n}$ is the intuitionistic fuzzy judgment matrix. After the calculations using Formula (2), the judgment matrix $\overline{R}=\left(\overline{r_{ij}}\right)_{n\times n}$, which needs to be tested for consistency, is obtained. The method is:

(1) When $q > p+1$,

$$\overline{t}_{pq} = \frac{\sqrt[q-p-1]{\prod_{v=p+1}^{q-1} t_{pv} \times t_{vq}}}{\sqrt[q-p-1]{\prod_{v=p+1}^{q-1} t_{pv} \times t_{vq}} + \sqrt[q-p-1]{\prod_{v=p+1}^{q-1} \left(1-t_{pv}\right)\times\left(1-t_{vq}\right)}}$$
$$\overline{f}_{pq} = \frac{\sqrt[q-p-1]{\prod_{v=p+1}^{q-1} f_{pv} \times f_{vq}}}{\sqrt[q-p-1]{\prod_{v=p+1}^{q-1} f_{pv} \times f_{vq}} + \sqrt[q-p-1]{\prod_{v=p+1}^{q-1} \left(1-f_{pv}\right)\times\left(1-f_{vq}\right)}} \quad (2)$$

(2) When $q = p+1$ or $q = p$, set $\overline{r}_{pq} = r_{pq}$.

(3) When $q \le p+1$, set $\overline{r}_{pq} = \left(\overline{f}_{qp}, \overline{t}_{qp}\right)$.

After conducting the calculations mentioned in the previous three steps, the consistency of the new judgment matrix is evaluated using Formula (4).

If the value of $d(R,\overline{R}) < \tau$, the judgment matrix R is considered acceptable in terms of consistency. τ represents the threshold for consistency, generally $\tau = 0.1$. On the other hand, if, $d(R,\overline{R}) > \tau$ it indicates that the judgment matrix, R fails the consistency test and the judgment matrix R needs to be amended. The process of amending the judgment matrix R involves adjusting the value of σ iteratively until it satisfies the consistency test. The adjustment procedure is outlined as follows [21]:

Set the parameter σ, $\sigma \in [0,1]$.

$$\tilde{t}_{pq} = \frac{\left(t_{pq}\right)^{1-\sigma}\left(\overline{t}_{pq}\right)^{\sigma}}{\left(t_{pq}\right)^{1-\sigma}\left(\overline{t}_{pq}\right)^{\sigma} + \left(1-t_{pq}\right)^{1-\sigma}\left(1-\overline{t}_{pq}\right)^{\sigma}}$$
$$\tilde{f}_{pq} = \frac{\left(f_{pq}\right)^{1-\sigma}\left(\overline{f}_{pq}\right)^{\sigma}}{\left(f_{pq}\right)^{1-\sigma}\left(\overline{f}_{pq}\right)^{\sigma} + \left(1-f_{pq}\right)^{1-\sigma}\left(1-\overline{f}_{pq}\right)^{\sigma}} \quad (3)$$

By following the aforementioned steps, the adjusted intuitionistic fuzzy consistency judgment matrix, denoted as $\tilde{R} = \left(\tilde{r}_{pq}\right)_{n\times n}$, is obtained. Subsequently, this matrix is subjected to consistency checking using Formula (4) iteratively until the matrix passes the consistency test.

$$d(\tilde{R},R) = \frac{1}{2(n-1)(n-2)}\sum_{p=1}^{n}\sum_{q=1}^{n} \left(\left|\tilde{t}_{pq} - t_{pq}\right| + \left|\tilde{f}_{pq} - f_{pq}\right| + \left|\tilde{\pi}_{pq} - \pi_{pq}\right|\right) \quad (4)$$

Step 3: Calculation of weights for individual-level indicators. Following the approach used by Xu and Liao [22], the weights of different indicators belonging to the same upper-level indicator are determined using Formula (5).

$$\omega_p = \left(t_p, f_p\right) = \left(\frac{\sum_{q=1}^{n} t_{pq}}{\sum_{p=1}^{n}\sum_{q=1}^{n}\left(1-f_{pq}\right)}, 1-\frac{\sum_{q=1}^{n}\left(1-t_{pq}\right)}{\sum_{p=1}^{n}\sum_{q=1}^{n} f_{pq}}\right), p = 1,2,\ldots,n. \quad (5)$$

Utilize Formula (6) to calculate the score weight of each indicator that belongs to the same upper-level indicator.

$$G_p = \frac{1-f_p}{1+\pi_p}, p = 1,2,\ldots n \quad (6)$$

Where $\pi_p = 1 - t_p - f_p$.

By following Formula (7), the weight of each index can be normalized, and the normalized weights of the indicators are then obtained.

$$\lambda = \frac{G_p}{\sum_{p=1}^{n} G_p} \quad (7)$$

Comprehensive Evaluation Model Based on the GRA-TOPSIS Model

The GRA-TOPSIS model combines the GRA method with TOPSIS. The Gra method, first proposed by Deng [23], is primarily rooted in the discipline of system engineering. Its main focus is to address problems involving unknown factors. This method focuses on studying uncertain systems with "partial known information and partial unknown information". By making full use of the known information and extracting valuable knowledge, it aims to accurately describe the operating patterns of the system and is suitable for studying gray systems with multiple levels and complex mechanisms [24]. TOPSIS is a commonly used multi-criteria decision analysis method for limited alternatives. It primarily relies on the initial solutions of the decision problem to construct the positive ideal solution and the negative ideal solution. Then, the relative distances of each initial solution to these two ideal solutions are calculated and ranked to determine the optimal solution.

However, the traditional GRA method prioritizes curve shapes and disregards the relative relationship between data series, while the traditional TOPSIS solely focuses on calculating relative distances and overlooks the trends in geometric shapes [25]. The Euclidean distance utilized in the TOPSIS method is used to calculate the difference, leading to a linear relationship between the variable value and the evaluation outcome. Nevertheless, the obtained solution may be rigid, whereas the evaluations of index values examined in this study and the intricate internal relationships caused by their outcomes do not consistently exhibit linear behavior [26]. By combining the GRA with TOPSIS, we can take advantage of both the flexible measurement of Gra and the straightforward calculation of Euclidean distance, achieving results that balance rigidity and flexibility [27].

The specific calculation steps are as follows:

(1) The first step involves establishing the multi-attribute evaluation matrix. Given that there are m factors impacting green development levels and n provinces/municipalities, the evaluation matrix is: $A = \left(a_{pq}\right)_{m\times n}$.

