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Eco-Efficiency of the Urban Agglomerations: Spatiotemporal Characteristics and Determinations

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Abstract: Attaining optimal eco-efficiency is of paramount importance in promoting the sustainable and harmonious development of the economy and environment within urban agglomerations. Firstly, this paper utilizes the Super-SBM model with undesirable output to measure the eco-efficiency (*EE*) of 64 cities in the Beijing–Tianjin–Hebei metropolitan region (BTHMR), the Yangtze River Delta (YRD), the Pearl River Delta (PRD), and the Chengdu–Chongqing Economic Zone (CCEZ) from 2006 to 2019. Secondly, this study puts forth a novel and comprehensive index system aimed at evaluating the urbanization efficiency and sheds light on the spatiotemporal changes in *EE* and urbanization efficiency. Finally, the STIRPAT model is used to examine the influencing factors of *EE* and to investigate the correlation between *EE* and urbanization efficiency. The study found that the overall *EE* of the four typical urban agglomerations is high, but the trend varies with a decrease of about 12.9% from 2006 to 2019. The mean *EE* is in the order of CCEZ > PRD > BTHMR > YRD, with mean values of 0.941, 0.909, 0.842, and 0.732, respectively. The level of science and technology and the urbanization efficiency have a significant positive impact on *EE*, while population, industrial structure, *FDI*, and greening level have an inhibitory effect on urban eco-efficiency. Based on the results, policy suggestions such as paying attention to regional heterogeneity and giving full play to the government's macro-regulatory role in shaping the economic and industrial structure are proposed to serve as a guide for the coordinated development of urban agglomerations under the Dual Carbon Target.

Keywords: eco-efficiency; urbanization efficiency; US-SBM; STIRPAT; influencing factors; urban agglomerations

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1. Introduction

Following China's reform and opening up, the nation's urbanization rate has experienced a rapid surge, with urban agglomerations emerging as the key regions driving China's economic development. As of 2019, 19 urban agglomerations in China accounted for 75% of the country's population and contributed 88% of its GDP [1]. The "people-oriented" new-type urbanization is more in line with the development law and meets people's aspirations for better living quality. In this context, the collaborative development of urban agglomerations has become an important trend and Chinese urbanization mainstream [2]. In particular, major regional strategies such as the coordinated development of the Beijing–Tianjin–Hebei region, integrated development of the Yangtze River Delta, and the construction of the Guangdong–Hong Kong–Macao Greater Bay Area have been further implemented. The construction of the Chengdu–Chongqing economic Zone in southwest China has been actively promoted. City agglomerations and urban areas have expanded, significantly enhancing economic and international influence. At the same time, rapid development has been accompanied by neglect of the urban population carrying capacity, shortage of natural resources, and deterioration of the ecological environment. Extensive development, consuming high levels of energy, producing high levels of pollution, and operating with low efficiency, still exists. Urban agglomerations, the central focus of China's new urbanization, have become the key propellant of high-quality economic and social progress. They are entrusted with the dual responsibilities of promoting economic development and environmental protection through measures such as building a strong economic base, optimizing the industrial structure, and promoting coordinated regional development [3]. China's economic growth is shifting from the pursuit of 'high speed' to a focus on quality growth. The previous extensive development pattern is clearly inappropriate. How to encourage the urban agglomerations growth while effectively maximizing economic output, minimizing environmental degradation, and achieving sustainability, has become an important concern.

Eco-efficiency (*EE*), a tool for assessing the low carbon extent and the economic sustainability of a region [4], effectively gauges the correlation between economy, environment, resources, and development [5]. It is not only an inherent requirement for the coordinated development of new-type urbanization and ecology, moreover, it serves as a crucial foundation for evaluating the efficacy of the construction of urban ecological civilization [6]. Understanding *EE* has a practical significance in addressing and achieving socio-economic development, and further delving into its connection with urbanization can offer guidelines and policy suggestions for putting the "innovation, coordination, green, open and shared" concept into practice, thus promoting achievement of sustainability under the Dual Carbon Target.

In view of this, this paper takes typical urban agglomerations in China as case examples to scientifically measure eco-efficiency and urbanization efficiency and explore the spatiotemporal evolution in urban agglomerations. We further identify factors affecting eco-efficiency, delve into its relationship with urbanization, and provide guidance and policy recommendations for achieving sustainable development.

The remainder of this paper is structured as follows: Section 2 is a literature review. Section 3 outlines the research methodology and provides an overview of the data sources employed. Section 4 presents the findings pertaining to *EE* and the urbanization efficiency, and subsequently undertakes an analysis of their interrelationship. Section 5 constitutes a discussion of the research outcomes and offers recommendations for policy formulation. Finally, in Section 6, the paper concludes with a summary of main conclusions and policy implications.

2. Literature Review

Eco-efficiency was first proposed by Schaltegger and Sturm [7]. Subsequently, the strategy was further elaborated and promoted by the World Council for Sustainable Development and the Organization for Economic Development Cooperation. The crux of eco-efficiency lies in attaining optimal economic gains through minimal resource consumption and environmental expenses [8], existing research of which is mainly focused on the selection and measurement of indicators, spatial and temporal patterns, spatial convergence and spillover effects, evaluation, and optimization. Several researchers have discussed and analyzed the spatiotemporal evolution of *EE* at the national, provincial, and municipal scales, successfully applying the results to a wide range of fields, subjects, and sectors, such as industrial, agricultural, and eco-economic efficiency. Urbanization efficiency, as a crucial benchmark of high-quality urban development, is frequently assessed by comparing the output or efficacy of input resources. Scholars that explored urban [9], district, and county development efficiency as well as urban industrial efficiency [10], have conducted research on methods and models for measuring efficiency [11].

Research on assessing *EE* has attracted a great deal of academic attention. The indicator system approach [12], life cycle assessment [13], data envelopment analysis (DEA) [14], and stochastic frontier analysis (SFA) [15] are the key techniques for measuring *EE* and urbanization efficiency. Wursthorn et al. (2011) established an accounting framework for evaluating eco-efficiency in European countries. This approach combines economic and ecological indicators to provide a comprehensive assessment [16]. Margarita et al. (2015) specified a new stochastic frontier model to evaluate the resource and environmental efficiency of European countries [17]. Compared to SFA models, DEA models and their extended versions based on linear programming, which do not require the specification of a specific form of production function, are more objective and widely used [18]. For example, Bai et al. (2018) employed a super-efficient DEA model to assess the correlation between urbanization and urban eco-efficiency in China between 2006 and 2013 [19]. Shi et al. (2023) used a two-stage DEA model to measure and analyze the eco-efficiency of urban agglomerations over the past 15 years, based on four major urban agglomerations along the eastern coast of China, to reveal the internal connections between integrated efficiency and sub-stage efficiency [20]. However, DEA is radial in nature and solely accounts for proportional transformations in input or output elements. As a result, it ignores non-radial slack variables and does not include non-desired output indicators, which can easily lead to high measured efficiency values. In this regard, Tone et al. (2001) proposed a non-radial, non-oriented SBM based on slack variables, which effectively solves the problems posed by slack variables [21]. However, the SBM cannot distinguish and rank multiple valid decision units. For this purpose, Tone et al. (2002) further presented the Super-SBM and constructed the undesirable slacks-based measurement (Undesirable SBM) to distinguish the attributes of outputs, this approach effectively addresses the challenge of comparing multiple decision-making units [22]. Using a panel dataset from 2005–2014, Zhou et al. (2018) assessed the eco-efficiency of 21 cities in Guangdong Province, China, which was achieved through the utilization of the Super-SBM that considers undesirable output and the Topsis [23]. Based on previous research, in this paper, we employ a Super-SBM model incorporating undesirable outputs to gauge the *EE* and urbanization efficiency.

