Analysis of Spatial Differences and the Influencing Factors in Eco-Efficiency of Urban Agglomerations in China

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Abstract: In the context of climate change, studying the ecological efficiency (EE) of urban agglomerations is of great significance in promoting sustainable development. First, night light data are used as the expected output to build an evaluation index system based on the five major urban agglomerations, namely, the Yangtze River Delta, Pearl River Delta, Beijing–Tianjin–Hebei, the middle reaches of the Yangtze River, and Chengdu–Chongqing urban agglomerations. Second, the super-efficient Epsilon-based (super-EBM) model and the input–output redundancy rates are used to measure the EE of the five major urban agglomerations from 2006 to 2018. Then, their spatial differences are explored with the help of the Gini coefficient. Finally, the spatial differences in the EE drivers of urban agglomerations are analyzed using Geodetector. The results reveal the following. (1) The EE of the five major urban agglomerations present the decline fluctuation trend of “∧”. However, this trend has slowed down. From the perspective of urban agglomeration, Beijing–Tianjin–Hebei > The Pearl River Delta > Chengdu–Chongqing > Yangtze River Delta > the middle reaches of the Yangtze River. The lowest efficiency of the Yangtze River’s middle reaches has “high investment, low output, and high pollution” characteristics. (2) The EE of the five major urban agglomerations had weak synergistic development and noticeable spatial differences. The primary sources are inter-group differences and hypervariable density. (3) From the perspective of influencing, the difference in technological innovation levels (TEC) is the single leading factor in the differences in the EE space of urban agglomerations. In addition, the interaction combination of industrial structure upgrades (IDS) and traffic infrastructure (TRAF) is a crucial combination driver. However, the core influencing factors of spatial differences in EE in five urban agglomerations are heterogeneous. Among them, the nature-influencing factors of the EE space differences in the Beijing–Tianjin–Hebei and the Chengdu–Chongqing urban agglomerations are environmental regulations (ER). Meanwhile, the influencing factor in the Yangtze River Delta urban agglomeration is the development of urbanization (URB). Moreover, the prominent factor in the middle reaches of the Yangtze River and the Pearl River Delta urban agglomerations is foreign direct investment (FDI). On this basis, this study aims to promote ecological civilization construction in urban agglomerations and optimize regional integrated spatial patterns.

Keywords: urban agglomerations; EE; super-efficient EBM; night-time light data; input-output analysis; Gini coefficient; Geodetector

1. Introduction

According to the report by the Intergovernmental Panel on Climate Change (IPCC), the global surface temperature from 2001 to 2020 was 0.99 °C higher than that in 1850–1900, while the global surface temperature from 2011 to 2020 was 1.09 °C higher than that in 1850–1900 [1]. The United Nations Office for Disaster Risk Reduction released the “Cost of the Disaster 2000–2019” report in October 2020, stating that the occurrences of global climate disasters in the first 20 years of the 21st century have risen rapidly [2]. Human economic activities have seriously affected climate change [3]. Global climate change is one of the significant challenges facing human survival and development in the 21st
As such, actively coping with climate change and promoting sustainable green development has become the global consensus [6,7].

Ecological efficiency (EE) is a production process that yields larger economic outputs with smaller resource inputs and smaller environmental pollution outputs from economic development; hence, it has become an important tool for analyzing sustainable economic development [8].

As the first echelon, the five major city clusters of the Beijing–Tianjin–Hebei, Yangtze River Delta, Pearl River Delta, Middle Yangtze River, and Chengdu–Chongqing urban agglomerations have collectively become an important carrier and engine of China’s regional economic development [9]. As of 2018, the total GDPs of the five major city groups reached 48.5 trillion, thus accounting for 53.7% of the country’s GDP. However, urban agglomeration has become increasingly conspicuous in national economic development due to non-collaborative development, high-intensity operations, unreasonable spatial organizations, lack of unified environmental protection and governance mechanisms, etc. Urban agglomeration has also become a “pollution group,” which not only affects the health of residents but also restricts the construction of national ecological civilization and high-quality development [10,11]. Furthermore, it harms the sustainable development of the environment. At the same time, as a facet of economic development, urban agglomerations should pay attention to the collaborative governance of the ecological environment. The EE of urban agglomerations must also be improved. Given the apparent spatial heterogeneity of regional natural conditions, resource endowment, and economic development level, the EE of different urban agglomerations often varies [12]. An in-depth exploration of the EE of China’s five major urban agglomerations calls for further comparison of the spatial differences in the EE of urban agglomerations and their influence mechanisms. Such exploration can provide a scientific basis and reference for decision-making to promote the comprehensive green development of urban agglomerations. In addition, as the second largest economy and manufacturing country in the world, China’s five major urban agglomerations are the economic engines of China and even Asia. Focusing on the spatial evolution characteristics and dynamic mechanisms of their EE can also provide experiences for the sustainable urban development of other countries, which has essential international demonstration significance.

1.1. Literature Review

EE was first proposed by Schaltegger and Sturm [13]. Then, it was further elaborated and promoted by the World Council for Sustainable Development and the Organization for Economic Development Cooperation. Research on EE is mainly conducted on the following aspects:

(1) Measurement of EE. The representative evaluation methods concerning EE are stochastic frontier analysis (SFA), data envelopment analysis (DEA), etc. [14–19]. However, in the SFA method, the estimation of EE is assumed to deviate [20]. Meanwhile, the DEA model has been gradually applied to the evaluation of EE in recent years because it does not need to assume the function form and is not affected by the index dimension (Table 1).

Table 1. EE evaluation literature. Data envelopment analysis (DEA), slacks-based measure (SBM).

| Reference                  | Sample                                            | Model                                      | Input                     | Desirable Output            | Undesirable Output                   |
|----------------------------|---------------------------------------------------|--------------------------------------------|---------------------------|-----------------------------|--------------------------------------|
| Fan et al. [21] (2017)     | 40 industrial parks in China (2012)               | Charnes–Cooper–Rhodes (CCR) and Banker–Charnes–Cooper (BCC) DEA models | Land, energy, and water   | Industrial value added      | Wastewater, solid waste, COD, and SO₂ |
| Rybczewska-Blazjowska and Gierulski [22] (2018) | 28 member states of the European Union (2015)    | Life cycle assessment (LCA) and BCC DEA model | Labor, capital, and energy | GDP                          | SO₂                                  |
### Table 1. Cont.

| Reference          | Sample                                      | Model                        | Input                                                                 | Desirable Output                           | Undesirable Output                      |
|--------------------|---------------------------------------------|------------------------------|----------------------------------------------------------------------|--------------------------------------------|------------------------------------------|
| Pan et al. [23] (2019) | 30 provinces and municipalities in China (2000–2016) | SBM model with undesirable outputs | Urban unit employment population, capital stock, and energy consumption | Real GDP                                   | Total CO₂ emission                      |
| Zheng et al. [24] (2019) | The EE of the 31 Chinese provinces (2000–2015) | The SBM model with undesirable outputs | Water footprint, labor force, capital, cost of resource and environment, and land consumption | GDP                                        | Gray water footprint and environmental pollutants |
| Ma et al. [25] (2019) | 285 prefecture level cities in China (2005–2016) | Super-SBM model with undesirable outputs | Capital stock, employment, water, and electricity consumption | GDP, green coverage, and public financial expenditure | Industrial wastewater discharge, PM₂.₅, SO₂, and unemployment rate |
| Wu et al. [26] (2020) | 31 cities in Yangtze River Delta (2000–2021) | BCC DEA models               | Total water consumption, area of built-up area, energy consumption, employment, and capital input | Actual regional output value               | Total discharge of industrial waste gas, waste water, and solid waste |
| Wang et al. [27] (2021) | 31 Chinese provinces (1997–2016) | The SBM model with undesirable outputs | Input: Labor, capital, water, and energy | Revenue from tourism                       | Tourism waste discharge, tourism SO₂, and tourism CO₂ |