To ensure that the evaluation results are not influenced by index types and dimensions, the index is standardized by using maximum and minimum normalization methods [28].

When it is a positive index, the index is standardized by the equation: $a_{pq} = \frac{a_{pq} - \min a_{pq}}{\max a_{pq} - \min a_{pq}}$

When it is a negative index, the index is standardized by the equation: $a_{pq} = 1 - \frac{a_{pq} - \min a_{pq}}{\max a_{pq} - \min a_{pq}}$

(2) The IFAHP method determines the index weight, the weight of the q-th index is λ_p, and the weight matrix is $\lambda = [\lambda_1, \lambda_2, \cdots, \lambda_n]$. The evaluation matrix is calculated by the equation: $A = \lambda * (a_{pq})_{m \times n}$.
The positive and negative ideal solution of is: a_{pq}

$$\begin{aligned} R_p^+ &= \{(\max_p a_{pq} |\ p \in I)|\ p = 1,2,\cdots m\} \\ &= (a_1^+, a_2^+, \cdots a_n^+)(q = 1,2,\cdots,n) \\ R_p^- &= \{(\min_p a_{pq} |\ p \in I)|\ p = 1,2,\cdots m\} \\ &= (a_1^-, a_2^-, \cdots a_n^-)(q = 1,2,\cdots,n) \end{aligned} \tag{8}$$

(3) d_q^+ represents the Euclidean distance between a_{pq} and its positive and negative ideal solutions:

$$\begin{aligned} d_q^+ &= \sqrt{\sum_p^n (a_p^+ - a_{pq})^2}\ (q = 1,2,\cdots,n),\ d_q^- \\ &= \sqrt{\sum_p^n (a_p^- - a_{pq})^2}\ (q = 1,2,\cdots,n). \end{aligned} \tag{9}$$

Then the closeness between the green development level of the q-th province/municipality and the ideal green development level is: $G_q = \frac{d_q^-}{d_q^+ + d_q^-}(q = 1,2,\cdots,n)$.

(4) The GRA method is utilized to establish the degree of relevance. The correlation coefficient matrix between each comparison sequence and the best reference sequence, as well as the worst reference sequence, is presented below:

$$R^+ = r_{pq}^+ = \frac{\text{minmin}|a_{pq}^+ - a_{pq}| + \lambda\,\text{maxmax}|a_{pq}^+ - a_{pq}|}{|a_{pq}^+ - a_{pq}| + \lambda\,\text{maxmax}|a_{pq}^+ - a_{pq}|} \tag{10}$$

$$R^- = r_{pq}^- = \frac{\text{minmin}|a_{pq}^- - a_{pq}| + \lambda\,\text{maxmax}|a_{pq}^- - a_{pq}|}{|a_{pq}^- - a_{pq}| + \lambda\,\text{maxmax}|a_{pq}^- - a_{pq}|}$$

The equation used to determine the gray correlation degree is as follows:

$$\begin{aligned} r_q^+ &= \frac{1}{n}\sum_{p=1}^{m} r_{pq}^+ (q = 1,2,\cdots,n),\ r_q^- \\ &= \frac{1}{n}\sum_{p=1}^{m} r_{pq}^- (q = 1,2,\cdots,n) \end{aligned} \tag{11}$$

(5) Non-dimensional treatment of the Euclidean distances d_q^+ and d_q^- and the gray correlation degree r_q^+ and r_q^-:

$$D_q^+ = \frac{d_q^+}{\max_q d_q^+};\ D_q^- = \frac{d_q^-}{\max_q d_q^-};\ R_q^+ = \frac{r_q^+}{\max_q r_q^+};\ R_q^- = \frac{r_q^-}{\max_q r_q^-}.$$

(6) Take a comprehensive approach to the GRA-TOPSIS method. This involves amalgamating the dimensionless Euclidean distances, denoted as D_q^+ and D_q^-, along with the Grey correlation degrees, represented as R_q^+ and R_q^-, to compute the overall evaluation score. In cases where D_q^- and R_q^+ have higher values, it signifies that the green development level is closer to the ideal level. Conversely, when D_q^+ and R_q^- are higher, it indicates that the green development level is moving further away from the ideal one. The equations are as follows:

$$C_q^+ = e_1 D_q^- + e_2 R_q^+,\ C_q^- = e_1 D_q^+ + e_2 R_q^- \tag{12}$$

where C_q^+ and C_q^- represent the degree of proximity of the samples to the positive ideal solution and the negative ideal solution, respectively. e_1 and e_2 are preference coefficients, with the constraint that $e_1 + e_2 = 1$. In this study, we set $e_1 = e_2 = 0.5$.

Finally, the comprehensive evaluation score for each province/municipality is calculated using the following formula:

$$S_q = \frac{C_q^+}{C_q^+ + C_q^-}(q = 1,2,\cdots,n). \tag{13}$$

Results and Discussion

Construction of an Evaluation Index System

Selection of Evaluation Factors

Constructing a comprehensive and well-structured indicator system for green development is fundamental to assessing the levels of green development. Drawing upon pertinent research [29-31] and taking into account both operability and scientificity, the evaluation index system proposed in this paper is constructed following a hierarchical decomposition approach. This study also adhered to the following construction ideas and principles: Firstly, from a systemic and ecological perspective, the green development index system is divided into four dimensions: economic, social, resource, and environmental aspects. Secondly, attention is paid to the regional imbalances in the development of the central and eastern regions, with a focus on indicators that can be compared in terms of quantifiability. That is, all the indicators should be premised on the principles of systematization and comparability [32]. Thirdly, we prioritize choosing indicators that are incorporated into the statistical criteria of both local government and central government statistical departments to guarantee data reliability and accessibility. Fourthly, given the new characteristics exhibited by current social and economic development, it is necessary to construct a green development assessment index system that is in line with the current economic and social development status.

By referring to relevant research [2, 33, 34] and considering the current green development situation in central and eastern China, we constructed an evaluation index system for green development that comprises four dimensions, thirteen first-level indicators, and thirty-five second-level indicators (Table 1). The first-level indicators include economic green development, social green development, resource green development, and environmental green development. Economic green development plays a significant driving and supportive

Table 1. Indicators of green development levels of central and eastern China.

