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Assessment of Urban Green Development Efficiency Based on Three-Stage DEA: A Case Study from China's Yangtze River Delta

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Abstract: With the march of global urbanization, there are looming problems including environmental degradation and remediation all over the world. In this case, urban green development is the key to overcoming climate crisis, biodiversity loss and pollution. In this paper, a three-stage DEA model was employed to study the urban green development efficiency (GDE), with cities in the Yangtze River Delta (YRD) as the object. In the study, the regional economic foundation, urbanization level, industrial structure and government planning were used as external environmental variables, and the impact of objective external environmental factors was tested empirically, thereby eliminating the adverse environmental impact and statistical noise to obtain more truthful GDE. According to the results, first, the influence of external environmental factors and stochastic disturbance on GDE was effectively removed by virtue of the three-stage DEA model, and the GDE of the YRD was measured in a true and objective manner. The GDE of the YRD in Stage III was notably higher than that in Stage I since the GDE in Stage I was underestimated under the influence of objective environmental variables. Second, the GDE level showed heterogeneity in different cities, which behaved better in coastal and southeastern regions than in central, western and northern regions. Third, regarding the impact of external environmental variables, the GDE was enhanced by increasing the proportion of the tertiary industry and the green area of built districts but weakened when the area of built districts (ABD) reflecting urban construction was expanded. The index gross regional product (GRP) reflects local economic development level, the impact of which on GDE was not determined in this paper. As a consequence, in the process of urban development, it is suggested to focus on the innovation and application of green technology, upgrade the industrial structure, cultivate green talents, and formulate reasonable green transformation policies.

Keywords: urban green development efficiency; Yangtze River Delta; three-stage DEA analysis; China

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1. Introduction

As the global economy develops, the scale of cities has continued to expand and the urban population has risen sharply, impacting the environment in many aspects. The area of cities only accounts for 3% of the world's land, and cities contribute 80% of the gross world product (GWP) at the expense of 70% of the world's resources and 75% of the global greenhouse gas emissions [1,2]. With global urbanization, human beings consumed natural resources and energy over the past 100 years, reaching an unprecedented level in human history. Accordingly, resource consumption and greenhouse gas emissions have sharply deteriorated the global ecological environment. Moreover, urban environmental problems are no longer limited to cities, but environmental problems involving all regions and all countries. As Anwarul K. Chowdhury, the Chairman of the Global Forum on Human Settlements (GFHS) and former Deputy Secretary-General and High Representative of the United Nations, said, "The world is undergoing a process of urbanization, and a new urban age has come. It is conceivable that the global urbanization level will be as high as 70% in the next 40 years. Sustainable urban development is one of the most serious challenges for human society in the 21st century. As a growing number of people settle in cities, cities will face the greatest challenges in the world at all levels, so concerted efforts and sincere cooperation are required from all over the world". On 18 November 2021, the United Nations Environment Program (UNEP) and UN-Habitat jointly released the Global Environment Outlook for Cities report, calling for urgent action to achieve net-zero recycling cities that are resilient, sustainable, inclusive and equitable, thus providing feasible solutions for the construction of environmentally friendly and green cities. Urban green development is the key to overcoming climate crisis, biodiversity loss and pollution, and it is also an important way to build urban ecological civilization and promote economic transformation by improving the green development level [3]. Not only is green development an idea describing a green environment from all aspects, but it also puts a premium on coordinated economic, social and environmental development, which is a comprehensive model aiming at efficiency, development and sustainability [4]. The economic vitality, innovation and competitiveness serving high-quality urban development are closely linked to green development. In the absence of green development, economic development will lose driving force and vitality, and similarly, there will be a lack of foundation and support concerning innovation and competitiveness [5].