Recently, the government of China works fixedly to achieve sustainable urban development, which aims to strike a balance between economic outputs and environmental protection. The analysis of influential factors of eco-efficiency assists positively in enhancing eco-efficiency and the achievement of sustainable regional development. Current research methods on influencing factors include spatial panel regression techniques [24], IPAT models, STIRPAT models [25,26], geodesic probes [27], Tobit regression models [28], quantile regression models [29], systematic GMM models, and spatial econometric models [30]. Fang and Wang (2013) performed a theoretical examination of the interactive coercive effects between urbanization and ecology [31]. Wang et al. (2014) presented a thorough system of indicators to assess urbanization and *EE* and analyze their correlation [32]. The IPAT was first proposed by Ehrlich and Holdren (1971), who attributed the effects of human activities on the surroundings to population, affluence, and technology level [33], and subsequent researchers developed an extend STIRPAT by introducing differential elasticity and random error terms [34]. In recent years, STIRPAT has become widespread in impact factor analysis. Scholars have extended the traditional STIRPAT from the perspectives of urbanization, trade, and investment, using a series of improved panel models to explore the interaction between urbanization and *EE* and the external influences on *EE*. Zhang et al. (2018) used STIRPAT to evaluate the influence of urbanization on CO_2 emissions in 141 countries [35]. Luo et al. (2013) utilized STIRPAT to investigate the correlation between urbanization and *EE* with empirical data at the provincial level [36]. Grossman further revealed the intrinsic "U" shaped pattern between urbanization and ecology (EKC) [37]. Moreover, the *EE*'s influential factors of different cities vary due to factors such as regional conditions, resource endowment, economic development patterns, and policy orientation [38]. Existing studies in the literature suggest that *EE* is influenced by environmental regulation, foreign direct investment, industrial infrastructure, urbanization efficiency, technological innovation, and economic agglomeration [39]. Chang et al. (2020) argued that foreign investment brought negative ecological benefits and that the Yangtze River Delta overall was in line with the "pollution paradise" hypothesis. Wu et al. (2016) found a high proportion of secondary sectors inhibited *EE* when studying its factors in Jiangsu Province [40]. In this paper, we select the most appropriate influencing factors based on their frequency of occurrence and the availability of relevant data and use an extended STIRPAT model to analyze their relationship with eco-efficiency.

However, the majority of scholars have concentrated on analyzing eco-efficiency either on a macro level throughout China or in a particular geographical area, and there is a paucity of research conducted on several significant urban agglomerations in China. Moreover, few studies on the spatiotemporal evolution patterns among the four major urban agglomerations in China have covered recent years, and studies on the factors influencing urban eco-efficiency are relatively scarce. Some studies have even ignored assessing unexpected outputs. Therefore, based on the 2006–2019 panel dataset, the Super-SBM model incorporating undesirable outputs was developed to gauge the *EE* and urbanization efficiency of 64 cities located within the BTHMR, the YRD, the PRD, and the CCEZ. Furthermore, we applied an extended STIRPAT model combined with spatial panel Tobit analysis to explore the determinants of urban *EE*.

3. Methodology and Data

3.1. Study Area

Based on the relevant research results on urban agglomerations in China [41,42], and taking into account the defined scope and data availability of the planning documents of each urban agglomeration, 64 cities in four national urban agglomerations (Figure 1) were taken as the spatial scale research objects, namely the Beijing–Tianjin–Hebei metropolitan region (BTHMR), the Yangtze River Delta (YRD), the Pearl River Delta (PRD) and the Chengdu–Chongqing Economic Zone (CCEZ), which are key construction areas. The research samples covered four municipalities directly under the central government, namely Beijing, Tianjin, Shanghai, and Chongqing, as well as cities at the prefecture level and above in six provinces, namely Hebei, Jiangsu, Zhejiang, Anhui, Guangdong, and Sichuan.

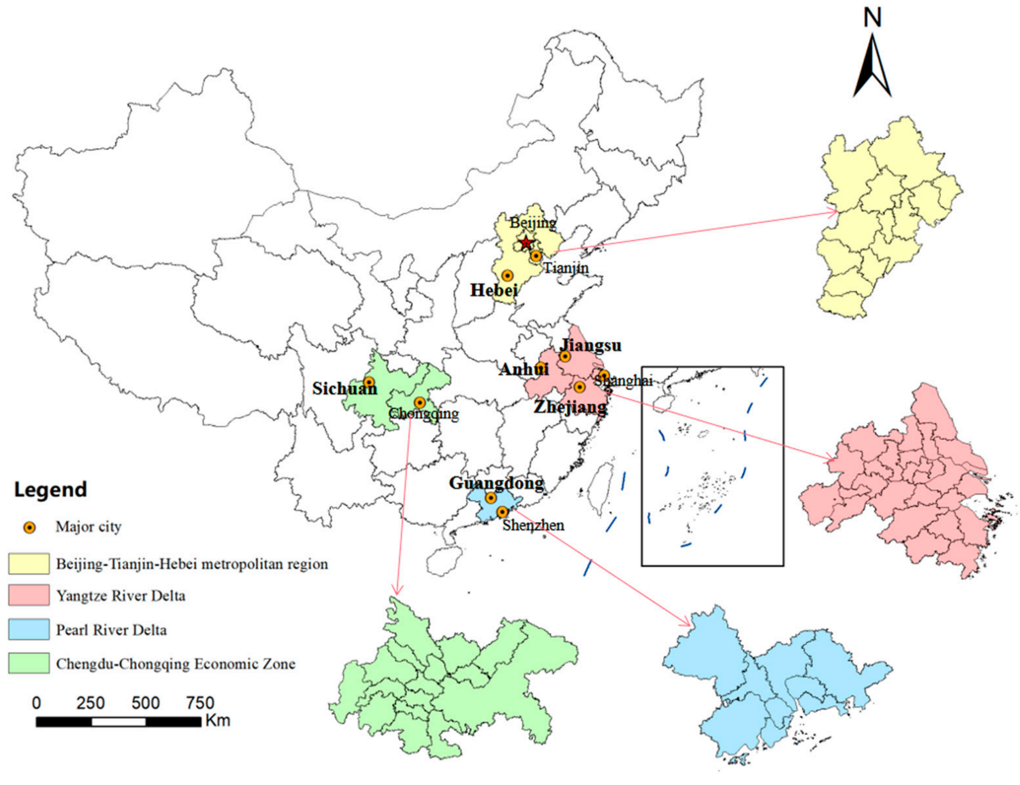

Figure 1. Distribution of the four typical urban agglomerations.