Indicator dimensions	First-level indicators	Second-level indicators	Properties
Economic green development	Economic development and structure (A1)	GDP growth rate (B1)	Positive
		Per capita GDP (B2)	Positive
		Ratio of tertiary industry to GDP (B3)	Positive
		Amount of foreign capital actually utilized (B4)	Positive
	Science and technology development (A2)	Percentage of general fiscal expenditure allocated to science and technology (B5)	Positive
		R&D expenditure intensity (B6)	Positive
		Number of science and technology personnel per 10,000 people (B7)	Positive
		Number of patents granted per 10,000 people (B8)	Positive
		Growth rate of technology market transaction (B9)	Positive
Social green development	Employment situation (A3)	Number of new urban employment (B10)	Positive
		Urban registered unemployment rate (B11)	Negative
	Education expenditure (A4)	The proportion of education expenditure to public budget expenditure (B12)	Positive
	Urban development (A5)	Urbanization rate (B13)	Positive
		Ratio of urban-rural income (B14)	Negative
	Per capita medical resources (A6)	Number of beds in hospitals per 10,000 people (B15)	Positive
		Hospital doctors per 10,000 people (B16)	Positive
	Social security (A7)	Insurance density (B17)	Positive
		The proportion of social security and employment expenditure to public budget expenditure (B18)	Positive
Resource green development	Energy consumption (A8)	Energy consumption per unit of GDP (B19)	Negative
	Water and gas supply (A9)	Water coverage rate (B20)	Positive
		Gas coverage rate (B21)	Positive
	Energy production and utilization (A10)	Annual raw coal production (B22)	Negative
		Annual electricity production (B23)	Negative
		Ratio of industrial solid wastes comprehensively utilized (B24)	Positive
Environmental green development	Living environment (A11)	Number of days when air quality reached grade-two of the national standard (B25)	Positive
		Per capita green area (B26)	Positive
		Green coverage rate in urban built-up area (B27)	Positive
		Number of buses per 10,000 people (B28)	Positive
		Number of environmental incidents (B29)	Negative
	Environmental pollution (A12)	Industrial wastewater emissions (B30)	Negative
		Industry sulfur dioxide emissions (B31)	Negative
		Industrial soot (dust) emissions (B32)	Negative
	Environmental governance (A13)	Urban sewage treatment proportion (B33)	Positive
		Harmless treatment rate of domestic garbage (B34)	Positive
		Proportion of environmental expenditure to fiscal expenditure (B35)	Positive

role in the process of regional green development, constituting a significant aspect of green development. Economic green development encompasses two first-level indicators, namely economic development and structure and science and technology development, along with nine second-level indicators, including GDP growth rate, per capita GDP, the percentage of general fiscal expenditure allocated to science and technology, etc. Social green development is another important component of regional green development. The primary objective of green development is to enhance the social welfare of individuals [35]. Regional green development seeks to drive overall social progress and development and improve the well-being of residents. This involves strengthening infrastructure construction, elevating the quality of public services, and ensuring that residents have access to more and higher-quality services in education, culture, healthcare, etc. Five first-level indicators were chosen to assess the quality of life and social well-being of the inhabitants. To be specific, the first-level indicators of social green development were employment situation, education expenditure, urban development, per capita medical resources, and social security. The second-level indicators of social green development include nine indicators, such as the number of new urban employment, urbanization rate, ratio of urban-rural income, hospital doctors per 10,000 people, insurance density, etc. Resource green development levels reflect the situation of energy production and consumption and the availability of common domestic energy sources in the regions. The focal point for promoting green development lies in enhancing the efficiency of resource utilization and increasing the proportion of clean energy usage [36]. Given the above consideration, three first-level indicators were formulated to assess resource green development in this research, which were energy consumption, water and gas supply, energy production, and utilization. The second-level indicators of resource green development include energy consumption per unit of GDP, gas coverage rate, annual raw coal production, etc. Environmental green development is a particularly important aspect of green development, reflecting the levels of development in aspects such as the living environment, environmental pollution, and environmental management. Green development aims to minimize unnecessary damage to the ecological environment. The environmental management department should establish scientific, strict, and comprehensive legal regulations on environmental pollution and energy consumption. Environment green development includes three first-level indicators, namely living environment, environmental pollution, and environmental governance, and eleven second-level indicators, such as green coverage rate in urban built-up areas, industry sulfur dioxide emissions, harmless treatment rate of domestic garbage, etc.

Table 2. Scoring scale of intuitionistic fuzzy judgment matrix.

Linguistic variables	Scales
Factor f is exceedingly superior to factor t	(0.05,0.95,0.00)
Factor f is strongly superior to factor t	(0.15,0.8,0.05)
Factor f is obviously superior to factor t	(0.25,0.65,0.1)
Factor f is slightly superior to factor t	(0.35,0.55,0.1)
Factor t is equivalent to factor f	(0.5,0.4,0.1)
Factor t is slightly superior to factor f	(0.65,0.25,0.1)
Factor t is obviously superior to factor f	(0.75,0.15,0.1)
Factor t is strongly superior to factor f	(0.85,0.1,0.05)
Factor t is exceedingly superior to factor f	(0.95,0.05,0)

IFAHP Method to Determine Index Weight

Experts were invited to make pairwise comparisons between different indicators that belong to the same upper-level indicators. The obtained qualitative preference relationship is then transformed into an intuitionistic fuzzy number according to Table 2. This leads to the construction of an intuitionistic fuzzy judgment matrix: $R=\left(r_{pq}\right)_{n\times n}=\left(t_{pq},f_{pq}\right)_{n\times n}$.

By following the aforementioned Equations (1) and (2), the first-level indicators and all second-level indicators of the original matrixes have not passed the consistency test, which means $d(R,R)<\tau$. It indicates that all the judgment matrixes R need to be amended. By following formulas (3) and (4), the adjusted intuitionistic fuzzy consistency judgment matrix, denoted as $\tilde{R}=\left(\tilde{r}_{pq}\right)_{n\times n}$, is obtained. When the σ value of first-level indicators is set to 0.6, $d(\tilde{R},R)<0.01$, which is less than 0.1, indicating that the matrix has passed the consistency test. When conducting the consistency test for the second-level indicators, with σ set to 0.8, all the values of of matrices of secondary indicators are less than 0.1, indicating that they all pass the test for consistency.

By following Formula (5-7), the normalized weights of first-level and second-level indicators are then obtained (Table 3).