The green development level can be measured by two main methods including the comprehensive index system and green development efficiency (GDE). For the first method, the regional green development status is evaluated by constructing an index system. Zhang et al. (2021) established an index system to measure the GDE in the Yangtze River Delta (YRD) on the strength of four dimensions: social development, economic development, energy consumption and ecological environment. Yang et al. (2019) evaluated the green development of resource-based cities in China and found that the green development level in the east of China was higher than that in the west [6]. The second method is usually realized by parametric stochastic frontier analysis (SFA) and nonparametric data envelopment analysis (DEA)) [7]. SFA is commonly applied to a single output scenario and requires the estimation of specific functional forms, but incorrect results may be caused by an incorrect functional form [8,9]. As a linear programming technique, DEA is widely used in the evaluation of the relative efficiency of homogeneous decision-making units, especially for multiple input-output scenarios [10–12]. Hence, there are an increasing number of scholars using DEA and its extended models to evaluate regional GDE. For instance, Wu et al. (2020) analyzed the GDE of 30 provinces in China in 2015 using a multi-objective DEA model from the perspective of resource allocation [13]. According to the annual cross-sectional data of different regions, Yang et al. (2015) employed the super-efficiency DEA model and the Malmquist index model to calculate the GDE of 31 regions in China during 2008–2012 [14].

Notwithstanding, environmental variables and statistical noise bring about considerable impacts in the traditional DEA, so the estimation of results may be biased and inaccurate [15]. In order to solve this problem, Fried et al. proposed a three-stage DEA model, that is, after calculating the efficiency value with the traditional DEA, the changes in the environment, statistical noise and management efficiency were analyzed with the help of the SFA model, the original input variables were adjusted, and then a second DEA calculation was performed to obtain the real efficiency value [16,17]. The three-stage DEA model has been applied by many scholars to calculate the efficiency of different subjects in different fields, and the results obtained are superior to those obtained through the traditional DEA model [18–20]. At present, there is still little information on GDE at the city level in a region since GDE is calculated using the traditional DEA in most of the existing studies.

To fill this gap, in this paper, based on the three-stage DEA model, cities in the YRD were selected as the object of the study. In the study, the regional economic foundation, urbanization level, industrial structure and government planning were served as external environmental variables, and the impact of objective external environmental factors was tested empirically, thereby eliminating environmental factors and statistical noise to obtain a more truthful GDE, as well as policy suggestions for improving the urban environment. The other parts of the paper are organized as follows: The second part contains the scope of the study, variable selection and description, and computation model description. The GDE calculation is conducted in the third part, and further discussion on the results is revealed in the fourth part. Finally, the conclusions are summarized, and some suggestions and implications for the sustainable ecological development of cities in the future are put forward.

2. Materials and Methods

2.1. Scope of Study

China is a developing country with the largest energy consumption and carbon dioxide emissions in the world, where sustainable urban development faces severe challenges. Benefited from the policy dividends of reform and opening up and the high attention of the State, the YRD is one of the regions with the most active economic development, the highest degree of openness, and the strongest innovation capability in China, which holds a pivotal strategic position in the national modernization and all-round opening-up pattern. According to the Outline of the Integrated Regional Development of the YRD approved by the State Council in 2019, the YRD covers an area of 358,000 km^2, including Shanghai municipality and three provinces, i.e., Jiangsu, Zhejiang, and Anhui provinces, as shown in Figure 1.

