

## Article

# Spatial–Temporal Evolution of Interprovincial Ecological Efficiency and Its Determinants in China: A Super-Efficiency SBM Model Approach

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**Abstract:** This study delves into the temporal–spatial variations and influencing factors of interprovincial ecological efficiency in China, aiming to provide vital guidance for sustainable development and ecological equilibrium. Employing the super-efficiency SBM model, we compute ecological efficiency indices for 31 Chinese provinces from 2005 to 2021. Furthermore, utilizing Geodetectors, we conduct an in-depth analysis of the impact of key dimensions—economic factors, efficiency elements, environmental governance, pollution determinants, input factors, and natural components—consisting of 30 specific indicators of ecological efficiency. The findings unveil several significant insights. Firstly, interprovincial ecological efficiency in China has experienced undulating declines since 2005. Additionally, notable spatial agglomeration exists, with economically developed regions demonstrating elevated ecological efficiency, while less-developed areas exhibit lower levels. Moreover, among the influencing factors, (1) economic aspects hold a dominant role, where optimizing industrial structure and enhancing resource utilization efficiency can partially alleviate environmental pressure; (2) efficiency elements exhibit a progressive enhancement trend; (3) the impacts of environmental governance and pollution factors manifest complex dynamics, necessitating continuous policy support and comprehensive remediation; (4) despite the relatively weaker influence of natural components, vigilance remains imperative due to intensifying climate change and natural disasters; and (5) while input factors exert limited effects on ecological efficiency, their significance in resource allocation and sustainable development persists.

**Keywords:** interprovincial ecological efficiency; super-efficiency SBM model; spatial–temporal variation; influencing factors; sustainable development; China



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## 1. Introduction

With the rapid growth of the global economy and the accelerated industrialization process, ecological and environmental issues have garnered increasing attention on a global scale [1]. As one of the most populous countries in the world, China faces significant ecological challenges amidst its rapid development [2,3]. Environmental degradation not only poses a threat to economic sustainability, but also directly affects public health and social stability [4]. Therefore, enhancing ecological efficiency and achieving coordinated development between economic growth and environmental protection have become crucial components of China’s sustainable development strategy.

Ecological efficiency serves as a vital indicator for evaluating the relationship between economic development and resource utilization efficiency, aiming to measure the effectiveness of economic activities in utilizing natural resources and their impact on the environment [5,6]. Higher ecological efficiency implies that a unit of resource input can yield

more output while reducing adverse environmental impacts [7,8]. Against the backdrop of escalating global environmental challenges, the Chinese government places great emphasis on environmental protection, actively promoting the concept of green development, and striving to find a balance between economic growth and environmental conservation [9].

Since the early 1990s, research on provincial ecological efficiency in China has undergone a developmental progression from simple efficiency assessment to multidimensional analysis of influencing factors. Methodologically, the evolution has advanced from the traditional DEA model to an expanded DEA model that incorporates environmental considerations. Furthermore, more intricate non-radial super-efficiency models and panel data analysis methods have been introduced. In terms of research focus, the initial emphasis was on measuring ecological efficiency, followed by a gradual incorporation of economic, social, and environmental factors to explore their mechanisms of influence on ecological efficiency. In recent years, there has been a growing attention to the alignment of ecological efficiency with sustainable development goals, investigating how to strike a balance between enhancing ecological efficiency while simultaneously achieving economic development and environmental protection. However, there exist substantial disparities in ecological efficiency among different provinces in China, influenced by a combination of factors, including geography, economy, and policies [10–12]. In order to facilitate the sustained improvement of interprovincial ecological efficiency in China, there is an urgent need for in-depth understanding of the relationships and degrees of influence among these factors, necessitating systematic research.

This paper aims to utilize the Super-Efficiency Data Envelopment Analysis (DEA) SBM model to calculate the ecological efficiency index for 31 Chinese provinces from 2005 to 2021, exploring its spatial–temporal variation characteristics, and analyzing the impact of economic factors, efficiency-related factors, environmental governance, pollution-related factors, input-related factors, and natural factors on ecological efficiency. Through the use of geographic detectors, the quantitative identification of the driving forces behind ecological efficiency will provide decision-making support and scientific reference for achieving interprovincial ecological balance in China.

The remainder of this paper is organized as follows: Part two consists of a literature review and the contributions of this study; Part three includes the construction of the ecological efficiency evaluation index system, methodological overview, and data sources; Part four presents the analysis of temporal and spatial effects of interprovincial ecological efficiency in China; Part five delves into the analysis of influencing factors on interprovincial ecological efficiency in China; and finally, Part six presents the main conclusions and recommendations.

## 2. Literature Review

### (1) Ecological Efficiency and Sustainable Development

Ecological efficiency, as a crucial indicator for assessing the relationship between the economy and the environment, has garnered extensive attention in the field of sustainable development. Numerous scholars have explored the connection between ecological efficiency and sustainable development, emphasizing that enhancing ecological efficiency is a key pathway towards achieving sustainable development. Fukuda, K (2020) [13] and Strassburg, B (2020) [14] pointed out that improving ecological efficiency contributes to the efficient utilization of resources and environmental protection, ensuring the long-term health of the economy. Pérez Urdiales (2016) [15], Zhang, J. (2017) [16], Sunkar, A. (2022) [17], and Wang, L (2022) [18], among others, argue that ecological efficiency is a vital tool for balancing economic growth and environmental protection, and should be integrated into the core of sustainable development strategies.

### (2) Methods of Ecological Efficiency Measurement

Regarding the measurement of ecological efficiency, scholars have proposed various methods to evaluate the efficiency of economic systems in resource utilization and

environmental impact. Among these methods, the Super-Efficiency Data Envelopment Analysis (DEA) SBM model is commonly used. Färe, R. (1989) [19] first introduced the SBM model, used for calculating output-oriented and input-oriented ecological efficiency. Subsequently, Tone, K. (2001) [20] and Tone, K. (2010) [21] extended the SBM model to propose the super-efficiency SBM model, which evaluates the optimal efficiency of each unit compared to others within a specific time frame. This model overcomes the limitations of the traditional SBM model, possessing better applicability and interpretability. Hence, in this study, we will adopt the super-efficiency SBM model to calculate the interprovincial ecological efficiency index in China, further exploring its spatial–temporal variation characteristics and influencing factors.

### (3) Research on Interprovincial Ecological Efficiency in China

In recent years, a series of significant achievements have been made in the study of interprovincial ecological efficiency in China. Many scholars have used different methods to investigate the spatial–temporal variation and influencing factors of interprovincial ecological efficiency. Liu, Q. (2020) [22], Meng, M. (2022) [23], and others assessed the ecological efficiency of 31 provinces in China using the SBM model and analyzed its influencing factors. They found that economic factors, environmental governance, and technological progress were major determinants affecting ecological efficiency. Zhang, H. (2022) [24], Jiang, W. (2023) [25], and others, based on the Malmquist ecological efficiency index, studied the spatial–temporal evolution characteristics of interprovincial ecological efficiency in China. They discovered that the ecological efficiency in eastern regions was generally higher than in western regions and exhibited an overall upward trend over the years.