At present, the DEA model is easily affected by the input–output variables. Furthermore, GDP has been adopted as the expected output in the existing literature. However, given the influence of factors such as inconsistent statistical caliber and conversion error, the authenticity and objectivity of GDP data are questioned [28]. In recent years, with the continuous progress of technology, a growing number of scholars have considered nighttime light data as a proxy variable to measure the level of economic development, which can effectively overcome the lack of statistical data and human factor interference and has certain spatial attribute characteristics [29]. Moreover, Elvidge et al. [30] explored the link between the nighttime light index and regional GDP and used data from American countries for empirical testing. They concluded the feasibility of estimating the GDP using nighttime light data. Some domestic scholars have also started to use nighttime lighting data to examine the economic development of urban clusters one after another. For instance, Chao et al. [31] explored the economic differences among three major urban clusters in the Yangtze River economic belt based on nighttime lighting data. Moreover, Liu et al. [32] used satellite lighting data as the expected output. They applied the Malmquist productivity index to measure Chinese provinces’ green total factor productivity under the DEA framework and empirically examined its regional disparities and influencing factors.

The most widely used method for measuring EE is the traditional DEA model, including radial CCR and BCC models and non-radial SBM models. However, the radial CCR and BCC models require that input and output variables be changed in the same proportion while the measurement of relaxation variables is ignored [33]. The SBM combines undesired outputs and considers the non-radial slack of the input and output. However, this problem makes up for the defects of the radial CCR and BCC models to a certain extent but also loses the radial ratio information of the input and output variable. Notably, this scenario may cause EE assessment errors [34]. Tone and Tsutsui [35] proposed that the EBM model is a hybrid distance function that contains both radial and non-radial features, which can effectively solve the inherent problems of radial and non-radial models and provide a new solution idea.

(2) Study on the spatial difference of EE. One method is to use the spatio-temporal distribution and dynamic evolution revealed by kernel density estimation and spatial Markov chain method [36,37]. The other method is to construct the Theil index and Gini coefficient to explore the spatial difference and its source [38,39]. The Theil index is unable to describe the dynamic distribution of subgroup samples, thus resulting in insufficient accuracy of spatial difference analysis [40]. The Gini coefficient is better able to deal with cross-over within the sample data sets and is effective in identifying...
the specific sources of regional differences [41]. It has been widely used in the field of measuring the spatial difference of EE [42].

(3) Promote the improvement of EE. Existing literature research shows that EE is affected by urbanization, economic development level, industrial structure, technological innovation, and economic agglomeration [43–45]. To explore the relationship between EE and influencing factors, most existing studies have used traditional regression statistics and spatial analysis methods, which are relatively weak in examining the interactions of multiple drivers. As an emerging statistical method for measuring and mining spatial heterogeneity, Geodetector has unique advantages in identifying the drivers behind spatio-temporal evolution and their interactive effects [46]. It is gradually being applied in studies of regional economy, ecological economy, and poverty issues [47–49].

The existing literature still has much room for expanding the research on the EE of urban agglomerations. First, most of the research is currently on single urban agglomeration, provincial, and prefecture-level cities. Researchers rarely conduct an in-depth analysis of the EE of the five major urban agglomerations. Second, previous studies have mostly used GDP statistical indicators to measure the desired output, which lack objectivity. Third, although DEA models and their extensions have been widely used in EE studies, the application of EBM models, which are compatible with radial and non-radial models, needs to be strengthened.

1.2. The Aim of the Study

This article is based on the research objects of the Yangtze River Delta, Pearl River Delta, Beijing–Tianjin–Hebei region, Chengdu–Chongqing, and the middle reaches of the Yangtze River. First, this study will introduce the night light data to replace the traditional GDP statistical data to measure the expected output, eliminate the error to the maximum extent, and provide a new idea and empirical evidence for studying the EE of urban agglomerations. Second, the super-EBM (epsilon-based measure) model based on undesired output, input–output redundancy rates, and Gini coefficient is used to measure the EE of urban agglomeration from 2006 to 2018 and analyze its spatial differences. Third, the influence factors are discussed using the Geodetector model. The acquisition of related research conclusions can provide the necessary reference and policy inspiration for the five major cities to reduce the differences in EE space and improve EE.

2. Data and Methodology

2.1. Methodology

2.1.1. Super-EBM Model

The EBM model was proposed by Tone and Tsutsui [35]. Although the EBM model overcomes the shortcomings of radial CCR, BCC models, and SBM models, the efficiency value of the EBM model measurement does not exceed 1. When many DMUs are present at the forefront of production, their advantages and disadvantages can be compared further. Based on Andersen and Petersen [50], the ordinary EBM model is improved to a super-EBM model, and the best efficiency value is greater than 1 through the over-efficiency EBM. When the efficiency value is more than 1, the EE of DMU is considered to be in an effective state. When it is less than 1, the EE is considered invalid. The specific formula refers to Li et al. [51].

2.1.2. The Dagum Gini Coefficient

The Dagum Gini coefficient was proposed by Dagum [41] and can be used to analyze the spatial differentiation degree of the EE of urban clusters from the perspective of subgroup decomposition. The problem of the spatial sources of variation and crossover between subsamples is effectively solved by the following formula:
where $G$ is the overall Gini coefficient; $\bar{y}$ is the mean of the overall EE; $n$ is the number of cities; $k$ is the number of all city groups; $y_{ji}(y_{hr})$ denotes the EE of any municipality within $j(h)$ city groups; $n_{ji}(n_{h})$ is the number of towns within $j(h)$ city groups. The Gini coefficient $G_{jj}$ for city group $j$ and the Gini coefficients $G_{jh}$ for city groups $j$ and $h$ are denoted as:

$$G_{jj} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{jr}|}{2n_j^2\bar{y}_j},$$

$$G_{jh} = \frac{\sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ji} - y_{hr}|}{n_jn_h(\bar{y}_j + \bar{y}_h)}$$

The Gini coefficient has three main components: the within-group divergence contribution ($G_{w}$), the between-group divergence contribution ($G_{nb}$), and the hypervariable density contribution ($G_{t}$). The sum of the three constitutes the overall Gini coefficient $G$: $G = G_{w} + G_{nb} + G_{t}$. The formula refers to the Dagum [41].

2.1.3. Geodetector Model

The Geodetector model for spatial differences is used to examine the single primary factor and dual-factor interaction of the EE spatial differences in urban agglomerations [46,52]. Among them, single factor detection mainly analyzes EE differences through quantification factors and examines the degree of influence.

The specific calculation formula is as follows:

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

In the above equation, $L$ denotes the stratification of factor $X$ or dependent variable $Y$; $h = 1, 2,..., L$. $N$ and $N_h$ denote the total number of samples and the sample size of the $h$th stratum, respectively. $\sigma^2$ and $\sigma^2_h$ denote the sample variance and the sample variance of the first stratum, respectively. $SSW$ and $SST$ denote the sum of the intra-stratum variance and the variance of all urban groups, respectively. Furthermore, $q$ has a value range of $[0, 1]$. The larger the $q$ value is, the more excellent the impact of this factor will be on the distribution of the EE of urban agglomerations, and the smaller it will be.