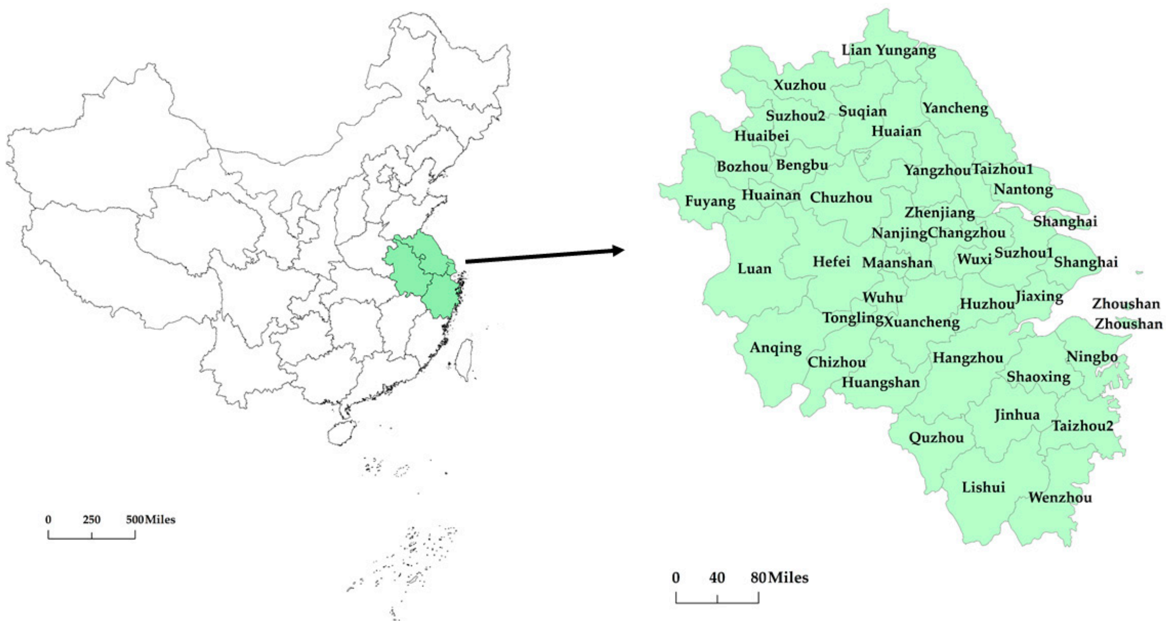


Figure 1. Distribution of 41 Cities in the YRD.

2.2. Variable Selection and Description

The GDE indexes shall be selected in accordance with the connotation of GDE. Based on previous studies, in this paper, GDE was defined as a fact that the maximum economic and social benefits are obtained with the minimum factor input and the minimum environmental output, so as to achieve a win–win situation of "economy–society–ecology". Comparatively, this definition better reflects the connotation of the social level than the previous definitions, which is completely consistent with the concept of urban green development.

For input indexes, the general input factors mainly include capital, labor, resources and technology [15,18]. Referring to the multilayer evaluation indexes on urban development systems of Feng and Xu (1999), Su et al. (2019), Zhang et al. (2021) [21–23], the investment in fixed assets (IFA) represents the capital input factor, the employment in the management of water conservancy and environment (EMWCE) indicates the elements of labor input, the annual electricity consumption (AEC) of the entire society stands for the input of energy factors, and the expenditure for education, science and technology (EEST) denotes the technical input factors. According to relevant study results and the availability of data, the total retail sales of consumer goods (TRSCG) were used as the desired output to represent the economic and social levels of a city. The volume of industrial wastewater discharged (VIWD) and volume of industry sulfur dioxide produced (VISDP) were selected to comprehensively investigate the environmental pollution factors.

Environmental variables in this study refer to factors that can affect GDE but cannot be controlled or changed by samples subjectively [24,25]. In this paper, the indexes gross regional product (GRP) [26], area of built districts (ABD) [22], the tertiary industry as a percentage of GRP (TIP) [27] and green covered area of complete area (GCA) [28] were selected as the environmental variables to indicate the economic development, urban construction, industrial structure and government planning, respectively.

With 41 cities in the YRD as the object of the study, the GDE there during 2009–2018 was evaluated, and corresponding data were obtained from the China Statistical Yearbook, China City Statistical Yearbook and official websites of the Bureau of Statistics of various cities. Table 1 presents the evaluation index system, where four inputs, three desirable outputs and four environmental variables are listed, and descriptive statistics of the selected data are exhibited in Table 2.

Table 1. Evaluation index system of GDE.

Variable	No.	Index	Unit
Input Variables	I1	AEC	10,000 kwh
	I2	IFA	10,000 yuan
	I3	EEST	10,000 yuan
	I4	EMWCE	person
Output Variables	O1	VIWD	10,000 tons
	O2	VISDP	ton
	O3	TRSCG	10,000 yuan
Environmental Variables	E1	GRP	10,000 yuan
	E2	ABD	sq. km
	E3	TIP	%
	E4	GCA	hectare

Source: Authors' work.

Table 2. Descriptive statistics.

Variable	Number	Mean Value	Standard Deviation	Min.	Max.
I1	410	1,828,000	3,031,000	67,166	31,820,000
I2	410	21,730,000	18,060,000	2,352,000	112,400,000
I3	410	1,022,000	1,572,000	64,104	13,440,000
I4	410	9873	12,761	455	93,600
O1	410	11,624	13,123	486	80,468
O2	410	43,067	45,387	1407	496,377
O3	410	13,540,000	16,900,000	791,784	126,700,000
E1	410	35,780,000	44,200,000	1,331,000	326,800,000
E2	410	176.5	186.4	31	1238
E3	410	0.42	0.0825	0.234	0.793
E4	410	7925	10,934	1256	139,427

Source: Authors' work.