### (4) Factors Influencing Interprovincial Ecological Efficiency in China

In the research on interprovincial ecological efficiency in China, scholars such as Yang, T. (2022) [26] and Guo, Y. (2022) [27] have conducted in-depth analyses of various factors influencing ecological efficiency, identifying economic factors as one of the primary drivers. Shang, H. (2022) [28] and Zheng, H. (2023) [29] highlighted that the varying economic development levels, industrial structures, and technological levels among provinces directly influence resource utilization and environmental protection efficiency. Additionally, Yang, H. (2022) [30], Matsumoto, K. (2021) [31], and Yuan, X. (2023) [32] found that efficiency-related factors, such as resource utilization efficiency, energy use efficiency, and production processes, significantly influence ecological efficiency levels. Ha, L. (2020) [33] and Zeng, L. (2020) [34] discovered that environmental governance and pollution-related factors play vital roles in environmental protection, with government investment in environmental governance and the implementation of pollution control policies impacting ecological efficiency levels among provinces. Moreover, input-related factors and natural factors also influence ecological efficiency, including factors such as fixed asset investment [35], energy input [36], R&D investment [8], and human resources [37], whose rational allocation and utilization are crucial for enhancing ecological efficiency. Additionally, Luo, K. (2022) [38] and Jia, H. (2023) [39] pointed out that natural factors such as climatic conditions and distribution of natural resources also affect interprovincial ecological efficiency, as regional variations in natural conditions lead to differences in resource utilization, subsequently influencing ecological efficiency performance.

### (5) The Impact of Policies and Governance on Ecological Efficiency

Policies and governance play a critical role in shaping interprovincial ecological efficiency in China [40]. The national government has implemented a series of policy measures in sustainable development and ecological civilization construction [41,42], such as the “14th Five-Year Plan” and environmental protection laws, aimed at promoting resource conservation and environmental protection during the process of economic development in various provinces. However, the implementation of policies and the effectiveness of governance vary by region, with some local governments not giving sufficient priority to

environmental protection, resulting in lower ecological efficiency, while, in other regions, the effective implementation of policies has achieved significant ecological benefits.

Current research on interprovincial ecological efficiency in China has some limitations, including a relatively short time span, methodological constraints, insufficient spatial analysis, and inadequate consideration of comprehensive factors, which restrict a comprehensive understanding and in-depth analysis of interprovincial ecological efficiency in China. Therefore, this study aims to fill these research gaps, providing a more accurate and comprehensive assessment of interprovincial ecological efficiency through systematic and integrated analysis, thereby offering robust support for relevant policy formulation.

### 3. Research Methods and Data Sources

#### 3.1. Ecological Efficiency Evaluation System

Building upon the groundwork laid by previous scholars such as Liu, Q. (2020) [22], Yang, T. (2022) [26], Zheng, H. (2023) [29], and Yuan, X. (2023) [34], this study establishes an ecological efficiency assessment framework. The model comprehensively integrates input indicators (labor, capital, land, energy, and water resources) and desired output indicators (economic output, general public budget revenue), as well as undesired output indicators (wastewater, waste gas, and solid emissions). Encompassing critical factors such as inputs, outputs, and environmental pollution, this framework objectively quantifies the resource utilization, economic output, and environmental pollution status across provinces. This holistic and systematic analytical framework provides an in-depth understanding of the ecological efficiency status among provinces (Table 1).

**Table 1.** Ecological efficiency evaluation index system.

| Indicator            | Variable             | Variable Description                                    |
|----------------------|----------------------|---------------------------------------------------------|
| Input Indicators     | Labor Force Input    | Number of employed personnel                            |
|                      | Capital Input        | Total social fixed asset investment                     |
|                      | Land Input           | Built-up area in urban districts                        |
|                      | Energy Input         | Electricity consumption                                 |
|                      | Water Resource Input | Total water consumption                                 |
| Expected Outputs     | Economic Output      | Gross Domestic Product (GDP)                            |
|                      | Fiscal Revenue       | Local general public budget revenue                     |
| Non-Expected Outputs | Wastewater Emission  | Chemical Oxygen Demand (COD) in wastewater emission     |
|                      | Gas Emission         | Sulfur dioxide (SO <sub>2</sub> ) emission in waste gas |
|                      | Solid Emission       | Hazardous waste generation                              |

#### 3.2. Research Methods

##### 3.2.1. Super-Efficiency SBM Model

Compared to the traditional Data Envelopment Analysis (DEA) model, the super-efficiency SBM model incorporates slack variables into the objective function, effectively addressing the issues of resource input, expected outputs, and non-expected outputs. Additionally, it considers the further distinction of decision-making units along the frontier. Therefore, the super-efficiency SBM model is adopted to measure interprovincial ecological efficiency in China and its formula is as follows:

$$\min \rho^* = \frac{1 + \frac{1}{m} \sum_{m=1}^M (S_m^x / X_m^t)}{1 - \frac{1}{l+h} \left( \sum_{l=1}^L S_l^y / y_{jl}^t + \sum_{h=1}^H S_h^b / b_{jh}^t \right)} \quad (1)$$

$$\begin{cases} x_{jm}^t \geq \sum_{j=1, j \neq 0}^n \lambda_j^t x_{jm}^t + s_m^x, \\ y_{jl}^t \geq \sum_{j=1, j \neq 0}^n \lambda_j^t y_{jl}^t - s_l^y, \\ b_{jh}^t \geq \sum_{j=1, j \neq 0}^n \lambda_j^t b_{jh}^t + s_h^b, \\ \lambda_j \geq 0, s_m^x \geq 0, s_l^y \geq 0, j = 1, 2, 3, \dots, n, \end{cases} \quad (2)$$

In this context,  $\rho^*$  represents the ecological efficiency index, and  $m$ ,  $l$ , and  $h$  denote the number of input, expected output, and non-expected output elements, respectively.  $S_m^x$ ,  $S_l^y$ , and  $S_h^b$  represent the corresponding slack variables for input, expected output, and non-expected output.  $x_j^t$ ,  $y_j^t$ , and  $b_j^t$  denote the input, expected output, and non-expected output of decision-making unit  $j$  at time period  $t$ . Furthermore,  $n$  represents the number of decision-making units and  $\lambda$  is the weight vector of decision-making units.

### 3.2.2. Spatial Autocorrelation

Spatial autocorrelation is a spatial statistical method used to assess the correlation and dependency of geographical spatial data [43]. It emphasizes the influence of geographical proximity by constructing a spatial weight matrix to represent the connectivity between different geographic locations. Moran's Index is a commonly used measure to quantify spatial autocorrelation, where positive values indicate positive spatial correlation, negative values indicate negative spatial correlation, and values close to zero indicate no spatial correlation. Spatial autocorrelation analysis helps us discover clustering patterns in spatial data, interpret geographic phenomena, and optimize spatial interpolation methods, providing extensive applications in fields such as ecology and geography. The calculation formula is as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n \omega_{ij} (x_i - \bar{x}) (x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n \omega_{ij}} \quad (3)$$

$$I' = \frac{x_i - \bar{x}}{S^2} \sum_{j=1}^n \omega_{ij} (x_j - \bar{x}) \quad (4)$$

In the formula,  $I$  represents the global Moran's Index,  $I'$  represents the local Moran's Index,  $n$  is the number of provinces,  $i$  and  $j$  represent different spatial units,  $x$  represents ecological efficiency closeness,  $\bar{x}$  and  $S^2$  are the mean and variance of ecological efficiency, and  $\omega_{ij}$  is the spatial weight matrix. In this study, if the spatial units are adjacent,  $\omega_{ij}$  is set to 1; otherwise, it is set to 0.