3.2. US-SBM Model

This study employs a US-SBM model that considers undesirable outputs and combines the advantages of the SBM and super-efficiency model. This model considers input relaxation and effectively measures the *EE* in the presence of undesirable outputs, enabling the comparison of multiple efficient DMUs and solving the issue of the inability to rank efficiency values. The super-SBM provides a more in-depth characterization of the cities' *EE* and sheds light on the characteristics and evolution process of green development in China's four national urban agglomerations. Specifically, this study constructs a Super-SBM with undesirable outputs (US-SBM) to measure the *EE* of 64 cities in the four national urban agglomerations and distinguishes efficient decision-making units at the boundary in the presence of undesirable outputs. Suppose there is n DMUs and each decision cell consists of m kinds of inputs (x), q_1 kinds of desired outputs (y^g) and q_2 kinds of undesirable outputs (y^b). The input variables x, the desired output variables y^g, and the undesirable output variables y^b are matrices, where $x = [x_1, x_2, \ldots, x_n]$, $y^g = \left[y_1^g, y_2^g, \ldots, y_n^g\right]$, $y^b = \left[y_1^b, y_2^b, \ldots, y_n^b\right]$, γ is the weight vector, and the set of production possibilities with variable payoffs to scale is $p = \left\{\left[\left(x, y^g, y^b\right) \middle| x \le x\gamma, y^g \le y^g\gamma, y^b \le y^b\gamma\right]\right\}$, the specific model is constructed as follows [43]:

$$\min\rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1 - \frac{1}{q_1+q_2}\left(\sum_{r=1}^{q_1}\frac{s_r^{g^+}}{y_{rk}^g} + \sum_{t=1}^{q_2}\frac{s_t^{b^-}}{y_{tk}^b}\right)} \tag{1}$$

$$s.t.\begin{cases} \sum\limits_{j=1, j\neq k}^{n} x_{ij}\gamma_j - s_i^- \le x_{ik} \\ \sum\limits_{j=1, j\neq k}^{n} y_{rj}\gamma_j + s_r^{g^+} \ge y_{rk}^g \\ \sum\limits_{j=1, j\neq k}^{n} y_{tj}^b - s_t^{b^-} \le y_{tk}^b \\ 1 - \frac{1}{q_1+q_2}\left(\sum\limits_{r=1}^{q_1}\frac{s_r^{g^+}}{y_{rk}^g} + \sum\limits_{t=1}^{q_2}\frac{s_t^{b^-}}{y_{tk}^b}\right) > 0 \\ s^- > 0, s^{b-} > 0, s^{g+} > 0, \gamma > 0 \\ i = 1, 2, \cdots, m; r = 1, 2, \cdots, q; j = 1, 2, \cdots, n(j \neq k) \end{cases} \tag{2}$$

where is the number of decision units, m, q_1, and q_2 represent the number of input indicators, desired outputs, and undesired outputs, respectively, k is the number of units being evaluated. i, r, t denotes the i-th input, the r-th desired output, the t-th undesired output, respectively. s^- is the number of input redundancies, s^{g^+} denotes the desired output shortfall, and s^{b-} denotes the undesired output redundancies. x_{ij} denotes the i-th input of the j-th decision unit. y_{rj} is the r-th desired output of the j-th decision unit and y_{tj} is the t-th undesired output of the j-th unit. ρ is the efficiency value, when $\rho < 1$, the decision unit is in an inefficient state; when $\rho \ge 1$, the decision unit is in an efficient state.

3.3. STIRPAT Model

This study examines the factors influencing *EE* and explores the relationship between urbanization and *EE* by the STIRPAT model. The factors considered in the model include population, industrial structure, urbanization efficiency, openness to foreign trade, technological innovation, and green coverage level. The original form of the STIRPAT is as follows:

$$I_i = aP_i{}^b A_i{}^c T_i{}^d \tag{3}$$

where I, P, A, and T denote environmental pressure, population size, affluence, and technology level, respectively, a is the model coefficient, and e is the error term.

In practical applications, the two sides of the model are usually logarithmized for regression analysis, and model (3) becomes:

$$lnI_i = lna + blnP_i + clnA_i + dlnT_i + lne_i \quad (4)$$

Based on the literature review conducted earlier on the factors influencing eco-efficiency, this study categorized these factors based on their frequency of occurrence and the availability of relevant data, the total population (*POP*), the Share of secondary sector in GDP (*IS*), the urbanization efficiency (*URB*), the expenditure on science and technology (*TEC*), the actual amount of foreign capital used (*FDI*), and the greenery coverage of built-up area (*GRE*) are used as explanatory variables and eco-efficiency (*EE*) serves as the explained variable in 64 cities from 2006 to 2019. We extended the STIRPAT model to the following form:

$$ln(EE) = a_0 + bln(POP) + cln(IS) + dln(URB) + eln(FDI) + fln(TEC) + gln(GRE) + e_0 \quad (5)$$

where b, c, d, e, f, and g correspond to the model parameters, respectively, and the positive elasticity coefficient of the explanatory variable indicates a positive effect on the explained variable and vice versa. Moreover, the magnitude of the elasticity coefficient reflects the strength of the relationship between the explanatory variable and the dependent variable [32]. The significance of the elasticity coefficient is determined using p-values. When the p-value is less than 0.1, 0.05, or 0.01, the elasticity coefficient is significant at the 10%, 5%, and 1% levels, respectively, e_0 is the error value.

The appropriate econometric method can be used to estimate the parameters of the above model under the meeting of the corresponding hypotheses. However, there may be heteroscedasticity issues and interference terms may be correlated between different cities within the same province at the prefecture level due to the use of city-level data in this study. Additionally, the Super-SBM model is utilized to calculate the dependent variable and has a lower limit of 0 due to truncation of the data. If ordinary least squares (OLS) regression is directly used, there may be biased and inconsistent parameter estimation issues [44–46]. Therefore, through the F-test and Hausman test, the fixed-effects Tobit regression is chosen to investigate the factors affecting *EE*.

3.4. Index System Construction

The World Business Council for Sustainable Development (WBCSD) provides a range of input–output indicators as alternative indicators, among which labor, material resources, land, and capital are the primary input indicators [47]. In accordance with the principles of scientific rigor, objectivity, systematic analysis, and data availability, this study constructed separate evaluation index systems for eco-efficiency and urbanization efficiency by referring to relevant literature [43,48]. The evaluation index system for *EE* includes five input indicators: total fixed asset investment, year-end number of employees, total water supply, administrative land area, and urban electricity consumption. Total fixed asset investment represents the capital element, year-end number of employees represents the labor element, and total water supply, administrative land area, and urban electricity consumption represent the resource element. The index system also includes four output indicators: regional GDP representing the regional economic scale, sewage discharge, exhaust emission (SO_2), and dust emission as undesirable outputs representing urban ecological benefits level.

The urbanization efficiency evaluation index system includes four input indicators, i.e., built-up area, total fixed assets investment, fiscal expenditure, and year-end numbers of employees, where the input indicators include the land element represented by the built-up area, the capital element represented by the total fixed assets investment and fiscal expenditure, and human capital represented by year-end numbers of employees. Output indicators are residents' savings deposits and total retail sales of consumer goods, which represent economic scale and social consumption level, respectively. The evaluation indicator system is shown in Table 1.