Green Development Assessment Results

Temporal Analysis

After the green development assessment index system had been constructed, we collected data on the green development levels of 16 provinces/municipalities in the central and eastern areas of China. Upon calculation using Formula (8-13), we acquired the values of green development levels for the sixteen provinces/municipalities during the period from 2016 to 2021 (Table 4).

Table 4 shows that the green development levels of the 16 provinces/municipalities in central and eastern China were within the range of 0.4 to 0.6. After ranking

Table 3. Weights of first-level and second-level indicators.

Number	Indicators	Weight	Number	Indicators	Weight	Number	Indicators	Weight	Number	Indicators	Weight
1	A1	0.069	13	A13	0.090	25	B12	0.070	37	B24	0.026
2	A2	0.074	14	B1	0.021	26	B13	0.049	38	B25	0.022
3	A3	0.066	15	B2	0.021	27	B14	0.049	39	B26	0.017
4	A4	0.070	16	B3	0.016	28	B15	0.031	40	B27	0.013
5	A5	0.098	17	B4	0.012	29	B16	0.031	41	B28	0.012
6	A6	0.062	18	B5	0.012	30	B17	0.035	42	B29	0.015
7	A7	0.070	19	B6	0.017	31	B18	0.035	43	B30	0.034
8	A8	0.092	20	B7	0.012	32	B19	0.092	44	B31	0.029
9	A9	0.054	21	B8	0.015	33	B20	0.028	45	B32	0.032
10	A10	0.083	22	B9	0.018	34	B21	0.026	46	B33	0.032
11	A11	0.078	23	B10	0.033	35	B22	0.032	47	B34	0.030
12	A12	0.095	24	B11	0.033	36	B23	0.025	48	B35	0.027

the average green development levels by year, we can observe that in 2019, the overall green development level in the central and eastern regions (0.512) was higher than that in 2020 (0.509), which, in turn, was higher than the level in 2021 (0.507). Additionally, in 2017 (0.507), the green development level was higher than that in 2018 (0.504) and 2016 (0.503). It can be seen that the overall green development levels in the central and eastern regions of China during the period from 2016 to 2021 exhibited a fluctuating upward trend. Compared to 2016, there was a growth of 0.72% in 2017, a growth of 0.14% in 2018, and a growth of 1.78% in 2019. However, in comparison to 2019, the green development level decreased by 0.6% in 2020, and it further decreased by 0.98% in 2021. The reason may be that after the initiation of the "green transformation" strategy by the Chinese central government in 2015, local governments in various regions of the central and eastern parts of China began to pay more attention to green development and allocated more resources to promote green development in these areas. However, in 2020 and 2021, the green development levels in these regions experienced a decline, possibly due to factors such as the impact of the COVID-19 pandemic. To allocate more resources in the fight against the COVID-19 pandemic, governments at all levels have reduced overall resource allocation for green development. The upward development trends in these regions in terms of the economy, society, resources, and environment were then disrupted. During these years, the top three provinces/municipalities with the highest average green development levels were Jiangsu, Beijing, and Shanghai, all of which are located in eastern areas. The bottom three provinces with the lowest average green development levels in these years are Shanxi, Hebei, and Henan, which are located in the central areas of China.

Fig. 2 offers a visual depiction of the overall green development status across China's central, eastern, and central-eastern regions from 2016 to 2021. In general, there was an upward trajectory in green development levels in both the Central and Eastern regions during the period. The variances between the central and eastern areas tended to exhibit a decreasing pattern of fluctuations. Specifically, we observed that the eastern region consistently maintained higher levels of green development compared to the central regions across all the years. This reflects the uneven nature of green development in China's central and eastern regions. Overall, the eastern region benefits from its well-established development infrastructure, geographical advantages, and strategic development policies. The eastern regions have stronger foundations for green

Table 4. The calculation results of the green development levels.

	Hebei	Beijing	Tianjin	Shandong	Jiangsu	Shanghai	Zhejiang	Fujian	Guangdong	Hainan	Shanxi	Henan	Anhui	Hubei	Jiangxi	Hunan
2016	0.444	0.587	0.513	0.477	0.569	0.566	0.538	0.516	0.522	0.497	0.402	0.471	0.503	0.506	0.471	0.473
2017	0.444	0.564	0.532	0.481	0.573	0.551	0.543	0.531	0.528	0.502	0.422	0.475	0.489	0.520	0.491	0.467
2018	0.423	0.573	0.531	0.469	0.570	0.553	0.546	0.516	0.523	0.483	0.408	0.487	0.503	0.522	0.496	0.463
2019	0.460	0.560	0.528	0.484	0.584	0.557	0.549	0.527	0.539	0.492	0.421	0.480	0.507	0.524	0.503	0.483
2020	0.456	0.546	0.502	0.498	0.599	0.547	0.545	0.527	0.536	0.508	0.432	0.482	0.492	0.499	0.494	0.486
2021	0.445	0.545	0.506	0.481	0.577	0.555	0.539	0.517	0.533	0.495	0.439	0.469	0.501	0.524	0.497	0.495

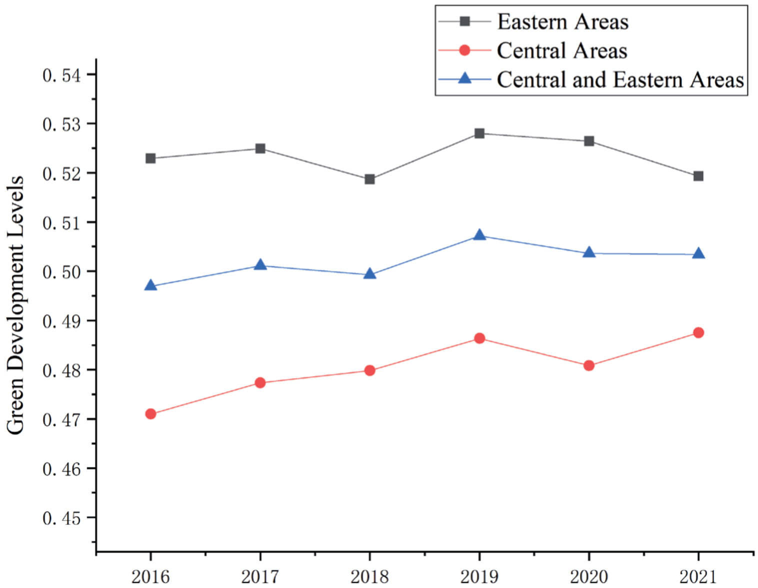

Fig. 2. The green development levels of eastern areas, central areas, and central and eastern areas.