### 3.2.3. GeoDetector

The GeoDetector is a powerful spatial regression analysis method that takes into account the complexity of geographic spatial data when studying geographical phenomena, with a particular emphasis on spatial non-stationarity and heterogeneity [44]. In the context of studying ecological efficiency, geographical spaces often exhibit significant variations, meaning that different regions may have notably different ecological efficiency levels. These variations can be attributed to a variety of factors, including the natural features of geographical spaces, resource distribution, population density, and more. Leveraging the GeoDetector allows for a more refined handling of spatial heterogeneity in the influencing factors, providing a better understanding of the spatial evolution of ecological efficiency within geographic spaces. Consequently, it enables us to establish models at a local spatial scale to better capture the distribution characteristics of ecological efficiency within geographical spaces.

The GeoDetector not only provides estimates of global spatial effects but also offers regression coefficients for local spatial effects. This capability enables us to identify hotspot and coldspot areas, which represent regions with exceptionally high or low ecological efficiency. Such information is crucial for formulating precise environmental protection policies

and resource allocation strategies. With the GeoDetector, we can forecast the ecological efficiency levels in unknown areas, aiding policymakers in taking more targeted actions.

In the field of ecological efficiency, the GeoDetector offers a solid scientific basis for crafting evidence-based environmental policies and sustainable development strategies. It not only reflects the disparities in ecological efficiency across geographical spaces but also unveils the spatial distribution patterns of the driving factors behind these disparities. This facilitates a more comprehensive understanding of the temporal and spatial evolution of ecological efficiency, providing precise information and guidance for the protection of the environment, optimization of resource allocation, and promotion of sustainable development.

$$q = 1 - \frac{1}{N\sigma^2} \sum_{h=1}^L Nh\sigma_h^2 \quad (5)$$

In the equation,  $q$  represents the correlation index of ecological efficiency and its value ranges from 0 to 1. A larger value of  $q$  indicates that the driving factors have a greater impact on ecological efficiency.  $h$  denotes the number of categories for the driving factors.  $N$  represents the number of provincial units and  $\sigma^2$  is the variance of ecological efficiency among the provinces.

### 3.3. Study Area and Data Sources

This study focuses on 31 provinces in China as the research area (Hong Kong and Macau are excluded due to data unavailability) (Figure 1). A total of 40 indicators are involved in this research, and their data are obtained from various official and reliable authoritative sources, including China Statistical Yearbook, provincial statistical yearbooks, China Environmental Statistical Yearbook, China Industrial Statistical Yearbook, and China Labor Statistical Yearbook. Some data are supplemented by official and reliable authoritative institutions such as the National Bureau of Statistics of China, relevant provincial-level statistical bureaus, water resources departments, science and technology departments, environmental protection departments, meteorological departments, and urban planning and construction departments.

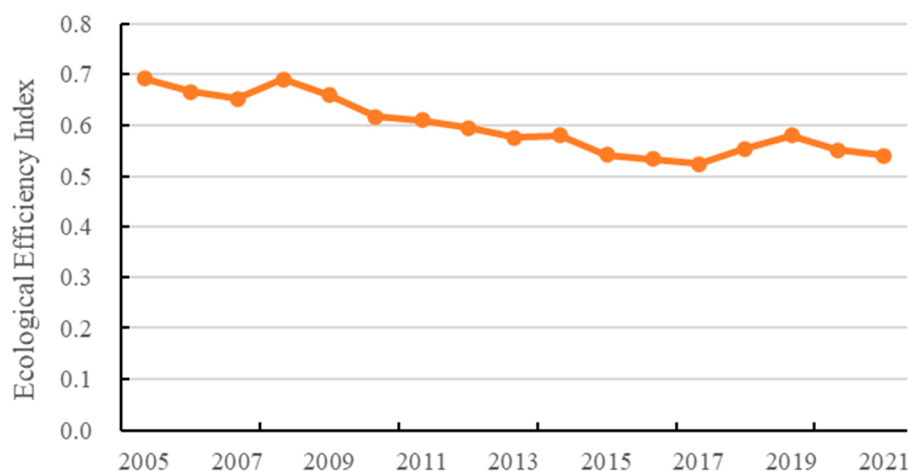


**Figure 1.** Study area overview and provincial distribution map.

#### 4. Spatial and Temporal Variation of Interprovincial Ecological Efficiency in China

##### 4.1. Temporal Analysis of Interprovincial Ecological Efficiency in China

Using the super-efficiency SBM model, we calculated the ecological efficiency index of 31 Chinese provinces from 2005 to 2021. Further, we calculated the average ecological efficiency of the provinces for each year, as shown in Figure 2. Since 2005, China's overall ecological efficiency has experienced fluctuations and declines. Initially, from 2005 to 2010, the ecological efficiency index declined from 0.691 to 0.616. This decline was closely related to the rapid economic growth in China during that period, which led to increased resource consumption and environmental pressure, consequently reducing ecological efficiency.



**Figure 2.** Trends in China's ecological efficiency index from 2005 to 2021.

From 2011 to 2014, China's ecological efficiency index remained relatively stable, fluctuating between 0.610 and 0.580. During this period, the Chinese government began to emphasize environmental protection and sustainable development, introducing a series of environmental policies and measures that contributed to the relative stability of ecological efficiency.

From 2015 to 2019, China's ecological efficiency index showed an increasing trend, rising from 0.580 to 0.554. This improvement was attributed to the government's increased efforts in environmental protection during this period, with the implementation of more environmental policies, as well as the impact of industrial restructuring and technological advancements.

From 2020 to 2021, China's ecological efficiency index experienced a slight decline. During this period, factors such as the COVID-19 pandemic, reduced foreign trade, and a declining population significantly increased financial pressure on various levels of the Chinese government. As a result, environmental protection investments were somewhat reduced to stabilize the economy and employment, leading to a slight decrease in the ecological efficiency index.

Table 2 presents the temporal evolution of ecological efficiency indices for the 31 provinces in China from 2005 to 2021. Significant disparities in ecological efficiency performance among different provinces are evident, with some regions consistently improving their ecological efficiency while others still lag behind. Firstly, in terms of overall trends, economically developed regions such as Beijing, Shanghai, Tianjin, Jiangsu, and Guangdong consistently exhibited higher ecological efficiency indices in most years. Conversely, economically relatively backward regions like Ningxia, Qinghai, and Gansu generally demonstrated lower ecological efficiency indices, reflecting the relationship between ecological efficiency and environmental awareness, economic development patterns, levels of environmental protection investment, and technological capabilities.