Table 1. Evaluation index system of urbanization efficiency and eco-efficiency.

Purpose	Variables	Criteria	Indicators	Unit
Eco-efficiency	Input variables	Capital element input	Total fixed assets investment	10^4 Yuan
		Resource element input	Administrative land area	km^2
			Urban electricity consumption	10^4 kwh
			Total water supply	10^4 t
		Labor factors input	Year-end number of employees	10^4 person
	Output variables	Desirable output	Regional GDP	10^4 Yuan
		Undesirable output	Sewage discharge	10^4 t
			Exhaust emission (SO_2)	t
			Dust emission	t
Urbanization efficiency	Input variables	Human capital input	Year-end number of employees	10^4 person
		Capital element input	Total fixed assets investment	10^4 Yuan
			Fiscal expenditure	10^4 Yuan
		Land element input	Built-up area	km^2
	Output variables	Scale of the city's economy	Total retail sales of consumer goods	10^4 Yuan
			Residents' savings deposits	10^4 Yuan

To reflect the comprehensive influence of population, industrial structure, technology, greening level, degree of external openness, and urbanization efficiency, respectively, we selected the total population, the Share of secondary sector in GDP, the expenditure on science and technology, the greenery coverage of built-up area, the actual amount of foreign capital used, and the urbanization efficiency, as influencing factors in this paper (Table 2).

Table 2. STIRPAT variable names and descriptions.

Variable Type	Variables	Symbols	Indicators	Unit
Explained variables	Eco-efficiency	*EE*	Eco-efficiency values	%
Explanatory variables	Population	*POP*	Total population	10^4 person
	Industrial structure	*IS*	Share of secondary sector in GDP	%
	Technology input	*TEC*	Expenditure on science and technology	10^4 Yuan
	Greening level	*GRE*	Greenery coverage of built-up area	%
	Degree of external openness	*FDI*	Actual amount of foreign capital used	10^4 $
	Urbanization efficiency	*URB*	Urbanization efficiency values	%

3.5. Data Source

This study utilized panel data spanning from 2006 to 2019, which was primarily sourced from the China City Construction Statistical Yearbook (2007–2020) and statistical yearbooks and bulletins from various provinces. For variables with missing data, mean imputation and moving average methods were employed for estimation. The related price indices were used to adjust the data to a common baseline of 2006 in order to take into account indicators that may be impacted by price factors, such as GDP and fixed asset investment. Descriptive statistical data of variables in the US-SBM model are presented in Table 3. It is noteworthy that some variables exhibit maximum values tens of times greater than their corresponding minimum values, indicating significant differences between cities and considerable temporal variation in urban economic activities.

Table 3. Descriptive statistics of input and output variables.

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
Total fixed assets investment [a]	10^8 Yuan	896	1000	158	12.14	10,400
Administrative land area	km^2	896	2637.54	4381.70	115	43,263
Urban electricity consumption	10^4 kwh	896	2,172,687	2,846,518	49,826	15,714,000
Total water supply	10^4 t	896	31,066.36	54,248.76	23	349,481
Year-end number of employees	10^4 person	896	74.54	131.46	2	819
Regional GDP [a]	10^8 Yuan	896	2320	40,100	41.8741	27,800
Sewage discharge	10^4 t	896	11,986.30	13,162.75	232	91,260
Exhaust emission (SO_2)	t	896	60,370.82	77,906.86	978	682,922
Dust emission	t	896	34,735.23	85,485.82	162	1,859,866
Fiscal expenditure [a]	10^8 Yuan	896	261.33	567.02	3.09	4740
Built-up area	km^2	896	228.94	301.17	19	1515
Total retail sales of consumer goods [a]	10^8 Yuan	896	1130	14,700	45.54	9450
Residents' savings deposits [a]	10^8 Yuan	896	1880	3610	42.84	25,600

[a] At 2006 price.

4. Results

4.1. Analysis of the Evolution of Spatiotemporal Patterns of Eco-Efficiency

Based on US-SBM, this study measured the *EE* of 64 cities in China's four typical urban agglomerations from 2006 to 2019. The findings revealed average *EE* in the four areas was 0.866 during this period, indicating a moderately high level of *EE*, and their development trends exhibited variations. However, the overall *EE* level showed a downward trend (Figure 2), declining by approximately 12.9%. During the period between 2006 and 2019, the *EE* mean values of the four clusters in China were sorted in decreasing order as follows: CCEZ > PRD > BTHMR > YRD, with mean values of 0.981, 0.909, 0.842, and 0.732, respectively. Further examination of the eco-efficiency within each urban cluster revealed that, in 2006, a total of 36 cities had mean eco-efficiency values greater than 1, which accounted for 56.25%, 77.78%, 61.54%, and 46.15% of the cities in the CCEZ, the PRD, the BTHMR, and the YRD, respectively. These cities were Zhoushan, Tongling, Shanghai, and Wuxi in the YRD; Dazhou, Deyang, Guang'an, Suining, and Ziyang in the CCEZ; Shenzhen, Guangzhou, and Foshan in the PRD; and Beijing, Tianjin, Xingtai, Cangzhou, Langfang, and Hengshui in the BTHMR. By 2019, the number of cities that had reached the optimal frontier surface had decreased to 25, accounting for 38.46%, 55.56%, 53.85%, and 18.75% of the YRD, the PRD, the BTHMR, and the CCEZ, respectively. More importantly, both the PRD and the CCEZ experienced significant declines in the number of cities that had reached the optimal frontier. In 2013, the mean *EE* values of the four urban agglomerations were relatively low, primarily due to the slowing down of economic growth in 2012. In an effort to maintain economic increase, the urban agglomerations accelerated the development of high-polluting, high-energy-consuming, and high-emission industrial projects, which caused a decrease in *EE*. However, since the Chinese government proposed the concept of high-quality development in 2017, governments at all levels have begun to attach greater importance to ecological environmental protection and the promotion of resource utilization efficiency. Consequently, the downward and fluctuating trend in *EE* has gradually slowed down. Analyzing observations from three cross-sectional time points in 2006, 2013, and 2019, Shenzhen was consistently ranked first in eco-efficiency. As the window of China's reform and opening up, Shenzhen not only presents as a highly developed modern international city, but also has been awarded the dual honors of being a national ecological civilization construction demonstration area and a "Clear waters and green mountains are as valuable as mountains of gold and silver" practice innovation base in China. Shenzhen fully implemented the concept of ecological civilization, adhered to the synchronous development of park construction and special zone construction, and led the way in China. Conversely, cities such as Luzhou, Leshan, and Handan have relatively backward industrial development levels and economic levels, with low efficiency in factor aggregation and allocation, resulting in less obvious production scale effects [49]. As a result, these cities have been consistently ranked at the bottom.