For indexes of desirable output, environmental factors are always considered undesirable outputs [7]. Given that the outputs of the DEA model are generally desirable, it is unreasonable to select the three-stage DEA method when environmental pollutants are undesirable outputs. Some scholars treat undesirable outputs as inputs [29,30], which only requires information on whether the data should be minimized or maximized but cannot reflect the real production process. Therefore, the above-required indexes should be converted accordingly. The data conversion function processing method is an ideal efficiency evaluation method proposed by Seiford and Zhu (2002), containing negative output, linear and nonlinear data conversion and other types. In this study, the method was specially selected for data conversion of the environmental pollutant indexes. The specific formula is $Y_i = -Y_i + D$, where D represents a very large vector to ensure that all converted output data are positive. Referring to the existing study results, the C value was set to 1.1 times the maximum value in the sample area.

Under the application conditions of the DEA model, the pollution emission index was transformed and processed. The industrial wastewater and sulfur dioxide emissions were reduced to a comprehensive index, and the pollution index was converted by the data conversion function processing method. The linear data conversion method for reinforcing the environmental pollutants after conversion can reasonably solve the problem of the undesirable outputs in the three-stage DEA model for efficiency evaluation, effectively maintaining the convex and linear relationship.

2.3. Computation Model Description

Leveraging the three-stage DEA model, the true GDE was calculated as per the steps below:

Stage I: The traditional DEA model was applied. Charnes, Cooper and Rhodes introduced a DEA method, also called the CCR model, to calculate the relative effectiveness of decision-making units (DMUs) under constant returns to scale [12]. Later, Banker, Charnes and Cooper decomposed the comprehensive technical efficiency in the CCR model into PTE (pure technical efficiency) and SE (scale efficiency) which have been used to measure the effectiveness of DMUs under variable returns to scale, also known as the BCC model [31]. This paper employed the BCC model to estimate the initial effectiveness of 41 cities in the study area, and the calculation process is expressed as follows:

$$\min_{\theta,\lambda} = \left[\theta - \left(e^t s^- + e^t s^+\right)\right] \tag{1}$$

$$\sum_{k=1}^{n} \lambda_i y_{rk} - s^+ = y_{0k} \tag{2}$$

$$\sum_{k=1}^{n} \lambda_i y_{rk} + s^- = \theta x_{0k} \tag{3}$$

where i = 1, 2, . . . , m and r = 1, 2, . . . , s. n indicates the number of measuring units, m represents the number of input indexes and s denotes the number of output indexes. x_{ik} $(i = 1, 2, \ldots, m)$ refers to the i_{th} input element of the k_{th} measuring unit, y_{rk} $(r = 1, 2, \ldots, s)$ stands for the r_{th} output element of the k_{th} measuring unit and θ indicates the valid value of DMUs. If $\theta = 1$ and $s^+ = s^- = 0$, the measuring unit is of DEA efficiency; if $\theta = 1$ and $s^+ \neq s^- \neq 0$, the measuring unit is of weak DEA efficiency; if $\theta < 1$, the measuring unit is of non-DEA efficiency.

Stage II: In the second stage, the input slacks in Stage I were decomposed with the SFA model for eliminating the influence of uncontrollable effects on efficiency. It was a regression equation with input slacks as the explained variable and environmental variables as the explanatory variable [32]. Input slack refers to the difference between the input of the i_{th} measuring unit and the optimal efficiency of a certain actual input in Stage I. According to the study by Fried et al. (2002), the input slacks in Stage I was decomposed into three components including the influence of environmental effects, managerial inefficiencies, and stochastic disturbance. In the case of n DMUs, every DMU contains p observable environmental variables $Z_i = [Z_{1i}, \ldots Z_{pi}]$. Input slacks can be decomposed into the following form:

$$s_{ik} = f^i\left(z_k; \beta^i\right) + v_{ik} + u_{ik} \tag{4}$$

where is the slack value for the i_{th} input of the k_{th} DMU and $f^i(z_k ; \beta^i)$ marks the environmental effects, which is denoted as $f^i(z_k ; \beta^i) = z_k \times \beta^i$. $v_{ik} + u_{ik}$ stands for the mixed error term, v_{ik} is the stochastic error term, and μ_{ik} refers to the managerial inefficiency. If $v_{ik} \sim N(0, \theta_{vi}^2)$, $v_{ik} \sim N^+(u^i, \sigma_{ui}^2)$, v_{ik} and u_{ik} are independent of each other. $\gamma = \sigma_{ui}^2/(\sigma_{ui}^2 + \sigma_{vi}^2)$ is defined. When γ tends to 1, the influence of managerial factors is dominant, and when γ tends to 0, the difference in efficiency is mainly attributed to stochastic disturbance.