Interactive detection is the detection of two different factor combinations: for example, whether two different factors, $X_1$ and $X_2$, affecting the EE of an urban agglomeration act together to change the explanatory power of EE. The relationship between the two factors acting together can be divided into the following five categories: non-linear weakening, single-factor non-linear weakening, two-factor independent, dual-factor enhancement, and non-linear enhancement.

2.2. Data Source and Indicator Selection

2.2.1. Study Area and Data Sources

The national urban agglomeration includes the five major urban agglomerations of the Yangtze River Delta, the Pearl River Delta, the Beijing–Tianjin–Hebei region, the middle reaches of the Yangtze River, and Chengdu–Chongqing as the research object. Among them, the Beijing–Tianjin–Hebei urban agglomeration includes Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, and Hengshui, thus comprising 13 cities. The Yangtze River Delta urban agglomeration includes Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, Taizhou, Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhourshan, Taizhou, Hefei, Wuhu, Maanshan, Tongling, Anqing, Chuzhou, Chizhou, and Xuancheng, thus comprising 26 cities. Meanwhile, the Pearl River Delta includes
This article analyzes the panel data of 92 cities in the five major city agglomerations of the above five cities from 2006 to 2018. Information on nighttime lights was obtained from the night-time light data (DMSP/OLS and NPP/VIIRS) published by the National Oceanic and Atmospheric Administration (NOAA). The DMSP/OLS data from 2006 to 2013 and NPP/VIIRS data from 2013 to 2018 were selected on the basis of time series, and the nighttime light data were cropped according to the administrative boundaries. Projection conversion and image resampling of both data sources were carried out, and the original data of geographic coordinates, WGS84, were converted to Albers equal-area projection. At the same time, the resampling was set to a 1 km image element. The vector data of Chinese administrative regions were obtained from the national 1:4 million databases of the National Basic Geographic Information Center. The processing of NPP/VIIRS data is mainly to synthesize annual data, resample, and adopt the values of the maximum value according to Wu and Wang [53]. Finally, the regression analysis method is based on the two data sources (2013) to establish a regression relationship between DMSP/OLS and NPP/VIIRS data and to use the regression model to integrate the NPP/VIIRS data from 2014 to 2018. The comparison and time continuity of class data were also determined. In the end, the NPP/VIIRS annual night light data value was comparable to the stable NPP/VIIRS, relative to DMSP/OLS, and the average night light brightness range was 0–63. Other selected data were obtained from the China Urban Statistical Yearbook, China Urban Construction Statistical Yearbook, and China Statistical Yearbook from 2007 to 2019. For the
missing values of variables, interpolation was first conducted according to the statistical bulletin of each city. Next, interpolation was used to make up for the missing values.

2.2.2. Indicators of EE Evaluation

With respect to previous studies and the connotation of urban EE, an EE indicator system has been constructed [21,54–56]. The specific construction indicators are described as follows: ① Capital input is calculated by the perpetual inventory method, and the specific formula is as follows. \( K_{i,t} = (1 - \delta_{i,t})K_{i,t-1} + I_{i,t} \), where \( K_{i,t} \) is the capital stock of city i in year t. \( K_{i,0} \) is the capital stock of the base period, and the ratio of the deflated total social fixed asset investment \( I_{i,0} \) of city i in the base period to the total social fixed asset investment in year t is used as \( I_{i,t} \). We refer to Zhang et al. [57] and divide the deflated total social fixed asset investment of each city in 2005 by 10% as the initial capital stock and set the depreciation rate \( \delta_{i,t} \) to 9.6%. ② Labor input is selected as the city’s year-end unit employees (10,000 people). ③ Energy input uses the total city energy consumption (million kWh). ④ For water consumption, the total urban water consumption (million t) is used. ⑤ The expected output indicators, DMSP/OLS nighttime lighting data, are selected to measure the level of regional economic development as a proxy variable for desired output. ⑥ For non-desired output, industrial waste gas \( \text{SO}_2 \) (t), industrial soot (t), and industrial wastewater emissions (million t) from the three industrial waste streams are used (as shown in Table 2).

| Type                  | First-Level Indicator          | Variable Description                   |
|-----------------------|--------------------------------|----------------------------------------|
| Input index           | Capital                        | Total fixed assets investment          |
|                       | Labor                          | Unit employee                          |
|                       | Energy consumption             | Urban energy power consumption         |
|                       | Water consumption              | Total urban water consumption          |
| Expected Output index | Economic development           | DMSP/OLS Night Light data total amount |
|                       | Air Pollution                  | Industrial \( \text{SO}_2 \) emissions |
|                       | Water pollution                | Industrial smoke and dust emissions    |
| Non-expected Output index | Industrial wastewater       |                                        |

2.2.3. The Geodetector Model Indicators

The influencing factors of EE are attributed to the influence and disturbance from outside of the EE system. We can analyze the socioeconomic environment that is closely related to the EE system. The following eight representative indicators are selected as the interpretation variable to explore the driving factor of the differences between the EE space of the urban agglomerations.

1. Economic development (GDP). As the level of economic development increases, more favorable use of resources and technological development leads to less resource input required for the same output. Moreover, the EE is enhanced. Wang et al. [58] is used as reference and for the research setting of the average of night light data.

2. Technological innovation (TEC). The emergence of technological innovation products and the development of green innovation are conducive to promoting the transformation of human production and lifestyle as well as promoting the sustainable development of the ecological environment. Along with these factors, the number of invention patent applications is selected to characterize the level of technological innovation [59,60].

3. Foreign direct investment (FDI). The opening up to the outside world is conducive to promoting industrial development and the transformation of the human advantage into a technological edge. This study adopts the ratio of real FDI to GDP [61].

4. Industrial structure upgrading (IDS). Industrial structure upgrading can change the mode of economic development, promote the realization of intensive growth, and
further improve the utilization rate of resources. Thus, industrial structure upgrading is an essential factor affecting EE. Referring to Wu [62], the added value of the tertiary industry accounts for GDP, and the added value of the secondary industry accounts for GDP.

(5) Environmental regulation (ER). The government regulates enterprises’ production behavior, thus reducing the negative externalities of production behavior and achieving green development [63]. Industrial wastewater, industrial sulfur dioxide, and industrial smoke (dust) emissions are used to construct a comprehensive index of environmental pollution through the entropy weighting method, and its inverse is a measure of ecological regulation intensity [64].

(6) Economic agglomeration (EA). The scale effect caused by economic aggregation is conducive to reducing enterprise costs and improving infrastructure utilization. A higher level of cleanliness of the agglomeration industry leads to a greater promotion of EE. The ratio of the output value of the secondary and tertiary sectors to the area of urban construction land is used [65].

(7) Urbanization (URB). Urbanization is an important symbol of economic development. It can promote EE improvement through technological innovation, structural transformation, etc. The ratio of the built-up area to the municipal area is selected to measure urbanization [66].

(8) Infrastructure (TRAF). Infrastructure construction can ensure the efficient operation of other human activities through not only the scale effect but also complete economic activities with lower energy consumption; moreover, it can improve resource utilization, relieve the pressure of pollution on the environment, and ultimately promote EE [67]. Public transportation per 10,000 people is used for measurement.

To grasp the selected influencing factors indicators further, the variable data of the influencing factors are made more precise and intuitive, and the descriptive statistics of explaining variables and interpreting variables are studied. The descriptive statistics of the above indicators are shown in Table 3.