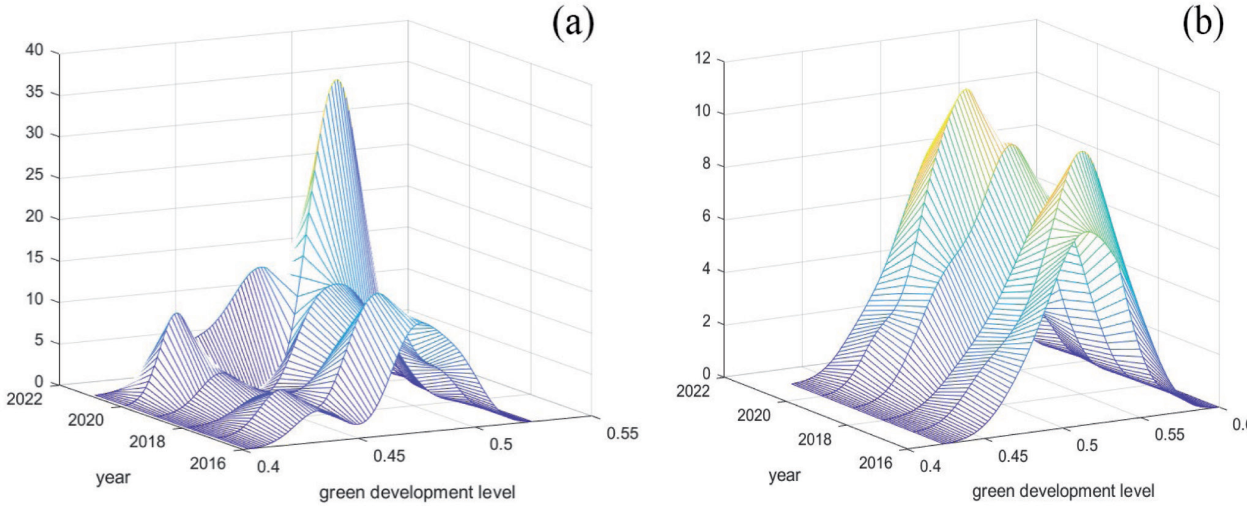

Fig. 3. Dynamic evolution of (a) central areas and (b) eastern areas.

development in terms of the economy, society, resources, and environment. The service sector, including commerce and trade, is well developed. The eastern regions derive additional advantages from their extensive coastline and numerous ports, which facilitate convenient import and export of goods.

Compared with the eastern areas, the central regions had a higher proportion of primary industry. For instance, the proportion of primary industry in Shanxi and Henan was more than 10% in 2017, which was higher than that in eastern areas [37]. The ratio of tertiary industry to GDP in the central regions was significantly lower than that in the eastern regions. For instance, in 2017, Henan, Hubei, and Jiangxi reported ratios of 44.05%, 48.32%, and 44.19%, respectively. In contrast, Beijing, Shanghai, and Guangdong showcased significantly higher ratios in 2017, recording figures of 82.69%, 69.18%, and 53.6%, respectively [37].

As can be seen in Fig. 2, the eastern regions as a whole were experiencing a green development pattern characterized by slow upward trends followed by a decline, then another upswing, and then a further decline. While the eastern areas, on the whole, had a higher level of green development compared with the central areas, the growth rate in their green development level was not particularly significant. In comparison to 2016, the eastern areas experienced a meager 0.41% growth in their green development level in 2017 and a modest 1.01% increase in 2019. The central regions exhibited a more pronounced increase in green development levels during the period from 2016 to 2021. During the period spanning 2016 to

2021, the central areas witnessed the following growth rates when compared with the year 2016: 1.31% in 2017, 1.81% in 2018, 3.25% in 2019, 2.12% in 2020, and 3.48% in 2021. The central areas have their own unique resource endowment and other advantages. Benefiting from China's "Central Rise" strategy and the exchange of industries with the eastern regions, the central areas have experienced rapid economic and social growth in recent years. Following the Chinese government's initiation of the "green transformation" strategy, the governments of central regions have been making significant efforts to optimize the structure and quality of energy input, as well as in other areas. Consequently, the levels of green development in the central regions have maintained relatively high growth rates, except for a slight decline in 2020. The reason for the slight decline in 2020 may be attributed to the significant impact of the COVID-19 pandemic.

To better observe the differences and dynamic evolution patterns of green development levels in these areas, we used Matlab 2022a and employed the kernel density estimation method to analyze their situation, ductility, and distribution. The results of the kernel density analysis are shown in Figs. 3(a) and (b). In these figures, the position of the curve distribution reflects the level of green development, with higher positions suggesting higher levels. The height and width of the peaks indicate the magnitude of regional differences, while the number of peaks suggests the degree of polarization [38]. The spread of the curve distribution reflects the spatial differences between the area with the highest level of green development and other regions, and the magnitude of these differences is linked to the length of the curve tails. Fig. 3(a) depicts the kernel density plot for the central regions, while Fig. 3(b) exhibits the kernel density plot for the eastern regions. In Fig. 3(a), the curves of the central regions display a bimodal characteristic and exhibit an oscillatory pattern of "rise-fall-rise". It indicates that there was a polarization in the green development levels among provinces in the central areas, and the disparity in green development levels between these provinces increased. It also implies a lack of sufficient coordination capacity for green development in the central regions. The rising peaks on the right side with increased width and leftward tails suggest that the majority of provinces and municipalities in the central areas had their green development levels predominantly in the middle to high range. It should be noted that in 2020, the right main peak showed a higher peak, indicating that the absolute gap in the green development levels in the central regions narrowed and the degree of dispersion was decreasing.

Compared with the central regions' kernel density plot, the eastern areas' kernel density curve was more regular. This indicates that the green development levels in the eastern regions were relatively stable and well-balanced and that the eastern areas demonstrated a strong capacity for communication and coordination regarding green development. From Fig. 3(b), it can also be observed that the main peak slightly rises in height. Despite fluctuations in peak heights in 2017 and 2021, there was a trend of increasing kurtosis year by year. This suggests that the absolute differences among the ten provinces/municipalities in the eastern areas were decreasing overall. Furthermore, the kernel density plot of central regions exhibited a distinct unimodal characteristic, suggesting the absence of evident polarization. Additionally, the peaks' positions were skewed to the right, with left tails, signifying that the overall levels of green development in the eastern areas were relatively high. The width of the main peaks was not shrinking or broadening, indicating that the overall green development levels in the eastern regions were relatively stable.