To adjust the measuring unit to the same external environment and stochastic factor state based on the most effective measuring unit, the unknown parameters were estimated by the maximum likelihood method, and then the original input was adjusted according to the formula below.

$$\hat{x}_{ik} = x_{ik} + \left[\max_k\left\{z_k\overset{\wedge}{\beta^i}\right\} - z_k\overset{\wedge}{\beta^i}\right] + \left[\max_k\left\{\hat{v}_{ik}\right\} - \hat{v}_{ik}\right] \tag{5}$$

$$i = 1, 2, \ldots, m;\ k = 1, 2, \ldots, n;$$

where $\hat{x_{ik}}$ is the adjusted input variable, and x_{ik} is the original input variable. The first square bracket indicates that the environment of DMU is adjusted to the same level, and the second indicates that the statistical noise of DMU is adjusted to the same situation. According to the above formula, statistical noise and managerial inefficiency shall be separated first. The statistical noise condition was estimated as:

$$\hat{E}[v_{ik}|v_{ik} + u_{ik}] = s_{ik} - z_k\,\overset{\wedge}{\beta^i} - \hat{E}[u_{ik}|v_{ik} + u_{ik}] \tag{6}$$

Fried et al. (2002) failed to provide an estimation formula for management inefficiency, but recommended the formula proposed by Jondrow et al. (1982), i.e., $\hat{E}\ [u_{ik} \mid v_{ik} + u_{ik}]$, to estimate the managerial inefficiency. However, the estimation formula by Jondrow et al. (1982) was based on the stochastic frontier production function, and the DEA model by Fried et al. (2002) was on the basis of the stochastic frontier cost function [33]. Some scholars failed to notice this point and misused the formula, resulting in low credibility of results [32,34,35]. Instead, the estimation formula of managerial inefficiency in the three-stage DEA model should be derived according to their methods. Luo (2012) proposed an estimation formula for the managerial inefficiency of the three-stage DEA model based on the assumption of uniform distribution, earning a more reasonable construction of the DEA model.

$$E(u|\varepsilon) = \sigma_*\left[\frac{\phi(\lambda\frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma}\right] \tag{7}$$

where $\sigma_* = \sigma_u\sigma_v/\sigma$, $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$, and $\lambda = \sigma_u/\sigma_v$, $\phi(.)$, $\Phi(.)$ refer to the density and distribution functions of the standard normal distribution, respectively.

Stage III: The adjusted input variable and the original output variable were put into the BCC model again, obtaining the efficiency value without the influence of environmental effects, managerial inefficiencies, and stochastic disturbance. Comparatively, this efficiency value was more objective and scientific than that obtained in Stage I.

See Figure 2 for the process framework of the whole model.