**Table 2.** The ecological efficiency indices of each province in China for the years 2005, 2010, 2015, 2020, and 2021.

| Serial Number | Country        | Ecological Efficiency Index |       |       |       |       |
|---------------|----------------|-----------------------------|-------|-------|-------|-------|
|               |                | 2005                        | 2010  | 2015  | 2020  | 2021  |
| 1             | Beijing        | 1.298                       | 1.359 | 1.325 | 1.438 | 1.444 |
| 2             | Tianjin        | 0.647                       | 1.061 | 1.145 | 0.504 | 0.464 |
| 3             | Hebei          | 0.529                       | 0.382 | 0.271 | 0.259 | 0.250 |
| 4             | Shanxi         | 1.025                       | 0.473 | 0.286 | 1.627 | 1.632 |
| 5             | Inner Mongolia | 0.249                       | 0.252 | 0.216 | 0.214 | 0.233 |
| 6             | Liaoning       | 0.456                       | 0.421 | 0.366 | 0.540 | 0.413 |
| 7             | Jilin          | 0.370                       | 0.258 | 0.252 | 0.211 | 0.202 |
| 8             | Heilongjiang   | 0.463                       | 0.347 | 0.236 | 0.197 | 0.195 |
| 9             | Shanghai       | 1.265                       | 1.196 | 1.226 | 1.278 | 1.269 |
| 10            | Jiangsu        | 1.052                       | 1.070 | 1.101 | 1.049 | 1.054 |
| 11            | Zhejiang       | 1.070                       | 0.801 | 0.616 | 0.692 | 0.681 |
| 12            | Anhui          | 1.086                       | 1.086 | 0.516 | 0.494 | 0.474 |
| 13            | Fujian         | 1.066                       | 1.107 | 1.051 | 1.034 | 1.019 |
| 14            | Jiangxi        | 1.083                       | 1.030 | 1.002 | 0.463 | 0.457 |
| 15            | Shandong       | 0.679                       | 0.592 | 0.458 | 0.444 | 0.452 |
| 16            | Henan          | 0.394                       | 0.282 | 0.236 | 0.223 | 0.205 |
| 17            | Hubei          | 0.419                       | 0.399 | 0.363 | 0.301 | 0.308 |
| 18            | Hunan          | 1.004                       | 1.013 | 1.045 | 1.042 | 1.035 |
| 19            | Guangdong      | 1.145                       | 1.157 | 1.181 | 1.176 | 1.165 |
| 20            | Guangxi        | 0.302                       | 0.290 | 0.251 | 0.222 | 0.219 |
| 21            | Hainan         | 1.037                       | 1.000 | 0.349 | 0.325 | 0.375 |
| 22            | Chongqing      | 0.424                       | 0.347 | 0.359 | 0.343 | 0.321 |
| 23            | Sichuan        | 0.457                       | 0.371 | 0.376 | 0.364 | 0.341 |
| 24            | Guizhou        | 0.258                       | 0.266 | 0.315 | 0.397 | 0.309 |
| 25            | Yunnan         | 0.346                       | 0.274 | 0.248 | 0.252 | 0.249 |
| 26            | Tibet (Xizang) | 1.000                       | 1.056 | 1.000 | 1.000 | 1.000 |
| 27            | Shaanxi        | 0.630                       | 0.450 | 0.393 | 0.344 | 0.330 |
| 28            | Gansu          | 0.231                       | 0.196 | 0.169 | 0.181 | 0.180 |
| 29            | Qinghai        | 0.175                       | 0.176 | 0.147 | 0.153 | 0.151 |
| 30            | Ningxia        | 1.000                       | 0.153 | 0.125 | 0.140 | 0.144 |
| 31            | Xinjiang       | 0.276                       | 0.235 | 0.162 | 0.165 | 0.165 |

Secondly, from 2005 to 2010, the ecological efficiency indices of the vast majority of provinces increased, indicating positive progress in environmental protection across various provinces in China during that period. However, from 2010 to 2015, some provinces, including Shanxi and Jiangxi, experienced a decline in their ecological efficiency indices, revealing challenges in balancing economic development and environmental protection efforts. Subsequently, from 2015 to 2021, ecological efficiency indices showed signs of improvement again, possibly influenced by strengthened environmental policies and technological advancements. Additionally, Tibet consistently maintained relatively high ecological efficiency indices in each year, likely due to its unique natural environment and ecological conservation measures.

The ecological efficiency indices of China's provinces have exhibited diverse temporal trends over the past decade, influenced by various factors such as regional economic development, implementation of environmental protection policies, and technological advancements. To enhance ecological efficiency, further analysis of spatial variations is needed, enabling different provinces to formulate more effective environmental protection measures, and promote the coordinated development of economic growth and environmental protection.

#### 4.2. Analysis of Spatial Variation in Interprovincial Ecological Efficiency in China

To further analyze the spatial disparities in interprovincial ecological efficiency in China, we classified the ecological efficiency index into five levels, namely Grade I to Grade

V, based on the yearly ecological efficiency indices of the 31 provinces from 2005 to 2021. The criteria for classification are listed in Table 3. Grade V indicates the highest ecological efficiency, with an ecological efficiency index greater than 1.

Table 3. Criteria for ecological valley efficiency grading.

| Level I  | Level II       | Level III      | Level IV   | Level V     |
|----------|----------------|----------------|------------|-------------|
| (0, 240] | (0.240, 0.320] | (0.320, 0.430] | (0.430, 1] | (1.0, 1.66] |

Based on the grading criteria, the provincial ecological efficiency indicators calculated from 2005 to 2021 were classified into five levels, as shown in Figure 3. The darker the color, the higher the ecological efficiency index, indicating a stronger ability to produce outputs with less material input. From Figure 3, we can observe that, in 2005, there were 2 provinces in Grade I, 4 provinces in Grade II, 5 provinces in Grade III, 9 provinces in Grade IV, and 11 provinces in Grade V. In 2010, there were 4 provinces in Grade I, 6 provinces in Grade II, 6 provinces in Grade III, 5 provinces in Grade IV, and 10 provinces in Grade V. In 2015, there were 7 provinces in Grade I, 6 provinces in Grade II, 6 provinces in Grade III, 4 provinces in Grade IV, and 8 provinces in Grade V. In 2021, there were 9 provinces in Grade I, 4 provinces in Grade II, 5 provinces in Grade III, 6 provinces in Grade IV, and 7 provinces in Grade V.