### Table 3. Statistical description of influencing factors.

| Variable | Obs | Mean | S.D | Min  | Max  |
|----------|-----|------|-----|------|------|
| EE       | 1196| 0.748| 0.593| 0.258| 18.849|
| GDP      | 1196| 14.501| 14.617| 1.030| 61.437|
| TEC      | 1196| 3.814| 9.072| 0.006| 95.527|
| FDI      | 1196| 0.388| 0.297| 0.003| 1.724|
| IDS      | 1196| 0.831| 0.412| 0.313| 4.347|
| ER       | 1196| 0.028| 0.080| 0.003| 2.778|
| EA       | 1196| 4150.788| 8393.116| 83.178| 109.451|
| URB      | 1196| 0.5431| 0.174| 0.031| 0.998|
| TRAF     | 1196| 8.900| 9.750| 0.320| 110.52|

### 3. Results

#### 3.1. EE Calculation

Using the super-EBM model, the Max DEA 8.0 software calculated the 13-year EE of 92 cities in the five major urban agglomerations. The result is shown in Table 4. Given the space restrictions, only the average values of each city’s EE from 2006–2018 are obtained.

According to the average EE of various cities from 2006 to 2018, as revealed in the existing research [68,69], all cities are divided into four levels. The first category, or Class I (EE > 1), represents cities with the highest EE, and their input and output are in a valid state. Class II (0.9 < EE < 1) has high EE but is still in an invalid state. Class III (0.5 < EE < 0.9) belongs to the medium level. Class IV (EE < 0.5) indicates that the urban EE is low.
Table 4. Average value of EE in each city in 2006–2018.

| Region          | City         | EE  | Region          | City         | EE  |
|-----------------|--------------|-----|-----------------|--------------|-----|
| Yangtze River   | Shanghai     | 0.660 | Zhaoqing       | 0.911        |     |
|                 | Nanjing      | 0.410 | Huizhou        | 1.050        |     |
|                 | Wuxi         | 0.497 | Dongguan       | 0.780        |     |
|                 | Changzhou    | 0.519 | Zhongshan      | 0.731        |     |
|                 | Suzhou 1.033 |     | Beijing 1.060  |              |     |
|                 | Nanjing 0.711 |      | Tianjin 1.020  |              |     |
|                 | Yangzhou 0.783 |   | Shijiazhuang 0.510 |          |     |
|                 | Yangzhou 0.694 | | Tangshan 0.954 |              |     |
|                 | Zhenjiang 0.617 |      | Qinhuangdao 0.666 |         |     |
|                 | Taizhou 0.762 |      | Handan 0.690   |              |     |
|                 | Hangzhou 0.554 |     | Beijing–Tianjin–Hebei |     |     |
|                 | Ningbo 0.725 |      | Xingtai 0.795  |              |     |
|                 | Jiaxing 0.659 |      | Baoding 1.020  |              |     |
|                 | Huzhou 0.694 |      | Zhangjiakou 0.846 |           |     |
|                 | Shaoxing 0.528 |    | Chengde 0.824  |              |     |
|                 | Jinhua 0.830 |      | Cangzhou 1.060 |              |     |
|                 | Zhoushan 0.846 |      | Langfang 1.025 |              |     |
|                 | Taizhou 0.855 |      | Hengshui 0.974 |              |     |
|                 | Hefei 0.603 |      | Wuhan 0.414    | Mianyang 0.576 |     |
|                 | Wuhu 0.570 |      | Huangshi 0.470 | Meshan 0.607 |     |
|                 | Maanshan 0.550 |   | Ezhou 0.841    | Ziyang 1.212 |     |
|                 | Tongling 0.533 |    | Huanggang 1.062 | Suijing 1.129 |     |
|                 | Anqing 0.611 |      | Xuanqian 0.751 |leshan 0.496 |     |
|                 | Chuzhou 1.047 |      | Xiaming 0.874  | Chengdu–Chongqing |     |
|                  |              |      | Middle Reaches of the Yangtze River |     |     |
|                  | Chuzhou 1.107 |      | Xiangyang 0.487 | Zipeng 0.948 |     |
|                  | Xuanxian 1.001 |     | Yichang 0.438  | Luzhou 0.479 |     |
|                  |              |      | Jingzhou 0.616  | Neijiang 0.675 |     |
|                  | Guangzhou 1.004 |    | Jingmen 0.504  | Nanchang 0.994 |     |
|                  | Shenzhen 1.150 |      | Changsha 0.741 | Yibin 0.392 |     |
|                  | Zhuhai 0.549 |      | Zhuzhou 0.399  | Dazhou 0.601 |     |
|                  | Foshan 0.627 |      | Xiangtan 0.384 | Guang’an 0.943 |     |
|                  | Jiangmen 1.030 |     | Yueyang 0.428  |                |     |
| Pearl River Delta | Guangzhou 0.711 |     | Beijing–Tianjin–Hebei | 0.880 | Chengdu–Chongqing | 0.794 |
|                  | Shenzhen 0.870 |      | Middle Reaches of the Yangtze River | 0.606 |                | 0.775 |
|                  | Zhuhai 0.870 |      | Overall average |                |     |

As shown in Table 4, the average EE of only 23 cities is more significant than 0.9, thus accounting for 25%. These cities are Suzhou, Luzhou, Chizhou, and Xuanxheng of the Yangtze River Delta; Ziyang, Suijing, Ya’an, Zigong, Nanchong, and Guang’an of the Chengdu–Chongqing urban agglomeration; Guangzhou, Shenzhen, Jiangmen, Zhaoqing, and Huizhou in the Pearl River Delta; Huanggang and Yingtian of the middle reaches of the Yangtze River; and Beijing, Tianjin, Baoding, Cangzhou, Langfang, and Hengshui of Beijing–Tianjin–Hebei. Among them, 18 cities have the highest efficiency. The number of towns with medium efficiency is 52, thus accounting for 56.5% of the total. They belong to the Yangtze River Delta, Chengdu–Chongqing, middle reaches of the Yangtze River, and Beijing–Tianjin–Hebei urban groups. Meanwhile, 16 cities have low efficiency, thus accounting for 17.4% of the total. All are distributed in the middle reaches of the Yangtze River. Overall, the EE of the five major city agglomerations from 2006 to 2018 is 0.775, which is a medium-efficiency level. The Pearl River Delta, Beijing–Tianjin–Hebei, and Chengdu–Chongqing urban groups have a higher EE value than the Yangtze River Delta and extended main city groups.

3.2. Time and Space Characteristics of EE of Urban Agglomerations

From 2006 to 2018, the fluctuation trend of the five major urban agglomerations is similar to the overall trend, thus presenting a decline fluctuation trend of “∧”. However, the decline fluctuation trend has slowed down (as shown in Figure 2). In particular, the “11th Five-Year Plan” and the “12th Five-Year Plan” have played a good role, and the EE of city agglomerations has improved. Moreover, the EE of the five major city agglomerations during the “12th Five-Year Plan” period is significantly higher than that during the “11th Five-Year Plan” period. Along with the improvement of awareness for resource conservation, the gradual restoration of ecology, and the economic development, the EE has been elevated. However, the EE of the five major city agglomerations was
significantly degraded in 2013 mainly because the economic development entered a new normal state in 2012 and the economic development rate slowed down. To stabilize the economic growth, the agglomerations accelerated the layout of the three industrial projects of high pollution, high energy consumption, and high emission, which in turn led to a decline in the EE of the city agglomerations. With the 19th National Congress of the Communist Party of China held and the high-quality development put forward in 2017, the governments at all levels began to attach importance to the protection of the ecological environment and promote the improvement of resource utilization rate under the influence of the construction of ecological civilization. Hence, the decline fluctuation trend has slowed down.

Figure 2. The trend of EE changes in the five major urban agglomerations from 2006 to 2018.