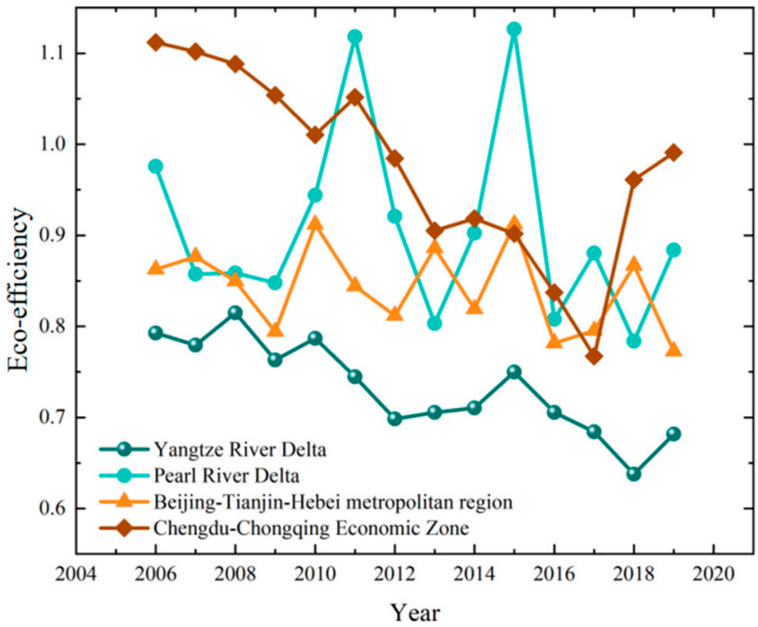

Figure 2. Changes of eco-efficiency in four urban agglomerations from 2006 to 2019.

EE values of the four urban agglomerations were classified into five levels using ArcGIS 10.3, according to the trend of changes observed. Level I (*EE* > 1.4) represents the highest *EE*, classified as a super-high level; Level II (1.1 < *EE* < 1.4) represents cities with high *EE*, classified as a high level; Level III (0.8 < *EE* < 1.1) represents cities with moderately high *EE*, classified as a moderately high level; Level IV (0.4 < *EE* < 0.8) represents cities with moderately low *EE*, classified as a moderately low level; and Level V (*EE* < 0.4) represents cities with low *EE* levels, classified as a low level. These five levels were used to classify urban efficiency into low, medium-low, moderately high, high, and super-high.

The overall mean *EE* of BTHMR is 0.842, ranking third among the four urban agglomerations. However, *EE* mean value fluctuated between 0.75 and 0.95, indicating an unstable development trend. The mean *EE* value in 2006 was 0.862, whereas in 2019, it decreased by approximately 10.3% to 0.773. The BTHMR demonstrated a mature cell-like structure [30], with Beijing, Tianjin, and the surrounding areas acting as the "cell nucleus" and the surrounding region of the capital economic belt serving as the "cell cytoplasm". From 2006 to 2019, *EE* of the BTHMR gradually illustrated a radial distribution pattern of moderately high in the middle and low in the periphery (Figure 3). Beijing and Tianjin have political advantages oriented toward resources, research advantages in knowledge innovation, quality advantages in environmental education, and tourism advantages in cultural history, which have less impact on the environment when promoting socio-economic development. In contrast, surrounding cities such as Shijiazhuang, Zhangjiakou, Tangshan, and Baoding mainly bear the upstream part of the regional industrial chain, which is dominated by resource-based industries in their development. They are affected by the pollution of industrial activities, which leads to a higher level of pollution discharge. Therefore, these cities play a significant role as the cornerstone among the urban clusters, while also posing threats to sustainability.

Figure 3. Spatial distribution of eco-efficiency in the typical urban agglomerations. (**a**–**c**) represent the EE of the BTHMR in 2006, 2013, 2019; (**d**–**f**) represent the EE of the YRD in 2006, 2013, 2019; (**g**–**i**) represent the EE of the PRD in 2006, 2013, 2019; (**j**–**l**) represent the EE of the CCEZ in 2006, 2013, 2019.

The overall average value of *EE* of the YRD is 0.732, and the average value remains around 0.7 in each year, with less fluctuation and more stable development. The average value of *EE* in 2006 is 0.793, while in 2019 it is 0.682, a decrease of around 14%. Cities like Shanghai, Zhoushan, Chizhou, and Tongling have been in the high-efficiency zone and are located on the optimal frontier surface (Figure 3). While vigorously developing their economies in recent years, the YRD has also been actively responding to and implementing policies related to ecological and environmental management, and strictly supervising and managing the pollution emission behavior of enterprises, making the development of *EE* more stable. Zhoushan and Tongling are national forest cities with relatively high *EE* by virtue of their reasonable industrial structure and lower resource consumption and environmental pollution. The spatial distribution structure of YRD is stable from 2006 to 2019, but local differences still exist. As the springboard for China's opening up to the world, Shanghai benefits from advantages of a platform for foreign exchanges, the transportation advantage of a port corridor, the resource advantage of natural landscape, and the industrial advantage of high technology; focusing on foreign trade and the information technology industry characterized by high profits and low consumption, its eco-efficiency is consistently at a high level. In recent years, the YRD, with its superior economic base and platform advantages, has seen the eastern coastal cities become the engine driving the region's development with high-tech, financial services, education, and healthcare, and the central and western cities become the cornerstone of regional development with industrial manufacturing, logistics, and transportation. The YRD is seeking a high-quality development path with parallel economy and ecology.

The overall average *EE* value of the PRD is 0.908, ranking second among the four urban agglomerations. The average *EE* value in 2006 was 0.976, compared to 0.884 in 2019, approximately a 9.43% decrease. Among the urban cluster, there were seven high-efficiency cities and only one low-efficiency city, Jiangmen, in 2006, indicating a high level of *EE* for the entire urban agglomeration. However, the number of high-*EE* cities decreased in 2013, leading to a decline in overall eco-efficiency compared to 2006. In 2019, the number of low and moderately low *EE* cities significantly increased, accounting for 44.44%. The continuous strengthening of regional economic cooperation and the comprehensive implementation of the Guangdong–Hong Kong–Macao Greater Bay Area construction have brought economic benefits to the PRD. However, this has also led to new regional environmental problems. The spatial distribution of *EE* value in the PRD exhibits a radial pattern centered on Guangzhou and Shenzhen, as shown in Figure 3. Cities such as Shenzhen, Guangzhou, Zhongshan, and Foshan have a strong industrial foundation, high-quality human resources, and environmentally friendly industries, primarily focused on foreign trade, financial services, and information technology. However, small and medium-sized cities such as Huizhou, Zhaoqing, and Jiangmen have more high-pollution industries such as electroplating and printing, a weaker industrial foundation, and have not fully utilized the ecological environment resources to bring higher economic benefits.

The CCEZ demonstrates a high level of eco-efficiency, with an overall mean *EE* value of 0.981, despite its location in the western region and relatively weak economic foundation due to the support of the "Belt and Road" and western development strategy, which have increased government investment in environmental governance. However, the *EE* mean value has fluctuated between 0.8 and 1.2, with a decline from a mean *EE* value of 1.162 in 2006 to 0.991 in 2019, representing a decline of approximately 14.7%. In terms of time span, a declining-then-increasing trend has emerged, with the lowest point being 0.767 in 2017. In terms of spatial distribution, as shown in Figure 3, Chengdu serves as the core leading city of the region, primarily focusing on environmentally friendly industries such as the internet, electronic circuits, and new energy, resulting in relatively high eco-efficiency. However, surrounding cities such as Mianyang, Yibin, and Luzhou are more involved in the resource extraction, processing, manufacturing, and logistics industries, resulting in greater environmental pollution. The Chengdu–Chongqing Economic Zone is mainly characterized by "low input, low output and low pollution" and the adjustment of input and output in the context of low economic growth rates [50]. The publication of the "Development Plan for the Chengdu–Chongqing Urban Cluster" in 2016 officially initiated the process of modernizing western urban areas, accelerating the socio-economic development of the CCEZ, strengthening the flow of economic and industrial elements between cities, and gradually forming an industrial distribution along the Yangtze River economic belt. With the migration of people and the enhancement of scientific and innovative capabilities, although the balance between ecosystem protection and economic growth has not yet been established, the high-*EE* value zone along the Chengdu–Chongqing double-loop economic corridor is gradually becoming clearer.