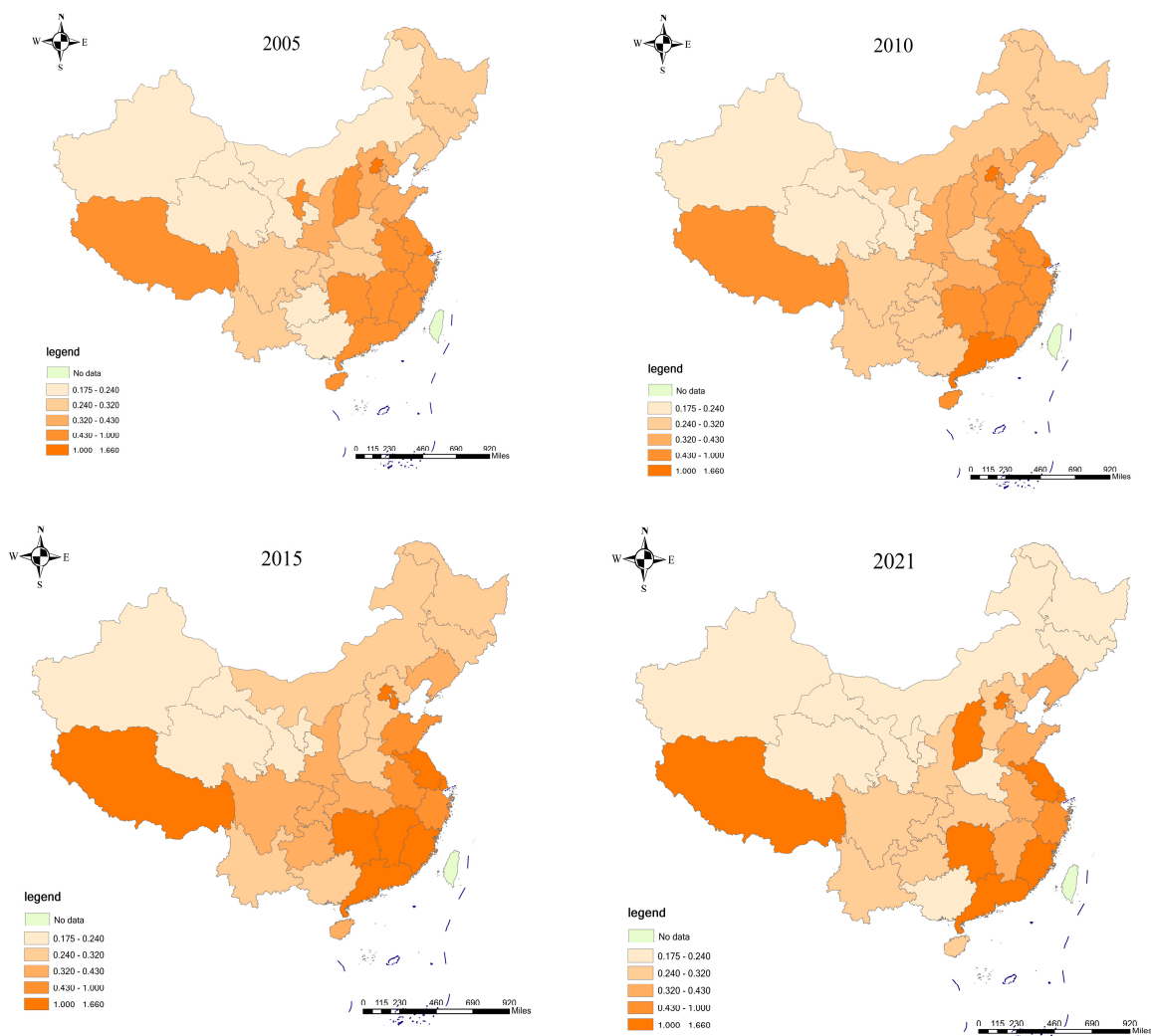


Figure 3. Spatial pattern of China’s provincial ecological efficiency index.

It can be observed that the number of provinces in Grade I with higher ecological efficiency has significantly increased from two in 2005 to nine in 2021. The provinces with stable higher ecological efficiency include Beijing, Shanghai, Jiangsu, Zhejiang, Fujian, Hunan, and Guangdong, consistently maintaining a high level (Grade V) of ecological efficiency from 2005 to 2021. This is attributed to their significant investments in resource management and environmental protection, driving sustainable development and the growth of the green economy. On the other hand, some provinces such as Tianjin and Guangxi experienced fluctuating declines in ecological efficiency due to increased resource consumption and environmental pressures during economic development.

Furthermore, the ecological efficiency in the western regions generally remains low but there is a trend of improvement over the years. Provinces in the western regions, such as Xinjiang, Ningxia, and Qinghai, exhibit lower ecological efficiency levels, possibly attributed to weaker economic foundations, higher levels of resource exploitation, and relatively weaker environmental awareness. However, some of these provinces have shown improvements in ecological efficiency in recent years, thanks to the government's increased focus on environmental protection and active implementation of relevant environmental policies.

Lastly, a few provinces have persistently low ecological efficiency levels and face challenges in improvement. Provinces such as Gansu and Guizhou have consistently maintained lower ecological efficiency levels for an extended period, and evident improvements are difficult to achieve. This could be related to their economic structure, resource endowment, and environmental governance levels. In these provinces, enhancing resource management, optimizing economic structure, and enforcing environmental protection policies may be crucial approaches to improve ecological efficiency.

#### 4.3. Spatial Correlation Analysis of China's Provincial Ecological Efficiency

##### 4.3.1. Global Spatial Autocorrelation Analysis

Using Stata 17.0 software, the global Moran's I index was calculated based on the adjacency spatial weight matrix for the time-series data of China's 31 provinces from 2005 to 2021 to reveal the spatial clustering pattern of ecological efficiency indices. The results are presented in Table 4. From 2005 to 2018, the global Moran's I index remained below 0.05, and the Z-values were generally greater than the critical value of 1.96, indicating significant spatial autocorrelation of ecological efficiency indices among China's provinces. Further observation showed that Moran's I index for the period 2005–2018 was consistently positive, indicating a positive spatial autocorrelation of provincial ecological efficiency during this period. For the years 2019–2021, the P-value for provincial ecological efficiency was 0.073, passing the 1% significance test. However, the Z-value was greater than the critical value of  $-1.65$ , indicating that Moran's I index did not pass the test and the existence of spatial autocorrelation cannot be confirmed.

**Table 4.** Global Moran's I index of interprovincial ecological efficiency in China from 2005 to 2021.

| Year | Moran's I | p Value | Z Value |
|------|-----------|---------|---------|
| 2005 | 0.326     | 3.250   | 0.001   |
| 2006 | 0.298     | 2.994   | 0.001   |
| 2007 | 0.242     | 2.492   | 0.006   |
| 2008 | 0.294     | 2.952   | 0.002   |
| 2009 | 0.326     | 3.242   | 0.001   |
| 2010 | 0.401     | 3.930   | 0.000   |
| 2011 | 0.384     | 3.777   | 0.000   |
| 2012 | 0.332     | 3.315   | 0.000   |
| 2013 | 0.286     | 2.912   | 0.002   |
| 2014 | 0.360     | 3.572   | 0.000   |
| 2015 | 0.314     | 3.169   | 0.001   |
| 2016 | 0.245     | 2.540   | 0.006   |
| 2017 | 0.211     | 2.253   | 0.012   |
| 2018 | 0.173     | 1.896   | 0.029   |

Table 4. Cont.

| Year | Moran's I | <i>p</i> Value | Z Value |
|------|-----------|----------------|---------|
| 2019 | 0.104     | 1.256          | 0.105   |
| 2020 | 0.054     | 0.814          | 0.208   |
| 2021 | 0.061     | 0.879          | 0.190   |

From Table 4, it can be observed that, from 2005 to 2018, the global Moran's I index declined from 0.326 to 0.173, showing an overall decreasing trend, and the spatial clustering pattern evolved from aggregation to dispersion. Analyzing the changes in interprovincial ecological efficiency indices since 2005, the indices first increased to 0.401 in 2010 and then decreased to 0.173 in 2018, exhibiting an overall trend of initially increasing and subsequently decreasing, reflecting fluctuations in spatial clustering and dispersion during the entire study period. The peak value of Moran's I index was observed in 2010 at 0.401, indicating the most pronounced spatial dispersion, and it declined to 0.257 in 2021, suggesting a weakening of spatial dispersion effects.

#### 4.3.2. Local Spatial Autocorrelation Analysis

Continuing with the analysis, we conducted a local spatial autocorrelation analysis of China's provincial ecological efficiency, as shown in Figure 4. Based on the Z-values, *p*-values, and Moran's I indices presented in the table, we gained further insights into the spatial relationships and influencing factors among different provinces' ecological efficiency.