To understand the differences in EE among city agglomerations better, according to the calculation of input–output redundancy rates in the thesis of Meng et al. [70], the input–output redundancy rates of the five major cities aggregations in 2006 and 2018 were obtained (as shown in Table 5). The overall EE of the Beijing–Tianjin–Hebei and Pearl River Delta city agglomerations was better than that of the Chengdu–Chongqing, Yangtze River Delta, and the middle reaches of the Yangtze River city agglomerations. The Pearl River Delta city agglomeration had clusters of elements, developed foreign trade, advanced green production system, industrial transformation and upgrading, and innovation capabilities. Thus, their EE was ahead of that of the city agglomerations of Chengdu–Chongqing, Yangtze River Delta, and the middle reaches of the Yangtze River. The efficiency value of the Pearl River Delta presented a fluctuating decline trend, decreasing from 0.868 in 2006 to 0.800 in 2018, and the number of cities with an efficiency value below 1 increased from three to four. The reason was that some heavy chemical areas in Dongguan, Foshan, Zhongshan, and Zhuhai had high pollution emissions under the redundancy of capital, energy, and water consumption. In 2018, the redundancy degree of energy input and unexpected emissions of the Pearl River Delta city agglomeration increased by 5 percent and 10.8 percent, respectively, compared with that of 2006. Furthermore, the problems of excessive energy consumption and excessive sewage discharge were more prominent. Improving the energy utilization efficiency, reducing the pollution emissions, and further improving the utilization efficiency of capital are pivotal for improving the EE development in the Pearl River Delta city agglomeration.

The EE of the Beijing–Tianjin–Hebei agglomeration was generally higher than that of the city agglomerations of Chengdu–Chongqing, Yangtze River Delta, and the middle reaches of the Yangtze River, which presented a declining trend in 2012 but surpassed the Pearl River Delta city agglomeration in 2015. The rapid recovery in efficiency in 2015 resulted from the situation in Beijing, Tianjin, Shijiazhuang, and other cities, which significantly reduced SO$_2$, smoke (dust), and wastewater emissions while reducing the capital, labor, and energy investment redundancy. In 2018, the Beijing–Tianjin–Hebei labor
force and energy redundancy increased. However, the GDP still had not risen, whereas the unexpected output redundancy had risen. Hence, the key to accelerating the improvement of the EE of Beijing–Tianjin–Hebei depended on intensifying energy conservation and emission reduction while promoting economic development.

Table 5. Relaxation rate of urban agglomeration in 2006 and 2018.

| Year | Region                  | Capital | Labor | Energy | Water | Economic | SO₂ | Smoke and Dust Emissions | Industrial Wastewater |
|------|-------------------------|---------|-------|--------|-------|----------|-----|--------------------------|------------------------|
| 2006 | Beijing–Tianjin–Hebei   | 5.10%   | 6.40% | 17.90% | 19.40%| 14.30%   | 26.30%| 22.00%                  | 9.20%                  |
|      | Yangtze River Delta     | 15.90%  | 12.60%| 30.30% | 36.40%| 4.40%    | 24.50%| 18.90%                  | 22.80%                 |
|      | Pearl River Delta       | 5.70%   | 12.10%| 21.30% | 26.00%| 18.60%   | 10.80%| 5.10%                   | 9.80%                  |
|      | Middle Reaches of the Yangtze River | 3.20% | 18.40%| 17.60% | 27.50%| 1.50%    | 27.30%| 20.40%                  | 20.60%                 |
|      | Chengdu–Chongqing       | 0.60%   | 10.50%| 10.70% | 16.60%| 1.60%    | 18.10%| 11.20%                  | 8.50%                  |
| 2018 | Beijing–Tianjin–Hebei   | 5.10%   | 6.60% | 18.20% | 19.30%| 12.20%   | 27.00%| 22.20%                  | 9.50%                  |
|      | Yangtze River Delta     | 14.60%  | 11.20%| 28.10% | 33.30%| 4.70%    | 23.60%| 18.30%                  | 22.60%                 |
|      | Pearl River Delta       | 5.50%   | 14.60%| 26.30% | 28.70%| 17.20%   | 12.50%| 10.60%                  | 13.40%                 |
|      | Middle Reaches of the Yangtze River | 2.20% | 17.40%| 16.10% | 25.40%| 1.50%    | 27.70%| 21.30%                  | 21.00%                 |
|      | Chengdu–Chongqing       | 0.40%   | 8.40% | 8.80%  | 13.50%| 1.50%    | 16.60%| 9.50%                   | 7.80%                  |

The EE of the middle reaches of the Yangtze River was the lowest among the five major city agglomerations. Moreover, a spatial development pattern of “central collapse” emerged. This result also further validated the research of Zhang and Dong [71] and Liu et al. [72]. Their relaxation rates of the unexpected indicators were higher than in other regions. The middle reaches of the Yangtze River coexisted with problems such as high input of factors, low output, and high pollution, which undertook a large number of pollution-intensive industries from the eastern region, thus increasing the burden of energy conservation, emission reduction, and environmental protection. Although the redundancy of capital, labor, land, and water inputs decreased in 2018 compared with 2006, the degree of relaxation of unexpected output increased, and the number of efficiency values in less than one city increased from 22 to 26. Besides energy conservation and emission reduction, improving capital utilization efficiency and strengthening innovation were also the focus of efficiency improvement in the middle reaches of the Yangtze River.

The EE of the Chengdu–Chongqing city agglomeration was higher than that of the Yangtze River Delta and the middle reaches of the Yangtze River agglomerations. Although they were located in the western region and the economic foundation was relatively weak, the government increased its investment in environmental governance with the support of the development strategy from the west, the “Belt and Road” initiative, and other policies in the new era. The efficiency was raised to 0.786 in 2018 due to the slowdown in factor investing and strengthening pollution control in Chongqing. In 2006, the index relaxation degree of the Chengdu–Chongqing city agglomeration was lower than that of the Yangtze River Delta and the middle reaches of the Yangtze River city agglomerations. By 2018, the input, expected output, and unexpected output index redundancy degrees of the Chengdu–Chongqing city agglomeration were reduced by 7.3%, 0.1%, and 3.9%, respectively. Although the problems of energy consumption and pollution had been alleviated, the issues of economics were still badly in need of improvement. These characteristics are different from the characteristics of “low input, high output, and low pollution” presented by the optimal efficiency unit of the Pearl River Delta city agglomeration. The Chengdu–Chongqing city agglomeration mainly showed the characteristics of “low input, low output, and low pollution,” which were manifested in the coordination of input and output at a low economic growth level.

Although the EE value of the Yangtze River Delta agglomerations increased from 0.654 to 0.664 from 2006 to 2018, the amount of increase was relatively low, and the EE has decreased significantly since 2012. The industrial structure and extensive growth mode dominated by resources, energy, and heavy industries in the Yangtze River Delta led to a
higher degree of factor input redundancy and output insufficiency, which restricted efficiency improvement. They were only more elevated than the middle reaches of the Yangtze River city agglomeration. However, the efficiency increased to 0.851 in 2012 due to 13 cities, such as Suzhou, Yancheng, Nantong, and Yangzhou, slowing down factor investment and strengthening pollution control. However, by 2018, the redundancy rates of SO2, waste gas, and wastewater were still 23.6 percent, 18.3 percent, and 22.6 percent, respectively, which were much higher than that of the Pearl River Delta and the Chengdu–Chongqing city agglomerations. The problems of high energy consumption and pollution severely needed improvement.

3.3. Spatial Differences in EE of Urban Agglomerations and Their Sources

The above analysis shows that the spatial distribution of the EE of the five major urban agglomerations in China has noticeable differences and presents the spatial distribution characteristics of central collapse. To analyze the spatial differences and sources of the EE of the five major urban agglomerations further, this article uses the Gini coefficient based on the formula to calculate the spatial differences and contribution rate of the EE of the five major cities. The result is shown in Table 6.