Spatial Correlation Analysis

The levels of green development in regions are generally not independent or random and frequently exhibit spatial dependence or spatial clustering relationships [39]. Therefore, this study employed spatial correlation analysis to investigate the spatial distribution characteristics of green development in the central and eastern regions of China. We utilized Moran's Index for a global spatial autocorrelation analysis to reveal the spatial clustering patterns. Specifically, Moran's I in Geoda 1.18 was used to assess the global spatial autocorrelation of the central and eastern areas of China. When the p-value is less than 0.05 and the corresponding z-value exceeds 1.96, the spatial distribution pattern is categorized as an agglomeration distribution. On the contrary, if the p-value surpasses 0.05 and the associated z-value falls below -1.69, it suggests a divergent pattern [40]. Table 5. shows the results of the global spatial autocorrelation analysis of the green development of central and eastern China from 2016 to 2021. As can be seen in Table 5., all values of Moran's I from 2016 to 2021 were greater than zero, all z-values were greater than 1.9, and all p-values were less than 0.05. It was suggested that the green development levels in the central and eastern areas of China had evident patterns of spatial agglomeration. The Global Moran's I value increased from 0.276 in 2016 to 0.383 in 2021, indicating that the spatial dependence of green development levels of central and eastern China was strengthened. In other words, highly green-developed provinces/municipalities tended to be adjacent to other highly green-developed cities, while low-green-developed provinces/municipalities tended to cluster together.

Table 5. Values of global Moran's I.

Year	Moran's I	z value	p value
2016	0.276	1.994	0.03
2017	0.288	2.264	0.02
2018	0.244	2.034	0.03
2019	0.333	2.330	0.015
2020	0.339	2.412	0.01
2021	0.383	2.683	0.009

To further examine the situation and variations in the green development levels of the sixteen provinces/municipalities in the central and eastern regions and to accurately describe and depict their spatiotemporal evolution characteristics, this study used ArcGIS 10.8 to conduct a cluster analysis of the green development levels of the central and eastern regions of China. For the sake of brevity, we only used the green development evaluation results from 2016, 2018, 2020, and 2021. The green development levels were categorized into three types (low, medium, and high) using the natural break classification method. The statistical results are shown in Fig. 4.

In Fig. 4, we can see that from 2016 to 2018, the number of high-level provinces/municipalities in the entire central and eastern regions increased from three to eight, decreased to six in 2020, and continued to decrease to five in 2021. The high-level regions are predominantly located in the eastern part, while the medium-low groups are mostly found in the central provinces/municipalities. From an annual variation perspective, in 2016, the high-level group included only Shanghai, Jiangsu, and Beijing. The medium-level group consisted of six provinces/municipalities: Tianjin, Hubei, Anhui, Zhejiang, Fujian, Guangdong, and Hainan, while the rest belonged to the low-level group. In 2018, the overall green development levels in the central and eastern regions witnessed significant improvement. The high-level category expanded to eight provinces/municipalities, specifically Beijing, Tianjin, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hubei. Meanwhile, the medium-level group consisted of six provinces: Shandong, Henan, Anhui, Hunan, and Jiangxi. The low-level group was reduced to two provinces, namely Shanxi and Hebei. By 2020, the overall green development levels in the central and eastern regions had slightly declined. Compared to 2018, the number of provinces/municipalities in the high-level group decreased by two in 2020, namely Hubei and Tianjin, which transitioned to the medium-level group, while the rest remained relatively unchanged. In 2021, the number of provinces/municipalities in the high-level group decreased further by one, with Fujian transitioning to the middle-level group. Additionally, the number of provinces/municipalities in the low-level group increased to three with the addition of Henan. It was evident that the COVID-19 pandemic, which emerged at the end of 2019, had a noticeable impact on the green development levels in central and eastern China.

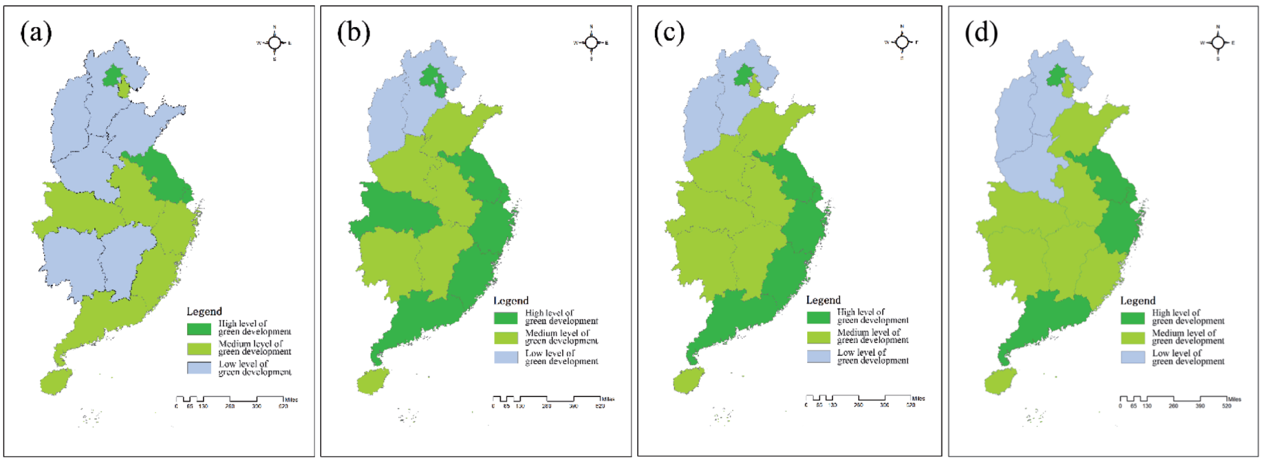

Fig. 4. Spatial distribution of green development level of central and eastern China in (a) 2016, (b) 2018, (c) 2020, (d) 2021.