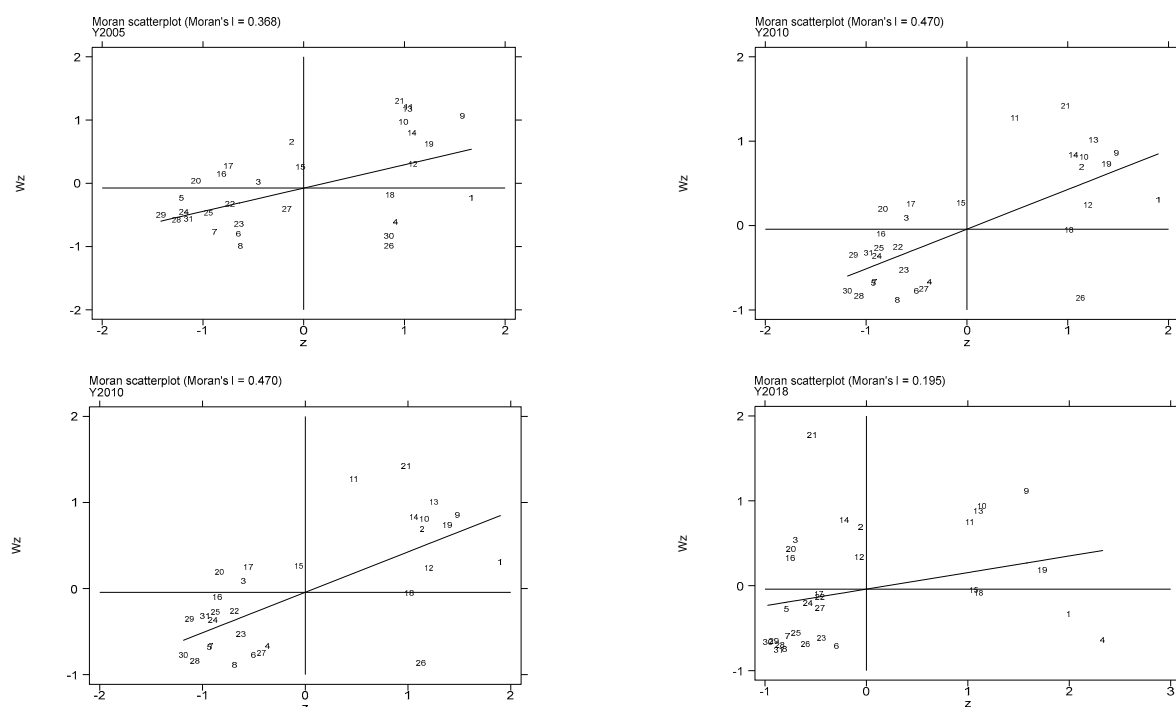


Figure 4. Local spatial autocorrelation map of China's provincial ecological efficiency.

In the years 2005, 2010, 2015, and 2018, provinces such as Beijing, Shanghai, Jiangsu, Zhejiang, Fujian, and Guangdong exhibited significant positive spatial autocorrelation (*p*-value < 0.05) in their ecological efficiency. This indicates that the ecological efficiency of these provinces is similar and significantly clustered with neighboring provinces. This clustering can be attributed to their higher levels of economic development, resource utilization efficiency, and substantial investments and efficient management in ecological protection. In contrast, in 2018, Xinjiang and Tibet showed significant negative spatial

autocorrelation ( $p$ -value < 0.05) in ecological efficiency, indicating that their ecological efficiency contrasts significantly and is clustered with neighboring provinces. This can be attributed to their unique geographical environment, resource allocation, and economic structure. Over the years, provinces such as Hebei, Shandong, Hubei, Hunan, and Guangxi had Moran's  $I$  indices close to 0, indicating a random spatial distribution of ecological efficiency. This implies the absence of significant spatial autocorrelation and is related to their economic structure, resource allocation, and policy implementations, requiring further research into the factors influencing their ecological efficiency.

By comparing data from different years, we observed changes in the spatial autocorrelation of certain provinces over time. For example, Inner Mongolia exhibited significant positive spatial autocorrelation in 2005 and 2010 but not in 2015 and 2018. This reflects the varying impacts of economic development and ecological protection policies during different periods. Changes in spatial autocorrelation for provinces like Inner Mongolia result from a combination of factors, including shifts in economic structure, resource development and environmental policies, technological advancements, and industrial upgrading. As time progresses, changes in economic development, resource utilization, and environmental policies in the regions may alter the spatial distribution patterns of ecological efficiency.

In conclusion, the spatial distribution pattern of China's provincial ecological efficiency is influenced by various factors, including geographical backgrounds, economic characteristics, and policy measures. Coastal regions in the eastern part of China exhibit better ecological efficiency, owing to their economic prosperity and policy support. In contrast, western regions face ecological vulnerability and developmental pressures, necessitating more policies and technological support to improve ecological efficiency. To achieve ecological balance nationwide, differentiated ecological protection policies should be formulated based on regional characteristics and needs, fostering the sustained improvement of ecological efficiency among provinces.

## 5. Analysis of Factors Influencing China's Provincial Ecological Efficiency

As evident from the previous section, there exists significant variation in ecological efficiency levels among Chinese provinces, and numerous factors influence ecological efficiency. Building upon the work of scholars such as Tie Y.B (2022) [45], this study selects 30 specific indicators from six aspects: economic factors, input factors, pollution factors, efficiency factors, natural factors, and environmental governance (Table 5). In this section, we quantitatively identify the degree of influence of each driving factor on the spatial differentiation of ecological efficiency among Chinese provinces using the GeoDetector.

**Table 5.** Factors influencing China's interprovincial ecological efficiency.

| Factors   | Factor Abbreviation                                                                                                                             | Impact Indicators                                                                                                                                                                               |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Economic  | X1: Economic Level<br>X2: Economic Structure<br>X3: Urbanization Level<br>X4: Fiscal Revenue                                                    | Per Capita GDP<br>Proportion of Tertiary Industry<br>Urbanization Rate<br>General Public Budget Revenue                                                                                         |
| Input     | X5: Labor Input<br>X6: Capital Input<br>X7: Water Resource Input<br>X8: Electricity Input<br>X9: Agricultural Land Input<br>X10: Research Input | Number of Employed Persons<br>Total Social Fixed Asset Investment<br>Total Water Consumption<br>Electricity Consumption (Physical Quantity)<br>Effective Irrigated Area<br>Research Expenditure |
| Pollution | X11: Wastewater Emissions<br>X12: Gas Emissions<br>X13: Solid Waste Emissions<br>X14: Industrial Pollution Intensity                            | Chemical Oxygen Demand (COD) Emissions in Wastewater<br>Sulfur Dioxide Emissions in Gas<br>Hazardous Waste Generation<br>Industrial Wastewater Emissions                                        |

Table 5. Cont.

| Factors                  | Factor Abbreviation                                | Impact Indicators                                      |
|--------------------------|----------------------------------------------------|--------------------------------------------------------|
| Efficiency               | X15: Economic Cleanliness                          | Water Use Efficiency per 10,000 GDP                    |
|                          | X16: Industrial Water Use Efficiency               | Water Use Efficiency per 10,000 Industrial Added Value |
|                          | X17: Agricultural Water Use Efficiency             | Water Use Efficiency per Unit of Cultivated Land       |
|                          | X18: Residential Water Use Efficiency              | Per Capita Domestic Water Consumption                  |
| Natural                  | X19: Natural Precipitation                         | Annual Average Precipitation                           |
|                          | X20: Abundance of Water Resources                  | Per Capita Water Resources                             |
|                          | X21: Source of Water Resources                     | Surface Water Supply Volume                            |
|                          | X22: Water Resources Stress                        | Water Resources Development and Utilization Rate       |
|                          | X23: Forest Coverage                               | Forest Coverage Rate                                   |
| Environmental Governance | X24: Water Supply Facility Construction            | Water Supply Coverage Rate (County-level)              |
|                          | X25: Urban Greening Level                          | Green Coverage Rate in Built-up Areas (Urban District) |
|                          | X26: Ecological Environmental Protection Intensity | Proportion of Nature Reserve Areas                     |
|                          | X27: Ecological Environmental Governance Intensity | Per Capita Environmental Water Use                     |
|                          | X28: Industrial Pollution Governance Intensity     | Industrial Pollution Control Investment                |
|                          | X29: Wastewater Treatment Rate                     | Wastewater Treatment Rate                              |
|                          | X30: Wastewater Treatment Capacity                 | Wastewater Treatment Capacity                          |