Table 6. Intra-group and overall Dagum Gini coefficients of EE of five major urban agglomerations and their decomposition results.

| Year | Overall Differences | Beijing–Tianjin–Hebei | Yangtze River Delta | Middle Reaches of the Yangtze River | Pearl River Delta | Chengdu–Chongqing | Within the Group | Intergroup | Super Variable Density |
|------|---------------------|-----------------------|---------------------|-------------------------------------|------------------|-----------------|-----------------|-----------|------------------------|
| 2006 | 0.225               | 0.158                 | 0.181               | 0.246                               | 0.142            | 0.267           | 26.97%          | 30.94%    | 42.09%                  |
| 2007 | 0.211               | 0.138                 | 0.181               | 0.224                               | 0.161            | 0.230           | 25.39%          | 33.25%    | 41.34%                  |
| 2008 | 0.225               | 0.132                 | 0.193               | 0.244                               | 0.174            | 0.241           | 23.15%          | 33.91%    | 42.93%                  |
| 2009 | 0.223               | 0.124                 | 0.167               | 0.233                               | 0.206            | 0.265           | 23.70%          | 31.84%    | 44.45%                  |
| 2010 | 0.200               | 0.108                 | 0.152               | 0.216                               | 0.144            | 0.252           | 22.61%          | 32.01%    | 45.37%                  |
| 2011 | 0.196               | 0.091                 | 0.123               | 0.205                               | 0.165            | 0.186           | 21.78%          | 29.27%    | 48.93%                  |
| 2012 | 0.186               | 0.124                 | 0.138               | 0.224                               | 0.210            | 0.171           | 25.49%          | 28.47%    | 46.03%                  |
| 2013 | 0.191               | 0.124                 | 0.138               | 0.224                               | 0.210            | 0.171           | 25.49%          | 28.47%    | 46.03%                  |
| 2014 | 0.198               | 0.085                 | 0.169               | 0.197                               | 0.213            | 0.184           | 18.88%          | 37.46%    | 43.65%                  |
| 2015 | 0.210               | 0.117                 | 0.183               | 0.191                               | 0.204            | 0.204           | 23.83%          | 37.23%    | 38.92%                  |
| 2016 | 0.208               | 0.129                 | 0.186               | 0.208                               | 0.161            | 0.183           | 24.67%          | 35.63%    | 39.68%                  |
| 2017 | 0.205               | 0.120                 | 0.177               | 0.135                               | 0.180            | 0.241           | 27.71%          | 40.94%    | 31.33%                  |
| 2018 | 0.212               | 0.121                 | 0.181               | 0.160                               | 0.214            | 0.249           | 26.25%          | 39.19%    | 34.54%                  |
| Average | 0.207         | 0.118                 | 0.168               | 0.207                               | 0.177            | 0.220           | 23.81%          | 34.14%    | 42.05%                  |

3.3.1. Overall Spatial Variation Degree and Sources

The overall EE of the five major urban agglomerations decreased from 0.225 in 2006 to 0.212 in 2018 during the inspection period. The development trend of the Gini coefficient’s EE of the five major urban agglomerations did not strictly decrease during the inspection period. The EE synergy development of the five major city agglomerations is relatively weak. The overall Dagum Gini coefficient composition shows a pattern whereby super-variable density is higher than inter-group variation, while inter-group variation is higher than intra-group variation. The total contribution rate of hypervariable density and inter-group variation is over 76.194%, i.e., inter-group interpretation constitutes the primary source of the overall spatial variation of urban agglomerations. In comparison, the contribution rate of intra-group variation is about 23.806%, which weakens the spatial variation of the EE of urban agglomerations. This scenario indicates that the inter-group differences in EE among the five major urban agglomerations are more significant, and the inter-group differences increase in fluctuation with the evolution of time. This finding implies that if the EE gap between regions is allowed to grow, it will not only deviate from the development goal of comprehensive green transformation but also make the coordinated development of urban agglomerations more difficult.
3.3.2. Intra-Group Variation

Table 6 demonstrates that the intra-group variation coefficients of Beijing–Tianjin–Hebei, the Yangtze River Delta, the middle reaches of the Yangtze River, and Chengdu–Chongqing urban agglomerations show a decreasing trend of alternating down-up fluctuations from 2006 to 2018. In contrast, the Pearl River Delta city group shows a rising trend of alternating rising-declining changes. In terms of mean values, the Gini coefficients of the Chengdu–Chongqing, middle reaches of the Yangtze River, and the Pearl River Delta urban agglomerations are higher, at 0.220, 0.207, and 0.177, respectively, due to the polarization of Chongqing and Chengdu, Ezhou and Yingtan, and Guangzhou and Shenzhen in their respective city groups. In contrast, the Dagum Gini coefficients of the Beijing–Tianjin–Hebei and Yangtze River Delta city groups are relatively low, at 0.118 and 0.168, respectively. The higher Dagum Gini coefficient is mainly due to the polarization of the central cities, while the higher Dagum Gini coefficient of the middle reaches of the Yangtze River is primarily due to the different implementation of the strategic positioning of ecological priority and green development by each city, thus resulting in significant differences in the development of EE within the urban agglomerations. The Beijing–Tianjin–Hebei and the Yangtze River Delta urban agglomerations are mainly influenced by the coordinated development of Beijing–Tianjin–Hebei and the in-depth implementation of the integrated strategy of the Yangtze River Delta, which have promoted the internal coordinated development of the EE of the Beijing–Tianjin–Hebei and Yangtze River Delta urban agglomerations.

3.3.3. Inter-Group differences

Table 7 reports the differences in the EE Dagum Gini coefficients among urban clusters. The discrepancies between urban sets show a fluctuating upward trend from 2006 to 2018. Moreover, regional heterogeneity is apparent. The differences are more significant between the middle Yangtze River–Pearl River Delta area and the middle Yangtze River–Chengdu–Chongqing area. The differences between the Beijing–Tianjin–Hebei–Yangtze River Delta area and the Beijing–Tianjin–Hebei–Pearl River Delta are smaller. In contrast, the spatial differences between major urban agglomerations and south-eastern coastal, western, and central urban agglomerations are large. Meanwhile, the differences between northern and southern urban agglomerations in eastern regions are slight. Overall, the regional collaborative governance strategy benefiting the development of urban agglomerations in China has made adequate progress and promoted the reduction of spatial divergence between adjacent urban agglomerations. However, the central and south-eastern coastal and western regions have not formed a spatially benign interaction pattern of cross-regional ecological collaborative governance and coordinated economic development.

Table 7. Dagum Gini coefficient of intergroup differences in EE of the five major urban agglomerations.
3.4. Analysis of EE Driving Factors of Urban Agglomerations

According to the above studies, the EE of the urban agglomeration and the differences between urban agglomerations still need further optimization. Therefore, a geographical detector is used to analyze the influencing factors to promote the advancement of EE between urban agglomerations and improve space differences.

3.4.1. Single of EE of Urban Agglomerations

Based on the Geodetector model, the influencing factors of spatial difference in urban agglomeration EE are analyzed, as shown in Table 8. Under the total sample, in 2006, the differences in ER are the main factors affecting the EE space of the overall urban agglomerations, thus indicating that the government’s strengthening of environmental supervision has promoted the improvement of EE to a certain extent. By 2018, the level of TEC exceeded other factors, thereby playing a leading role in improving the difference in the EE space. In addition, EA and URB have also played an essential role in the differences in the environmental efficiency space of the overall urban agglomeration.