4.2. Analysis of the Evolution of Spatiotemporal Patterns of Urbanization Efficiency

This study assesses the level of urbanization in the four urban agglomerations by constructing a novel comprehensive evaluation index system based on panel data from 64 cities between 2006 and 2019. US-SBM was employed for the evaluation, indicating the average urbanization efficiency demonstrating an upward trend from 2006 to 2019 (Figure 4). The overall urbanization efficiency of the four urban clusters during this period was 0.616, which falls within the medium to high range. Figure 5 displays the spatial distribution of *URB* in 2006, 2013, and 2019. The findings indicated that the urbanization efficiency was highest in eastern coastal cities such as Shenzhen, Guangzhou, and Shanghai. However, the spatial pattern of urbanization exhibited an uneven distribution, with urbanization efficiency gradually decreasing from east to west. Additionally, the number of cities with a relatively high degree of urbanization has increased, and the spatial pattern of cities with medium to high and medium urbanization efficiency has shown a trend of expanding from the east to the center. Overall, the spatial pattern of urbanization efficiency in the four urban clusters is consistent with China's strategic planning for urban transformation.

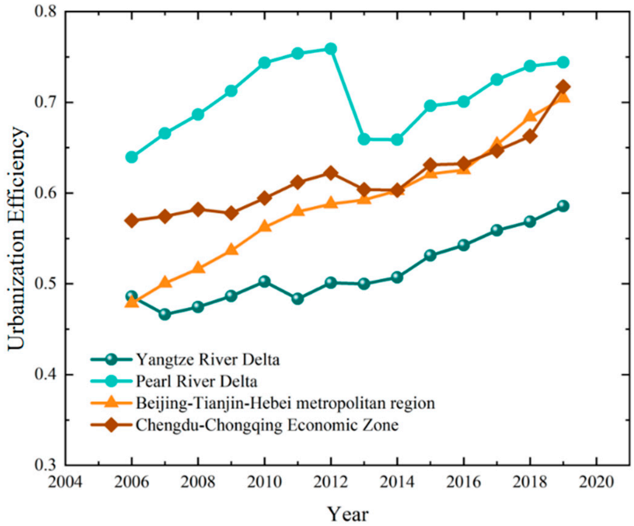

Figure 4. Changes of urbanization efficiency in the four urban agglomerations from 2006 to 2019.

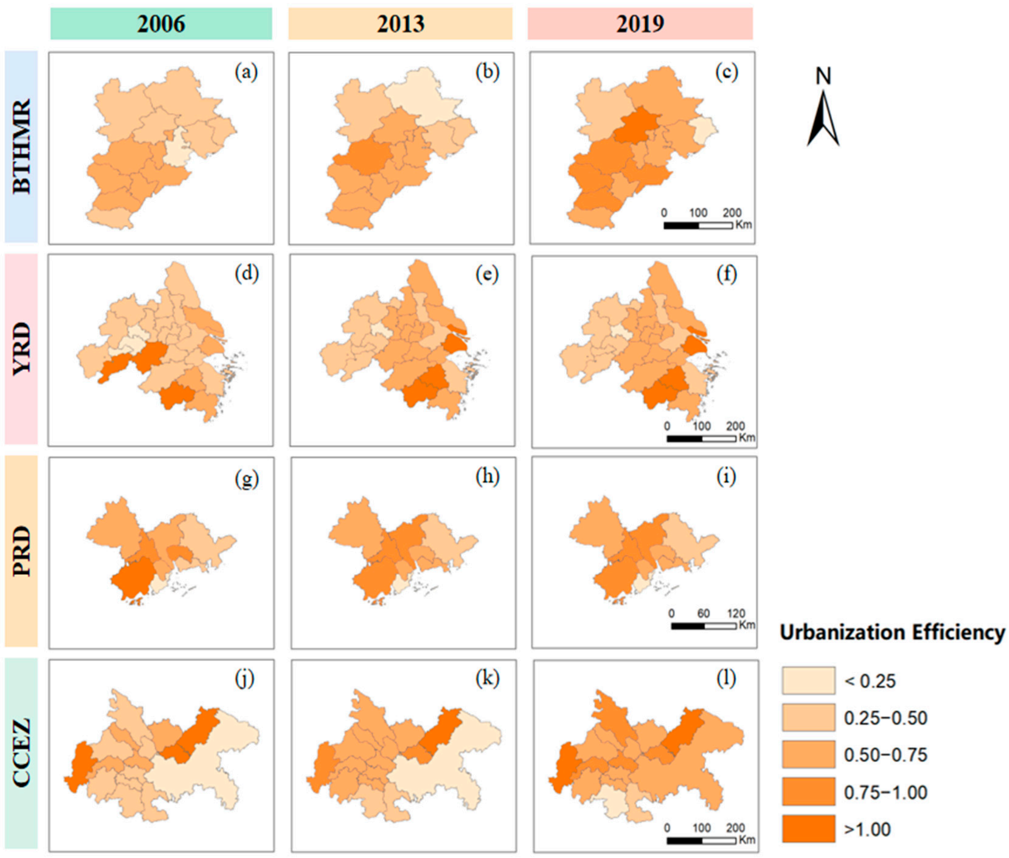

Figure 5. Spatial distribution of urbanization efficiency in the urban agglomerations. (**a**–**c**) represent the urbanization efficiency of the BTHMR in 2006, 2013, 2019; (**d**–**f**) represent the urbanization efficiency of the YRD in 2006, 2013, 2019; (**g**–**i**) represent the urbanization efficiency of the PRD in 2006, 2013, 2019; (**j**–**l**) represent the urbanization efficiency of the CCEZ in 2006, 2013, 2019.

4.3. Analysis of Factors Influencing Eco-Efficiency

Based on the aforementioned STIRPAT, an empirical analysis of the factors influencing EE in the four urban agglomerations was conducted using the STATA 16.0 software fixed-effects Tobit regression model, and the regression is shown in Table 4.

Table 4. Panel data regression results.

Explanatory Variable	Coefficient	Standard Error	*p*-Value
Cons	2.603565 ***	0.4538885	0.000
Population (ln*POP*)	−0.1036211 ***	0.0233198	0.000
Industrial structure (ln*IS*)	−0.3631796 ***	0.0827074	0.000
Urbanization (ln*URB*)	0.0760284 **	0.0358237	0.034
Foreign direct investment (ln*FDI*)	−0.0358348 ***	0.0133494	0.007
Technology input (ln*TEC*)	0.008113 *	0.0147322	0.082
Greenery (ln*GRE*)	−0.173352 **	0.0718395	0.016

Note: *, **, and *** represent coefficient significant at 10%, 5%, and 1%, respectively.