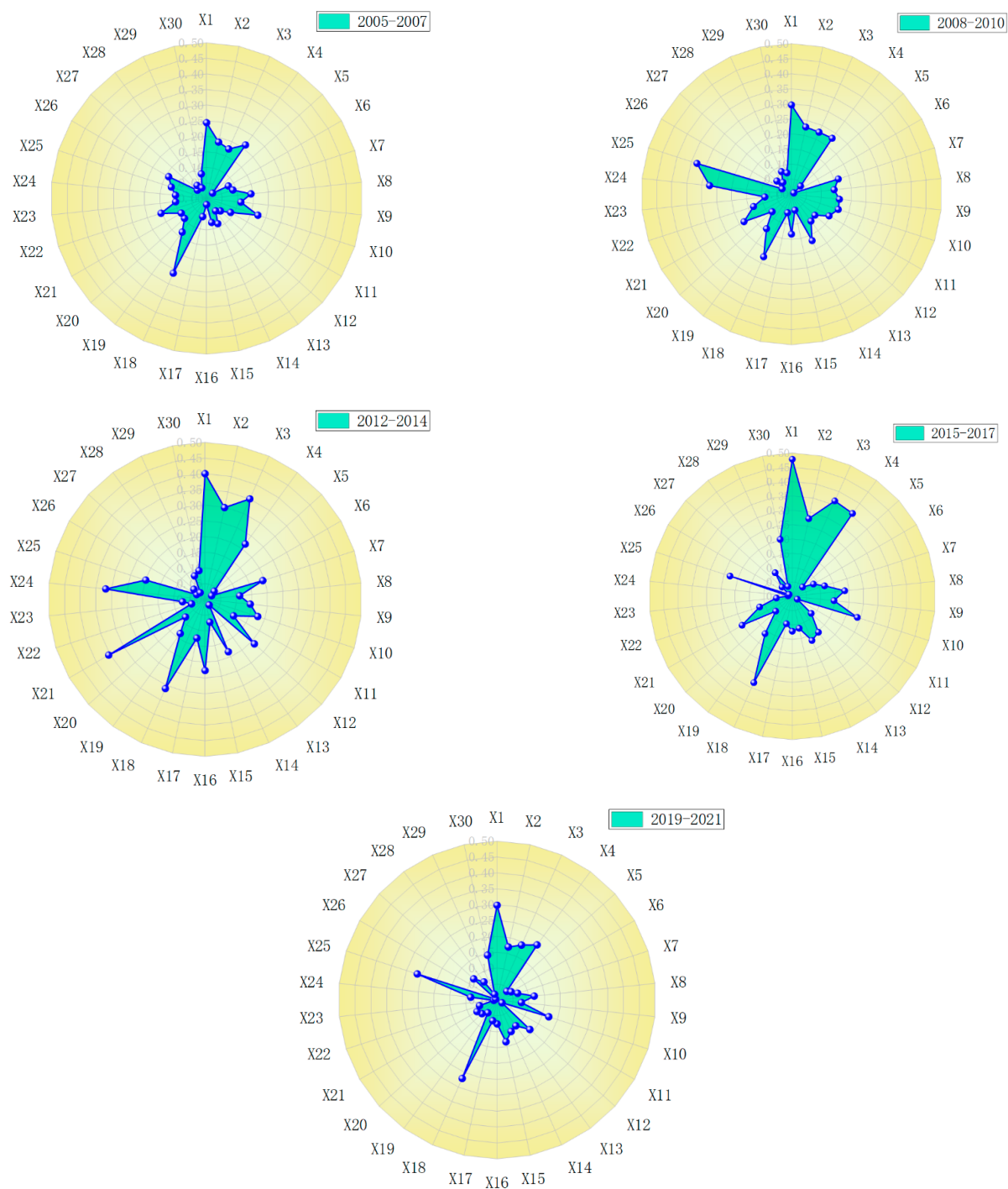
To mitigate the potential for random errors in a single year, the study period is divided into five data groups: 2005–2007, 2008–2010, 2012–2014, 2015–2017, and 2019–2021. Initially, a natural break method in ArcGIS10.7 software is employed to classify the indicators within each data group. Subsequently, in conjunction with the ecological efficiency indices of different provinces, the Geodetector’s factor detection component calculates the driving strength (q-value) of each indicator. The results are presented in Figure 5.

The ecological efficiency of different provinces in China is influenced by various factors. Table 6 presents the changes in driving intensity and ranking of different influencing factors on ecological efficiency from 2005 to 2021. Overall, during 2019–2021, economic factors exhibited the strongest impact on interprovincial ecological efficiency, followed by efficiency factors (0.137), environmental governance factors (0.098), pollution factors (0.091), input factors (0.088), and natural factors (0.051). Since 2005, efficiency factors have shown the largest increase in driving intensity, rising from 0.072 to 0.137 and advancing from the sixth to the second rank. Analyzing the data in the table, economic factors consistently remained the primary driver of interprovincial ecological efficiency, while efficiency factors, environmental governance, and pollution factors also exerted varying degrees of influence on ecological efficiency.

Table 6. Driving intensity and ranking of factors influencing China’s ecological efficiency from 2005 to 2021.

| Factors                  | 2005–2007 |   | 2008–2010 |   | 2012–2014 |   | 2015–2017 |   | 2019–2021 |   |
|--------------------------|-----------|---|-----------|---|-----------|---|-----------|---|-----------|---|
|                          | D         | R | D         | R | D         | R | D         | R | D         | R |
| Economic Factors         | 0.204     | 1 | 0.245     | 1 | 0.317     | 1 | 0.262     | 1 | 0.218     | 1 |
| Efficiency Factors       | 0.105     | 3 | 0.119     | 5 | 0.184     | 2 | 0.178     | 2 | 0.137     | 2 |
| Environmental Governance | 0.081     | 5 | 0.130     | 3 | 0.114     | 6 | 0.090     | 6 | 0.098     | 3 |
| Pollution Factors        | 0.072     | 6 | 0.132     | 2 | 0.130     | 4 | 0.132     | 4 | 0.091     | 4 |
| Input Factors            | 0.104     | 4 | 0.113     | 6 | 0.115     | 5 | 0.132     | 3 | 0.088     | 5 |
| Natural Factors          | 0.115     | 2 | 0.127     | 4 | 0.138     | 3 | 0.094     | 5 | 0.051     | 6 |

Note: D in the table is the driving intensity and R is the ranking.



**Figure 5.** Driving intensity of influencing factors on provincial ecological efficiency in China.

Firstly, economic factors consistently ranked first in driving intensity throughout the study period, highlighting their dominant influence on ecological efficiency. Factors such as per capita GDP and economic structure continuously improved, driving rapid economic growth, but also posing challenges in terms of excessive resource exploitation and increased environmental pressures. Although the driving intensity of economic factors on ecological efficiency declined from 2019 to 2021, sustained economic development still poses challenges to the ecological environment.

Secondly, efficiency factors maintained relatively stable rankings across different time periods but exhibited an overall increase in driving intensity. The continuous improvement in economic cleanliness, industrial water use efficiency, agricultural water use efficiency, and residential water use efficiency reflects China's achievements in resource utilization efficiency and environmental protection. Government efforts to promote energy conservation, emission reduction, and efficient resource utilization have laid the foundation for the continuous improvement of ecological efficiency.