Table 8. Geographical detection of EE factor in urban agglomerations.

| Year | Region                      | GDP  | TEC  | FDI  | IDS  | ER   | EA   | URB  | TRAF |
|------|-----------------------------|------|------|------|------|------|------|------|------|
| 2006 | Overall                     | 0.003| 0.041| 0.01 | 0.081| 0.113| 0.038| 0.033| 0.078|
|      | Beijing–Tianjin–Hebei       | 0.359| 0.190| 0.209| 0.209| 0.096| 0.098| 0.190| 0.190|
|      | Yangtze River Delta         | 0.113| 0.056| 0.303| 0.246| 0.194| 0.041| 0.177| 0.031|
|      | Middle Reaches of Yangtze River Delta | 0.046| 0.055| 0.247| 0.013| 0.189| 0.061| 0.075| 0.072|
|      | Pearl River Delta           | 0.179| 0.365| 0.025| 0.078| 0.644| 0.441| 0.525| 0.126|
|      | Chengdu–Chongqing           | 0.043| 0.035| 0.129| 0.023| 0.204| 0.065| 0.011| 0.456|
| 2018 | Overall                     | 0.013| 0.121| 0.032| 0.051| 0.024| 0.064| 0.062| 0.022|
|      | Beijing–Tianjin–Hebei       | 0.083| 0.122| 0.061| 0.082| 0.359| 0.298| 0.313| 0.154|
|      | Yangtze River Delta         | 0.043| 0.086| 0.064| 0.003| 0.018| 0.075| 0.133| 0.023|
|      | Middle Reaches of Yangtze River Delta | 0.097| 0.171| 0.269| 0.072| 0.083| 0.082| 0.138| 0.126|
|      | Pearl River Delta           | 0.289| 0.622| 0.652| 0.446| 0.205| 0.442| 0.253| 0.222|
|      | Chengdu–Chongqing           | 0.279| 0.067| 0.054| 0.058| 0.432| 0.174| 0.094| 0.385|

From the perspective of the Beijing–Tianjin–Hebei urban agglomeration in 2006, TRAF differences are the most critical factors in the EE space. In addition, the GDP predominantly affects the differences in the EE space. By 2018, the difference in the development level of ER had an important impact on the differences in the EE space. In addition, EA and URB have also had a significant effect on the differences in the environmental efficiency space of the city group.

From the perspective of the Yangtze River Delta urban agglomeration, in 2006, the differences in FDI had an essential impact on the EE space of the Yangtze River Delta urban agglomeration. IDS, ER, and URB also had different degrees of influence. By 2018, the effects of varying impact factors were relatively balanced, thus indicating that factors that promote EE improvement had increasingly diversified, with URB having a more significant impact on the differences in the environmental efficiency space. Compared with 2006, the effects of TEC and EA have significantly increased.

For the middle reaches of the Yangtze River, in 2006, the differences in FDI were the leading factor affecting the spatial difference in EE in this
By 2018, the difference in ER levels had an absolute advantage. It became the most critical factor affecting the differences in the EE space of the Chengdu-Chongqing urban agglomeration. The roles of GDP, TEC, IDS, and EA factors had all increased significantly.

3.4.2. Factor Interactive Detection of the EE of Urban Agglomeration

This study conducted two interactive detections of eight influencing factors affecting the EE of urban agglomerations (Tables 9 and 10). Factor interaction detection shows that the interaction between different influencing factors has an enhanced relationship, that is, the difference in EE results from the typical role of multiple influencing factors. In 2006, the interaction between TEC and other factors caused a significant difference in the EE space for urban agglomerations. Among them, the impact of TEC and URB interaction reached 0.231. The interaction of this influencing factor strengthened the effects of differences in the EE space. By 2018, the exchange of the influencing factor had improved. Among them, the impact of the interaction between FDI and IDS was 0.202. Meanwhile, the effect of the interaction between FDI and ER was 0.241. The result of IDS promotion and the interaction between TRAF was 0.320, thus indicating that the interaction between IDS and TRAF is a critical factor in the difference in the EE space of urban agglomeration.

Table 9. Interaction Detection of EE Impact Factors in Urban Agglomerations (2006).

| Impact Factor | GDP  | TEC   | FDI   | IDS   | ER   | EA   | URB   | TRAF   |
|---------------|------|-------|-------|-------|------|------|-------|--------|
| Gdp           | 0.013|       |       |       |      |      |       |        |
| Tec           | 0.213\< \<| 0.121 |       |       |      |      |       |        |
| Fdi           | 0.159\< \<| 0.215\< \<| 0.032 |       |      |      |       |        |
| Ids           | 0.157\< \<| 0.189\< \<| 0.141\< \<| 0.051 |      |      |       |        |
| ER            | 0.118\< \<| 0.212\< \<| 0.108\< \<| 0.141\< \<| 0.024 |      |       |        |
| EA            | 0.133\< \<| 0.220\< \<| 0.136\< \<| 0.163\< \<| 0.131\< \<| 0.064 |      |        |
| Urb           | 0.201\< \<| 0.231\< \<| 0.196\< \<| 0.198\< \<| 0.159\< \<| 0.148\< \<| 0.062 |        |
| Traf          | 0.123\< \<| 0.172\< \<| 0.082\< \<| 0.166\< \<| 0.115\< \<| 0.123\< \<| 0.116\< \<| 0.022 |

Note: The symbols indicate the following: \< \< non-linear enhancement relationship; \> \> two-factor enhancement relationship.

Table 10. Interaction detection of EE impact factors in urban agglomerations (2018).

| Impact Factor | GDP  | TEC   | FDI   | IDS   | ER   | EA   | URB   | TRAF   |
|---------------|------|-------|-------|-------|------|------|-------|--------|
| Gdp           | 0.003|       |       |       |      |      |       |        |
| Tec           | 0.086\< \<| 0.041 |       |       |      |      |       |        |
| Fdi           | 0.026\< \<| 0.080\< \<| 0.010 |       |      |      |       |        |
| Ids           | 0.152\< \<| 0.134\< \<| 0.202\< \<| 0.081 |      |      |       |        |
| ER            | 0.227\< \<| 0.155\< \<| 0.241\< \<| 0.297\< \<| 0.113 |      |       |        |
| EA            | 0.082\< \<| 0.096\< \<| 0.074\< \<| 0.166\< \<| 0.184\< \<| 0.038 |      |        |
| Urb           | 0.092\< \<| 0.089\< \<| 0.076\< \<| 0.196\< \<| 0.130\< \<| 0.085\< \<| 0.033 |        |
| Traf          | 0.145\< \<| 0.144\< \<| 0.164\< \<| 0.320\< \<| 0.228\< \<| 0.144\< \<| 0.138\< \<| 0.078 |

Note: The symbols indicate the following: \< \< non-linear enhancement relationship; \> \> two-factor enhancement relationship.

4. Discussion

4.1. Discussion

Based on climate change, research on sustainable development is of great significance. EE is the main criterion for measuring sustainable green growth. From this point of view, many scholars have applied the traditional DEA method to calculate the EE. However, on account of its inherent drawbacks, it may lead to measurement errors easily, and enhancements are needed for applications of compatible radial and non-radial EBM models. Moreover, GDP was applied to measure the expected output in most research. This statistical data can be easily influenced by inconsistencies in statistical caliber, conversion error, and so on, thus resulting in errors in the measurement results. Therefore, night lights
were applied in this thesis to measure the expected output, replace the GDP indicator, and assess the EE. Furthermore, the super-efficient EBM model was applied in this thesis to analyze the EE of five major city agglomerations. The results indicated that the overall EE of city agglomerations was still in the medium range and maintained a declining trend. This study differs from that of Chen et al. [73], which focuses on studying the positive growth of green efficiency in city agglomerations. The differences in measurement results should be attributed to the different expected output agent variables selected. GDP statistics will bring about a misleading facade, thus resulting in an overestimation of EE. Nevertheless, the night light data that did not involve human interference were applied in this thesis to represent the expected output. Thus, the EE data obtained may be more objective.