The effects of total population, industrial structure, *FDI*, and greenery on *EE* show significant negative correlation coefficients. Firstly, the total population has a significant negative impact on *EE* at the 1% level. A large population puts pressure on the economy, environment, and resources, which in turn leads to a reduction in *EE* and undermines sustainability of urban areas. Secondly, the analysis revealed that the coefficient of industrial structure on *EE* is significantly negative. Adjustments in this variable can cause changes in energy consumption and pollution emission intensity, which can have a significant impact on the environment. The study used the proportion of the secondary sector output to GDP to measure the industrial structure, and found heavy industries (fossil energy, machinery manufacturing, and assembly processing) account mainly for China's secondary industry and are characterized by high input and high pollution, which have a negative impact on *EE*. Thirdly, the results showed that *FDI* negatively affected *EE*, and the "pollution heaven" hypothesis is valid, which is consistent with the findings of Chang and others [51]. The study emphasized that regional competition leads to cities blindly introducing *FDI*, neglecting to examine the scale, direction, and quality of investment, resulting in a large proportion of foreign investment flowing into labor-intensive and low value-added traditional industries, which has an overall negative effect on the ecology. Additionally, the study found the short-term and long-term effects of *FDI* on the environment in China differ. In the short term, the structural and technological effects of foreign investment are greater than the scale effects, but as time increases, the scale effects of capacity expansion will gradually outweigh the technological spillover effects, with a corresponding increase in the scale of environmental pollution [52] and a consequent adverse impact on *EE*. Meanwhile, advanced production technologies can be introduced by way of *FDI* [53] to improve *EE*. Therefore, rational guidance in foreign direct investment is necessary. Lastly, this analysis revealed a negative correlation between the greening level and *EE* at a 5% significance level. The study highlighted that the main forms of greening in urban built-up areas, such as green belts and lawns, hardly constitute a complete ecosystem and to a large extent only serve to beautify the city. This is not conducive to improving environmental quality and instead reduces *EE* due to the high maintenance costs incurred later.

The technology inputs and urbanization have significant positive effects on *EE* at the 5% and 10% levels, respectively. Investing in science and technology has a significant catalytic impact on *EE*. "Innovation-driven" is a pivotal factor in economic transformation and a key driver of sustainable economic growth. Progress in science and technology can bring about technological and efficiency improvements in production and environmental protection, which are essential for establishing a favorable development environment for new urbanization. Technological progress can improve both factor utilization and resource utilization rates and can facilitate the formation of innovative and high-growth sectors, which can also increase the level of pollutant harmless treatment and effectively reduce resource consumption and ecological environmental pressure, thus contributing to the improvement of *EE*. The coefficient of urbanization efficiency on *EE* is positive, indicating that *URB* can enhance eco-efficiency to a certain degree. This may be due to the fact that young laborers from medium and small cities and rural areas will flock to regional center cities in large numbers, bringing about the labor scale effects and industrial agglomeration effects. Further urban development will increasingly emphasize sustainable urban transformation, thus promoting low-carbon, green, and sustainable urban construction, transforming the traditional extensive economy into an intensive one, and fostering the recovery of urban eco-efficiency.

5. Discussion and Policy Suggestions

5.1. Discussion

Eco-efficiency is utilized as a metric for assessing the environmental performance of economic activities [7] and has become a crucial criterion in the formulation of economic and environmental advancement policies in regions and countries across the globe. Further deepening the investigation of eco-efficiency holds immense importance in promoting sustainable development. Therefore, this paper uses the period 2006–2019 as the examination period; based on the urban agglomeration perspective, the Super-SBM model with undesirable output is applied to measure the *EE* and urbanization efficiency of 64 cities within the BTHMR, the YRD, the PRD, and the CCEZ, revealing the spatiotemporal evolution patterns of eco-efficiency in the four major urban agglomerations, further identifying the factors influencing *EE* by constructing the STIRPAT model, and exploring the relationship between urbanization and *EE*.

Firstly, this paper distinguishes itself from prior research by conducting a comparative analysis of *EE* of typical urban agglomerations in China, rather than focusing on a single region. Simultaneously, it provides an in-depth analysis of spatiotemporal evolution patterns of eco-efficiency. The US-SBM model, which addresses the factor relaxation issue and accounts for undesirable output, is used to overcome the limitations of traditional DEA and SFA models to a certain extent and provides a more accurate measurement of *EE*. The findings indicate that the four major urban agglomerations possess high levels of eco-efficiency, yet exhibit divergent development trends, with a general downward trajectory. This trend can be attributed to a development paradigm that prioritizes GDP growth, resulting in suboptimal resource allocation, resource depletion, and environmental degradation. During the period of 2006−2019, the average *EE* value for the four major urban agglomerations was 0.865, indicating a moderately high level of *EE*. Among them, the BTHMR exhibited considerable fluctuations in *EE* with an unstable development trend, the mean *EE* value decreased by approximately 10.3% from 2006 to 2019. The YRD exhibited a relatively stable development trend in terms of *EE*, with a decline of 9.43% over the examined period. In contrast, the *EE* trend line of the PRD demonstrated an overall "M" shape, characterized by significant fluctuations and a rising-declining-rising-declining trajectory. The CCEZ showed a development trend of initially falling and then rising, reaching its lowest point in 2017 before a subsequent increase. From 2006 to 2019, the average *EE* of the four typical urban agglomerations, in descending order, are: CCEZ > PRD > BTHMR > YRD. There are structural differences in the *EE* of cities within urban agglomerations, and the polarization effect of central cities needs to be strengthened. The spatial distribution of the BTHMR presents a cellular structure with Beijing, Tianjin, and their surrounding areas as the "cell nucleus" and the surrounding Beijing–Tianjin economic belt as the "cytoplasm," gradually showing a radial distribution characteristic of high in the middle and low in the surrounding area. The spatial distribution structure of the YRD remains stable from 2006 to 2019, but local differences still exist. The distribution of eco-efficiency values of the PRD presents a radiation pattern centered on Guangzhou and Shenzhen. The *EE* distribution characteristics of the CCEZ are relatively stable, with Chengdu as the core city, showing a distribution feature of high in the middle and low in the periphery.