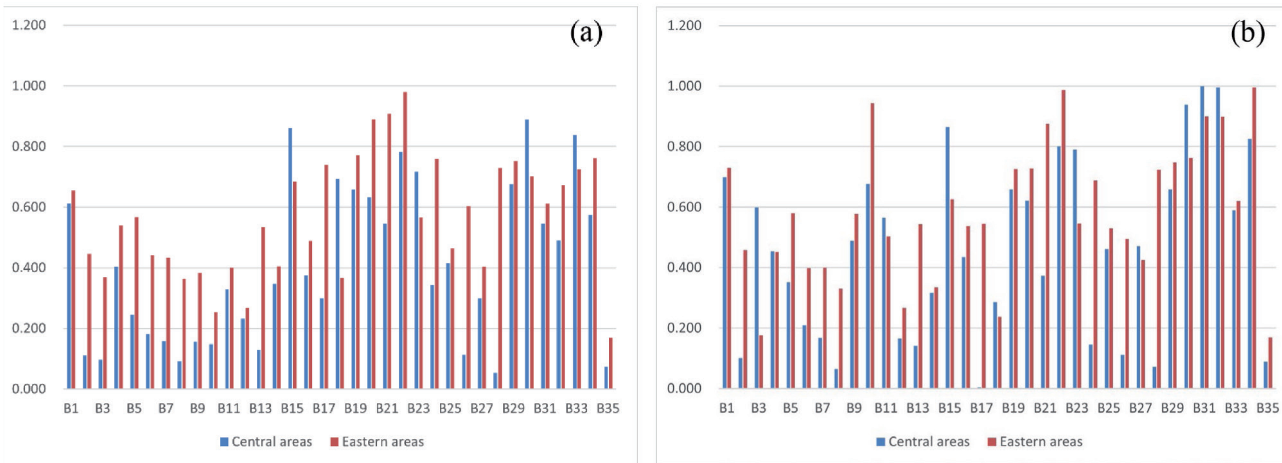

Fig. 5. Standardized values of second-level indicators of central and eastern China in (a) 2016 and (b) 2020.

Comparisons of Classifications

As can be seen in Fig. 5(a), in 2016, most of the green development values of second-level indicators of central areas were lower than those of eastern areas. Specifically, in the dimension of economic development and structure (A1), the values of GDP growth rate (B1), per capita GDP (B3), ratio of tertiary industry to GDP (B3), and amount of foreign capital actually utilized (B4) of eastern areas were all higher than those of central areas. In the field of science and technology development (A2), values in the central regions were consistently lower than those in the eastern areas. It is worth noting that the average number of patents granted per 10,000 people in central regions was only one-fourth of that in eastern regions. In terms of social green development (A2), the majority of values of indicators in central regions were less than those in the eastern areas, except for the number of beds in hospitals per 10,000 people (B15) and the proportion of social security and employment expenditure to public budget expenditure (B18). In the context of green resource development (A3), the central regions outperform the eastern regions in the indicator of annual electricity production (B23), while all other second-level indicators lagged behind those of the eastern regions. In terms of environmental green development (A4), the indicators of industrial wastewater emissions (B30) and urban sewage treatment proportion (B33) outperformed those in the eastern regions, while all other second-level indicators also fell short in comparison to the eastern regions.

As depicted in Fig. 5(b), in 2020, even though the overall level of green development in the central regions was still weaker than that in the eastern regions, the central regions made significant progress. In fact, some of the indicators of green development levels even surpassed those of the eastern regions. For instance, the values of amount of foreign capital actually utilized (B4), urban registered unemployment rate (B11), number of beds in hospitals per 10,000 people (B15), the proportion of social security and employment expenditure to public budget expenditure (B18), annual electricity production (B23), industrial wastewater emissions (B30), industry sulfur dioxide emissions (B31), and industrial soot (dust) emissions (A32) were all higher than those of eastern areas.

The overall trend is that the gap in green development levels between the central and eastern areas of China is narrowing. In 2016, the gap in green development levels between the central and eastern regions was 0.052. In 2017, it decreased to 0.048. In 2018, it was further reduced to 0.039. In 2019, the gap was 0.042. In 2020, the gap stood at 0.045. In 2021, the gap in green development levels between the central and eastern areas was 0.032.

In Fig. 5, it is evident that the central regions exhibited significant shortcomings. For example, the standardized "per capita GDP" (B2) in 2020 was merely a quarter of that in the eastern regions, while the "number of patents granted per 10,000 people" (B8) was less than a fifth of the eastern regions. Similarly, the "urbanization rate" (B13) in the central regions during 2020 was less than a quarter of the eastern regions. As for the "gas coverage rate" (B21), it was less than half of the eastern regions. Additionally, in terms of the "ratio of industrial solid wastes comprehensively utilized" (B24), the central regions represented only about a fifth of the eastern regions. Furthermore, the "number of buses per 10,000 people" (B28) in the central regions accounted for just a tenth of the figure in the eastern regions. While the overall green development level in the eastern areas was relatively high, it also had its shortcomings. For instance, the standardized value of the "ratio of tertiary industry to GDP (B3)" was only 0.451, and the standardized value of "R&D expenditure intensity (B6)" was only 0.397. Additionally, the "proportion of social security and employment expenditure to public budget expenditure (B18)" was standardized to only 0.238, and the standardized value of the "proportion of education expenditure to public budget expenditure (B12)" was just 0.266. All these indicators represent key areas where the central and eastern regions should focus their efforts in the future.

Conclusions

In order to solve ecological problems, such as environmental deterioration and resource exhaustion, the Chinese central government initiated the "green transformation" strategy in 2015. After 2015, local governments in China, especially those in the central and eastern regions, allocated significant resources to enhance the overall level of green development. The status of China's green development after 2015 is thus an intriguing topic worthy of research. Presently, there is limited scholarly attention directed towards this subject. To fill this gap, this paper aims to assess the green development status of central and eastern China, which are the most economically dynamic and densely populated areas of the nation and also showcase the most pronounced conflicts between energy, environmental, and economic development.