The Gini coefficient was used to analyze the differences in the EE space of the five major city agglomerations. The space differences are the primary sources of space differences in the five major urban agglomerations. The results of this research are further supported by Yu et al. [74]. The main reason is the difference between the development foundation and path differences among the middle reaches of the Yangtze River, the Pearl River Delta, and the Chengdu–Chongqing urban agglomerations.

The EE factors of the five major urban agglomerations were analyzed through geographical detectors. Technological innovation was found to be the most critical factor affecting the differences in the EE space of the overall urban agglomeration. This result is the same as that of the existing research [75–77]. The main reason is that urban agglomerations with relatively backward technological innovation and development levels often have problems such as extensive production methods and high pollutant emissions. Hence, they are not conducive to improving the utilization rate of factors and resource utilization, thereby curbing EE improvement.

The dual-factor interaction has an enhanced relationship compared with the single-factor effect. This conclusion is the same as that of the existing research [78]. Among them, the effect of IDS and the interaction with TRAF significantly impact the differences in the EE space of urban agglomerations mainly due to cities vigorously promoting green development, optimizing the industrial structure, continuously improving transportation infrastructure construction, promoting technological innovation and scale effects, and helping improve EE. Therefore, the comprehensive role of industrial design and transportation infrastructure is the most critical interactive driving factor affecting the differences in the EE space.

4.2. The Study’s Limitations

The above research is a solid supplement to the existing EE research system, which can provide a reference for China’s sustainable development and experience in the sustainable development of cities in other countries. Thus, the work has essential international demonstration significance.

However, this study still has some limitations, which should be resolved in future research. First, the definition of EE needs to rise to the level of philosophy and study the relationship among people, nature, and human generations in social development. In addition, the analysis of EE influence is based on social and economic development. It does not consider other social culture and biological variables, such as the educational level, green propaganda cultivation, and terrain. Finally, given that this article mainly analyzes China’s first gradient urban agglomeration, it has not explored EE in other regions. In the future, further studies must be conducted on the EE of urban agglomerations in various areas of the country. The differences and formation mechanisms between urban agglomerations at different levels of development in China must also be analyzed to put forward targeted policy suggestions to promote green growth in various regions.
5. Conclusions and Management Implications

5.1. Conclusions

With the help of nighttime lighting data as the desired output, an EE evaluation index system is constructed. Moreover, super-EBM and input–output redundancy rates measure the EE of the five major urban agglomerations from 2006 to 2018. Combining the Geodetector model to analyze the factors that affect the EE of urban agglomerations, the main conclusions drawn are as follows.

From the perspective of time development, the EE of the five major city agglomerations from 2006 to 2018 generally present the decline fluctuation trend of "∧". However, the decline fluctuation trend has slowed down. From the space perspective of urban agglomerations, the EE of the Pearl River Delta and Beijing–Tianjin–Hebei urban agglomerations is significantly ahead. The EE of the city group in the middle reaches of the Yangtze River is the lowest, and the development pattern of central collapse is present in space. The lowest efficiency of the middle reaches of the Yangtze River has high investment, low output, and high pollution characteristics.

During the study period, the synergistic development of the EE of the five major urban agglomerations was weak. From the decomposition of the Gini coefficient of the EE of urban agglomerations, the total contribution of super-variable density and inter-group variation is 76.194%, i.e., inter-group interpretation constitutes the primary source of the overall spatial variation of urban agglomerations. The key to promoting the coordinated development of the five major urban agglomerations lies in reducing the inter-group variation of urban agglomerations. Among them, the differences of the middle reaches of the Yangtze River–Pearl River Delta and the middle reaches of the Yangtze River–Chengdu–Chongqing urban agglomerations are significant.

TEC is the most critical factor affecting the differences in the EE space of the overall urban agglomerations. The dual-factor interaction has an enhanced relationship compared with the single-factor effect. The effect of IDS and the interaction with TRAF significantly impact the differences in the EE space of urban agglomerations. Furthermore, the core factors driving the differences in the EE space at all levels are as follows: ER for the Beijing–Tianjin–Hebei urban agglomeration and Chengdu–Chongqing urban agglomeration, URB for the Yangtze River Delta urban agglomeration, and FDI for the middle reaches of the Yangtze River and the Pearl River Delta urban agglomeration.

5.2. Management Implications

The medium level of urban agglomeration’s overall development level shows a downward trend. The importance and urgency of improving the EE of urban agglomeration must be clearly understood. The low EE is mainly due to redundant input, low expectations, and severe pollution. Therefore, we should actively take measures to integrate and optimize the allocation of resource allocation, improve resource utilization, stimulate consumption, strengthen technological innovation development, reduce environmental pollution, and promote the improvement of the EE of urban agglomerations.

According to the differences between urban agglomerations and the primary sources of EE differences, the space linkage strategy should be established. Therefore, we should firmly establish the “one game of chess” of the five major urban agglomerations and establish and improve the coordinated development mechanism of the region. For the urban agglomeration of Beijing–Tianjin–Hebei and the Pearl River Delta, the leading role of innovation must be strengthened further. In addition, the intensive and green utilization capabilities of urban resources must be enhanced, and a demonstration effect of resource utilization and innovative development must be formed. The urban agglomerations of the Yangtze River Delta, Chengdu–Chongqing, and the middle reaches of the Yangtze River should find differentiated paths to improve the potential of urban development by their resource endowment, development positioning, and radiation driving capacity. The transfer of the innovative resources of the Beijing–Tianjin–Hebei and the Pearl River Delta urban agglomerations must also be actively undertaken. Moreover, a complementary and
coordinated development pattern of the five major urban agglomerations must be formed. As such, the EE of the five major urban agglomerations is gradually being reduced.

According to different influencing factors and the improvement of the EE of urban agglomerations, the free flow of elements and products must be encouraged so that advanced production technology and management experience spread to cities with low EE of long-middle urban agglomerations. The current status of the EE space for urban agglomerations caused by technical differences must also be alleviated. The other two factors are more driven than the independent effects of various factors. Therefore, while promoting the EE of the urban agglomeration, splitting the management in the field of economic development will be impossible. Moreover, it is a close combination of industrial structure upgrade and traffic infrastructure to form a green coordinated development function of $1 + 1 > 2$. The Beijing–Tianjin–Hebei and the Chengdu–Chongqing urban agglomeration should strengthen the supervision of the environment and enhance the construction of environmental regulations. Meanwhile, the Yangtze River Delta urban agglomeration should vigorously promote the construction of new urbanization, promote multifunctional three-dimensional development and mixed-use construction land, build industrial parks, and accelerate urbanization. Furthermore, the middle reaches of the Yangtze River and the Pearl River Delta should focus on improving the threshold for regional environmental standards and market entry, accelerate the improvement of the quality of opening up, and form an intensive open-development model.

**Author Contributions:** D.L. is in charge of conceptualization, methodology, visualization, formal analysis, writing—review and editing, and supervision; K.Z. is in charge of data curation, software, validation, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by the Basic Scientific Research Fees Funding Project of Central Universities (Grant No.2722021EK005).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

**Acknowledgments:** We sincerely thank the academic editors and anonymous reviewers for kind suggestions and valuable comments.

**Conflicts of Interest:** The authors declare no conflict of interest.

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