Thirdly, environmental governance factors showed significant fluctuations in rankings over different time periods, with both driving intensity and rankings rising rapidly. Despite increased government investment in environmental governance, including infrastructure development and pollution control efforts, improving the ecological environment still requires time and collective efforts from society.

Fourthly, pollution factors consistently had relatively high driving intensity and stable rankings over each time period. Waste water emissions, air emissions, solid waste emissions, and industrial pollution levels negatively affected the ecological environment, highlighting the significant challenge of pollution control in improving ecological efficiency.

Fifthly, input factors exhibited relatively minor influence on ecological efficiency, with minimal changes in overall driving intensity. While labor input, capital input, water resources input, electricity input, and agricultural land input played a role in promoting economic development, their impact was relatively weaker compared to economic conditions and efficiency factors.

Finally, natural factors had a limited impact on ecological efficiency, with consistently lower rankings and relatively smaller driving intensity over each time period. Factors such as natural precipitation, water resource abundance, water resource sources, water resource scarcity, and forest coverage had limited influence on ecological efficiency, potentially influenced by climate change, human activities, and natural disasters.

In conclusion, China's interprovincial ecological efficiency is influenced by a variety of factors, with economic factors and efficiency factors playing dominant roles at different time periods. However, environmental governance and pollution control remain key challenges in improving ecological efficiency, requiring comprehensive policy measures and collective efforts from society. Going forward, China should continue to promote green development and ecological civilization construction to enhance ecological efficiency and achieve a win-win situation of economic growth and environmental protection.

In this paper, we investigate the influencing factors of provincial ecological efficiency in China using the Super-Efficiency Data Envelopment Analysis (DEA) SBM model. The study spans the period from 2005 to 2021 and explores the spatial and temporal variations of ecological efficiency among 31 provinces. We select 30 specific indicators from six dimensions, namely, economic factors, efficiency factors, environmental governance, pollution factors, input factors, and natural factors, to quantify the impact of these factors on the spatial differentiation of provincial ecological efficiency.

The research reveals that economic factors play a dominant role in affecting provincial ecological efficiency. Among these factors, per capita GDP and economic structure are the most significant indicators influencing ecological efficiency. While the advancement of economic development can lead to excessive resource exploitation and increased environmental pressure, optimizing the economic structure may contribute to reduced resource consumption and pollution. Additionally, efficiency factors have been gradually strengthening in recent years, particularly with improvements in economic cleanliness and industrial water use efficiency, which positively impact ecological efficiency. These findings suggest that China has made some progress in resource utilization efficiency and environmental protection; however, efforts to promote energy conservation, emissions reduction, and green development need to be further intensified.

The impact of pollution factors on ecological efficiency is complex. Factors such as wastewater emissions and air emissions have substantial negative effects on ecological efficiency, highlighting the urgent need to enhance wastewater treatment and air pollution

control. Meanwhile, environmental governance factors show certain improvements in ecological efficiency during specific time periods, but their influence is relatively limited in other periods. This emphasizes the requirement for sustained and comprehensive investment in environmental governance.

Natural factors demonstrate a relatively weaker impact on ecological efficiency, with natural precipitation and abundance of water resources showing lower driving effects. Although their influence is relatively limited in provincial ecological efficiency, it is crucial to consider the effects of climate change and natural disasters on ecological efficiency. In terms of input factors, labor and capital inputs demonstrate relatively lower driving effects on ecological efficiency. Therefore, in the investment process, greater consideration should be given to ecological environmental protection and sustainable development factors.

To promote sustainable development and ecological civilization, the government and society should comprehensively consider the interactions between these factors and strengthen efforts in ecological environment protection and governance. In future development, emphasis should be placed on improving resource utilization efficiency, optimizing industrial structures, strengthening environmental protection and pollution control, and proactively addressing challenges posed by climate change and natural disasters. These measures will contribute to the continued improvement of provincial ecological efficiency and advance comprehensive sustainable development in China.

## 6. Main Conclusions and Outlook

### 6.1. Conclusions and Recommendations

This study utilized the super-efficiency SBM model to calculate the ecological efficiency index of 31 Chinese provinces from 2005 to 2021. The analysis further investigated the variations in ecological efficiency among different years and provinces. By examining the driving forces of 30 influencing factors, the study explored the determinants of ecological efficiency in these provinces during the same period. The findings revealed an overall fluctuating downward trend in China's ecological efficiency since 2005. The rapid economic growth phase led to increased resource consumption and environmental pressure, resulting in a decline in the ecological efficiency index. However, from 2011 to 2019, influenced by government environmental policies and technological advancements, China's ecological efficiency index showed an upward trend. In 2020 and 2021, the index experienced a slight decline due to factors such as the COVID-19 pandemic.

Further analysis of the evolution of ecological efficiency across the 31 Chinese provinces revealed significant disparities. Economically developed regions such as Beijing, Shanghai, Jiangsu, and Guangdong consistently demonstrated higher ecological efficiency indices, while some economically less developed regions exhibited lower ecological efficiency. The variations in ecological efficiency among different provinces were influenced by various factors, including environmental awareness, economic development models, environmental investment, and technological levels.

Moreover, through global spatial autocorrelation analysis and local spatial autocorrelation analysis, the study discovered significant spatial clustering patterns in China's interprovincial ecological efficiency. Economically developed regions and western regions exhibited evident spatial autocorrelation in ecological efficiency, while some central regions displayed a random spatial distribution of ecological efficiency. Additionally, temporal changes in spatial autocorrelation were observed in certain regions, showing different trends during different periods.

In conclusion, economic factors play a dominant role in China's interprovincial ecological efficiency, while the influence of efficiency factors is gradually increasing. Environmental governance and pollution control remain crucial challenges for improving ecological efficiency. The impact of natural factors on ecological efficiency is relatively weak and the role of input factors is relatively limited.

Overall, to promote sustained improvements in China's ecological efficiency, the government and various stakeholders should comprehensively consider multiple factors,

including economic development, environmental policies, resource utilization efficiency, pollution control, and natural factors. It is essential to enhance efforts in ecological environment protection and governance, and to foster green and sustainable development. Additionally, tailored environmental policies should be formulated based on the unique characteristics and needs of different regions to promote ecological efficiency enhancement in each province. Only through comprehensive advancement in ecological civilization can we achieve a win–win situation between economic growth and environmental protection, ensuring ecological balance nationwide and promoting China’s sustainable development.

## 6.2. Limitations and Prospects

Although this study has yielded significant findings, there are also certain limitations that must be acknowledged. Firstly, this study predominantly focuses on the spatiotemporal dynamics of ecological efficiency among Chinese provinces. However, the intricate and complex interactions among various factors influencing ecological efficiency might not have been fully captured within the scope of this research. Secondly, while the comprehensive model used in this study provides a holistic assessment framework, there is room for improvement in terms of the components of the model and the factors analyzed using GeoDetectors. These improvements are essential for a better reflection of the intricacies of ecological interactions.

Looking ahead, within the dynamic context of Chinese provincial dynamics, the field of ecological efficiency holds numerous promising avenues for future research. One direction involves delving deeper into potential qualitative factors such as policy analysis, institutional factors, and local governance practices, which underpin the observed quantitative trends. Additionally, exploring emerging technologies, shifts in consumer behaviors, and market dynamics for their potential impacts on ecological efficiency could introduce new dimensions to the research domain. Furthermore, integrating remote sensing data, machine learning techniques, and advanced spatial analysis methods can provide a more detailed understanding of the spatial patterns and driving factors behind ecological efficiency.

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