It was found that the overall green development level in central and eastern China exhibited a trend of fluctuation with an upward trajectory after 2015. Regions with higher levels of green development are primarily concentrated in the economically advanced eastern regions, such as Beijing, Shanghai, Jiangsu, and Zhejiang. On the other hand, areas with lower levels of development are predominantly found in the less developed inland western regions, including provinces such as Shanxi and Hebei. We also found that from 2016 to 2021, the level of green development in the central regions demonstrated a noticeable improvement. Throughout the sampling duration, the general regional disparities in the construction industry's green development quality exhibited a fluctuating decline. The overall green development level in the eastern regions was generally in a relatively stable state. However, due to factors such as the COVID-19 pandemic, the green development level in the eastern regions decreased by 0.3% in 2020, and in 2021, it further declined by 1.4%. In contrast, although the overall green development level in the central regions decreased by 1.1% in 2020 compared to 2019, in 2021, it saw a growth of 1.3% compared to 2020. From a temporal perspective, although the number of high-level regions increased slightly from 2016 to 2021, overall, the proportion of low-level and medium-level regions in the central and eastern areas remained consistently above 50%. This implies that there is still room for improvement in the green development levels in these areas. From a spatial perspective, all Moran's I values from 2016 to 2021 are greater than zero, with z-values exceeding 1.9 and p-values below 0.05, indicating a distinct spatial agglomeration pattern in the green development levels of central and eastern China.

The results of comparisons of classifications show that there were regional differences between the green development levels of eastern areas and those of central areas of China. This further supports some findings from previous studies. For instance, by studying the state of green development in provinces in eastern and western China, Yang et al. found that the regional imbalance was evident, with the eastern region surpassing the average level significantly and the western region falling below the average [2]. Pan et al. found that there were great regional differences among the urban green development levels of different areas of the Yangtze River economic belt [41]. After studying the comprehensive competitiveness of green development in 30 sample provinces in China, Zhang et al. also discovered that the comprehensive competitiveness of green development in the eastern region was valued the highest among all the 30 sample provinces [33].

The significant disparity in green development levels in the central and eastern regions of China is influenced by various factors. Firstly, the eastern regions, as the most vibrant and economically advanced areas in China, have benefited from the reform and opening-up policies. For a considerable period following the implementation of the reform and opening-up policies, an imbalanced development strategy was put into effect by the central government, with priority given to the eastern areas, where some special economic zones were established [42]. The central government allocated significant resources to develop the eastern regions in areas such as science, education, culture, healthcare, environment, and trade. As a result, the eastern regions have enjoyed a relatively greater share of the dividends from reform and opening-up policies. They possess the capability to make reasonable investments in technology, healthcare, education, etc. Consequently, the eastern regions have a relatively larger number of high-tech professionals, strong scientific and educational institutions, well-equipped healthcare facilities, and a solid foundation in terms of living infrastructure, as illustrated in Fig. 5.

Many provinces in the central areas of China possess inherent advantages in terms of environmental resources and other kinds of resources [43]. However, their levels of green development were relatively lower. This may partly be attributed to their long-standing economic reliance on the extraction and utilization of natural resources. Both the quantity and quality of their industrial and commercial enterprises lag behind those in the eastern areas. Additionally, the central government allocated relatively fewer resources to the central regions in the fields of technology, healthcare, and education. Consequently, they had an uneven industrial structure, underdeveloped tertiary sectors, low technological output, and a greater prevalence of low-value industries and energy-intensive sectors. As an illustration, as can be seen in Fig. 5, in 2016, the central regions had a tertiary industry to GDP ratio (B3) of 45.93%, in contrast to the eastern regions, where this ratio reached 56.88%. Similarly, in 2016, the central regions saw only 9.039 patents granted per 10,000 people, while the eastern regions registered 29.35 patents per 10,000 people. As a result, the overall green development level of the central regions fell behind that of the eastern regions.

Based on the results of this study, we believe that the following efforts should be made to improve the green development levels in central and eastern China:

(1) Regional collaboration needs to be fortified, and a framework for synchronized development should be put in place. The results of this study reveal a notable spatial clustering of green development levels in central and eastern China, and the spillover effect of green development is quite significant in these areas. Consequently, it's imperative to enhance cooperation within China's central and eastern regions, fostering integrated and networked development where the eastern areas take the lead and support the development of the central regions. This will help boost the overall green development level of the central and eastern regions by leveraging the full potential of their respective resource advantages. Specifically, the central regions need to expedite exchanges and cooperation with the eastern regions in terms of talent, capital, and technology, ensuring high-quality input from various production factors to address their shortcomings. The eastern regions, in turn, should make better use of the central region's advantages in green energy, human capital, market space, etc. to further enhance the quality of green development.

(2) Local governments should formulate targeted policies for green development based on the local strengths and weaknesses in green development. The central regions should adjust their industrial structures, upgrade and transform low-end industries, reduce dependence on high-energy and high-pollution enterprises, and introduce and nurture emerging industries such as high-end equipment manufacturing, new materials, and green energy. At the same time, the governments of central regions should also increase investments in the fields of technology, education, healthcare, and environmental protection. Extensive training of skilled professionals and enhancing the region's abilities to attract various kinds of talents are necessary. Additionally, the central regions should leverage their natural resources and strategic geographical position to formulate a green development strategy that aligns with local circumstances. These measures will help

the central region break free from dependence on high-energy and high-pollution enterprises, achieving optimization and upgrading of its economic structure. The eastern areas of China should improve the quality of its tertiary industry and increase investments in education, social security, R&D, environmental protection, etc. In addition, they should leverage their strengths in technology, education, and capital to cultivate a greater number of high-tech talents and to improve both the quantity and quality of technological innovation output.

(3) Local governments should place greater emphasis on environmental management and protection and develop more comprehensive and stricter environmental policies. First and foremost, there should be strict regulations on the emission limits of environmental pollutants. As can be seen in Table 3, reducing pollutant emissions is crucial to raising the levels of green development in the regions. Second, the local government should make policies to promote the shift from an energy-dependent industrial development mode to an innovation-driven development mode. This transformation is particularly critical in regions with intermediate and low levels of green development, such as Shanxi and Hebei provinces. Last but not least, policies should be made to encourage enterprises to expedite the digital transformation of their production mode and supply chains, thereby reducing the volume of carbon emissions.

(4) Policies should be made to further improve the infrastructure for green development. Due to inadequate infrastructure, there is significant room for improvement in the current synergy efficiency of green development between the central and eastern regions of China. First, building more modern transportation infrastructure is necessary, so as to facilitate connectivity between the central and eastern regions of China and to promote the exchange of technology, talent, and capital. Second, further improving industrial development facilities, energy supply facilities, and environmental management facilities is also crucial. Third, governments should establish digital communication platforms that could promote collaboration and efficiency between the central and eastern regions. Consequently, the transaction and communication costs for green development could be reduced.

Acknowledgments

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Conflict of Interest

The authors declare no conflict of interest.

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