Furthermore, based on the extended STIRPAT model combined with fixed-effect Tobit regression, the factors influencing *EE* within the four primary urban agglomerations are identified and the correlation between urbanization and *EE* is explored. The results show the *TEC* and *URB* have significant positive effects on *EE*, while *POP*, *IS*, *FDI*, and *GRE* have a restraining effect on it. Among them, the effects of the level of science and technology as well as *FDI* on eco-efficiency are consistent with the results of Chang (2020) [51]. In other words, technological advances promote eco-friendly technology and *EE*. *FDI* leads to an increase in environmental pollution, indicating a current tendency that countries in less developed areas sacrifice resources for economic development and the lack of strict control of environmental protection regulations [54]. Provinces that are more open to the outside world may be more concerned about their city images. Major cities such as Shanghai and Shenzhen still manage to counteract the negative effects of *FDI* by improving technology, though this is not always effective. Moreover, the negative impact of industrial structure is contrary to the findings of Zhang (2021) [55], which may be attributed to the selection of indicators. This paper argues that China's current industrial structure presents developed third industries in developed cities such as Beijing, Shanghai, and Shenzhen. Even within the advanced economic urban agglomerations, it is still dominated by the export of labor-intensive products, heavy industry and heavy pollution. This industry structure limits industrial optimization and causes environmental pressures [56]. More notably, greening in urban built-up areas does not make a positive contribution to the *EE* of the four major urban agglomerations. It is likely that the chosen indicator only represents the amount of land allocated for greening. High greening rates on building sites can be low-quality vegetation cover or even barren land [57], and to some extent can also hinder the efficiency of building development resources. For example, the spacing of protective forest belts should be set at a reasonable scale to achieve the optimal effect of wind and sand control in a specific range of arrangement and prevent the resources waste with diminishing marginal benefits. In this regard, the General Office of the State Council has proposed guidelines for scientific greening.

5.2. Policy Suggestions

Through the analysis conducted in this paper, apparently, there is still room for improving the efficiency and balanced distribution of green development in China's four primary urban agglomerations. Additionally, it is essential for the green development of distinct urban agglomerations to align with their respective features to achieve a comprehensive and sustainable green transformation of China's economy and society. To this end, several targeted suggestions for green development in the four typical urban agglomerations are proposed for the future.

The growth of *EE* seeks the coordinated development of economy, society, and the environment, which requires structural adjustment, technical efficiency enhancement, and policy support. Firstly, it is essential to emphasize regional heterogeneity and facilitate coordinated development. For regions such as the YRD, the PRD, and the BTHMR, which are already relatively developed, the preeminent status of core cities should be reinforced, their diffusion effect amplified, and a virtuous competition mechanism of mutual support established. We should establish an integrated development consciousness, build a platform for information exchange and resource sharing, achieve functional complementarity through horizontal dislocation and vertical division of labor cooperation, promote the allocation of production factors in a reasonable and efficient manner, and achieve the transformation of the eco-efficiency of developed regions from "positive internalities" to "positive externalities" to low eco-efficiency cities in the surrounding areas. Specifically, the implementation of Beijing's capital function positioning should be carried out, and attention should be paid to the policy opportunities brought by the upgrading of energy strategies to neighboring cities. The YRD should maintain the green development momentum of two types of efficient cities with industrial and ecological advantages and promote the industrial optimization of inland cities in the Yangtze River Delta [58]. Consolidate the growth pole status of cities such as Guangzhou and Shenzhen, pull the green development of the eastern and western ends of the PRD, and capitalize on the achievements of the construction of the Guangzhou–Shenzhen–Hong Kong–Macao Science and Technology Innovation Corridor to inject the momentum of science and technology innovation into green development. For the CCEZ, it should proactively capitalize on our strengths and undertake the transfer of industries from major cities, take the industrial transfer and innovation drive as an opportunity to promote the division of labor and upgrading of industries in each city, thus improving the layout of the industrial chain.

Secondly, in order to achieve green, circular, and low-carbon development, it is imperative for the government to assume a macro-regulatory role in the economy and industrial structure. Specifically, the government should incorporate the improvement of eco-efficiency as a fundamental criterion in the performance assessment system of local governments. Moreover, it is recommended that the government increase financial support for environmental protection and pollution control, while simultaneously encouraging enterprises to engage in research, development, and innovation of green technologies such as low-carbon technologies, clean production technologies, and recycling technologies. Simultaneously, according to the changes in regional economic development, it is essential to promote the transformation and upgrading of the industrial structure, as well as the transition from old to new momentum. This can be achieved by increasing the proportion of technology-intensive industries and tertiary industries, enhancing the added value of industries, and fostering long-term, healthy, and sustainable development of the regional economy. Metropolitan areas can attract top-tier human resources through the implementation of a range of preferential policies, while also increasing population density within the limits of environmental carrying capacity. Through the utilization of scale and agglomeration effects, economic and environmental efficiency can be enhanced to promote sustainable development. The government should also further enhance environmental regulations and judiciously attract foreign investments while reducing excess investment in urban greening and planning the greening area of cities reasonably to avoid resource wastage caused by formalism. Furthermore, local governments should carry out reasonable planning of land and enhance the efficiency of urban land [59]. Based on the actual situation, a rational layout of land space should be carried out; this entails a proper distribution of production space, living space, and ecological space within urban areas, promoting coordinated spatial development of the city's economy, people's lives, and ecological environment. The government, in conjunction with enterprises and other market players, should vigorously promote the adoption of clean energy, improve the multi-track system of environmental regulation, reduce industrial pollution emissions, and promote greater awareness of environmental protection among all people.

6. Conclusions

Eco-efficiency is of vital importance in promoting the sustainable and harmonious development of urban agglomerations under the Dual Carbon Target. In this study, we applied the Super-SBM model incorporating undesirable outputs to measure the eco-efficiency and urbanization efficiency of 64 cities located in the four urban agglomerations during 2006–2019. For further analysis, we used an extended STIRPAT model combined with spatial panel Tobit analysis to explore the determinants of eco-efficiency. In terms of comprehensive time series development and spatial distribution, the average *EE* value of the four typical urban agglomerations is 0.866, which is at a relatively high level. However, the eco-efficiency level has demonstrated a declining trend over time, experiencing a reduction of approximately 12.9%. This trend can be attributed to a development model that prioritizes economic growth, leading to unsatisfactory resource allocation, resource depletion, and environmental degradation. There exists a notable regional heterogeneity in the structural distribution of eco-efficiency across each urban agglomeration. Major central cities, such as Beijing, Guangzhou, Shenzhen, and Shanghai, have achieved a commendable equilibrium between economic growth and environmental preservation. Additionally, these cities have a certain degree of radiation effect on neighboring regions with regards to green development, but the degree of influence varies depending on factors such as differing economic and industrial foundations and geographical locations. The level of technology and urbanization exhibits a significant positive effect on eco-efficiency, while population, industrial structure, *FDI*, and greening level demonstrate a suppressive effect on urban eco-efficiency.

The aforementioned study serves to supplement the extant *EE* research framework and can offer valuable insights and recommendations for the sustainable development of China as well as other nations and holds significant international demonstrative implications. For instance, we can promote coordinated regional development and realize the radiating effects of eco-efficiency through measures such as industrial restructuring and technological efficiency improvements. Alternatively, the government state strategically coordinates the ecological development of urban agglomerations through environmental protection regulations and scientific greening guidelines. However, there are still some limitations in this study: This paper investigates the spatiotemporal variations in *EE* and its influencing factors within China's four primary urban agglomerations, without delving into other regions. The present study's selection of determinants impacting *EE* is not exhaustive, as factors such as residents' consumption and level of education, as well as environmental policies, may also exert a certain degree of influence on *EE*. In the future, there is a pressing need to undertake a more comprehensive and exhaustive investigation of eco-efficiency and its determinants across various regions in China. Specifically, it is imperative to conduct a comprehensive analysis of the discrepancies and formation mechanisms between urban agglomerations at varying levels of development. Only this way will enable the formulation of targeted policy recommendations to facilitate sustainable development.

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