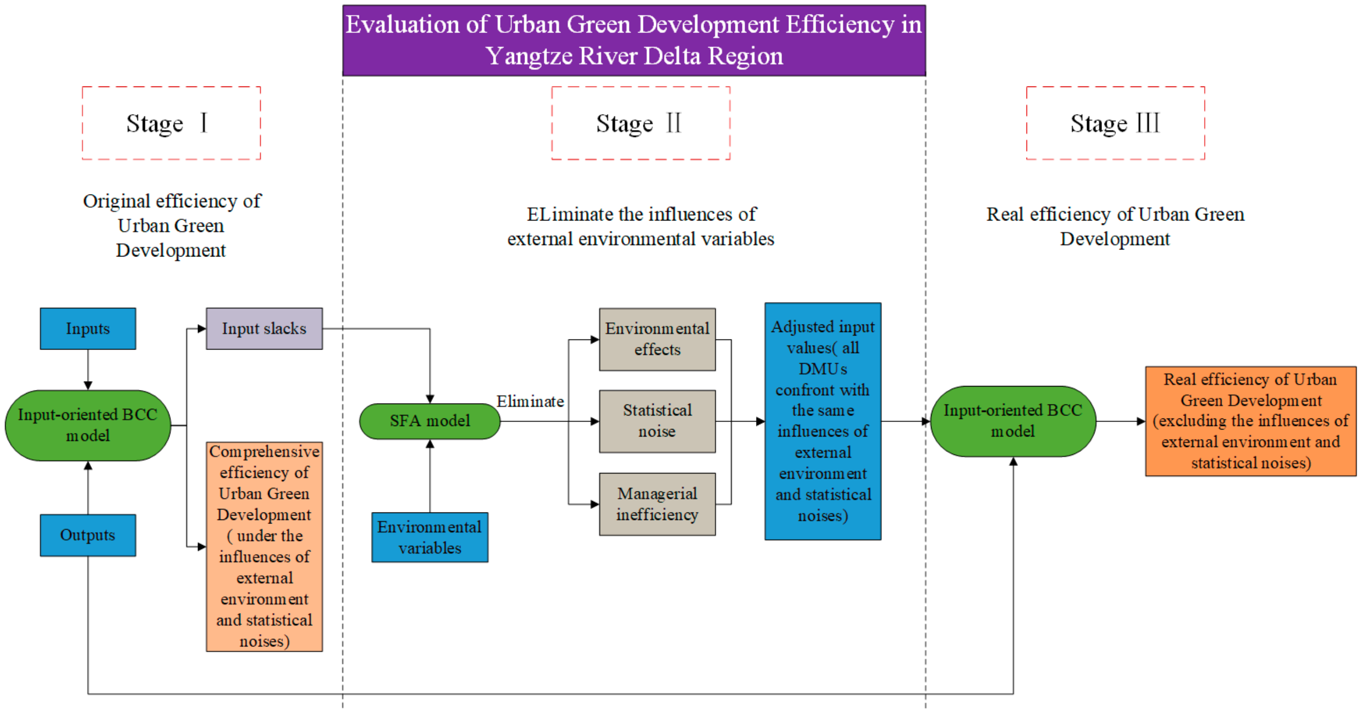


Figure 2. Calculation process of the three-stage DEA model for GDE in the YRD.

3. Results

3.1. Stage I: Comprehensive Technical Efficiency from the BCC Model

The GDE of 41 cities in the YRD during 2009–2018 was obtained using the input-oriented BCC model (Table 3). The mean comprehensive efficiency was 1 in both Wenzhou and Jinhua cities, being the highest among the 41 cities. The mean comprehensive efficiency was lower than 0.7 in Suqian, Wuhu and Huai'an cities, showing poor performance, which was 0.560, 0.593 and 0.655, respectively. The mean comprehensive efficiency was higher than 0.98 and lower than 1 in Nanjing, Quzhou, Huaibei, Lishui, Taizhou[2], Huangshan and Shanghai, showing excellent performance, which was 0.996, 0.996, 0.994, 0.992, 0.992, 0.985 and 0.980, respectively. The mean comprehensive efficiency of the other cities, Chuzhou, Lianyungang, Anqing, Suzhou[2], Lu'an, Ma'anshan, Taizhou[1], Hefei, Xuzhou, Bengbu, Zhenjiang, Ningbo, Yangzhou and Huainan, was lower than the mean of the overall mean comprehensive efficiency of the 41 cities in the YRD (0.859), which was 0.707, 0.709, 0.722, 0.734, 0.751, 0.770, 0.788, 0.792, 0.794, 0.797, 0.833, 0.837, 0.840 and 0.845, respectively. The mean comprehensive efficiency of Suzhou[1], Yancheng, Jiaxing, Zhoushan, Shaoxing, Nantong, Xuancheng, Hangzhou, Tongling, Changzhou, Bozhou, Wuxi, Fuyang, Huzhou and Chizhou was higher than the mean of the overall mean comprehensive efficiency of the 41 cities in the YRD (0.859), which was 0.861, 0.863, 0.868, 0.878, 0.881, 0.887, 0.891, 0.893, 0.909, 0.933, 0.939, 0.946, 0.95, 0.952 and 0.956, respectively. From 2009 to 2018, the GDE of some of the 41 cities in the YRD fluctuated greatly. For example, the GDE of Chizhou was 0.647 in 2016 and above 0.9 in the other years; the GDE of Wuxi was 0.740 in 2015 and above 0.9 in the other years; the GDE of Xuancheng was all above 0.9 from 2009 to 2015 and dropped to 0.646, 0.668 and 0.691 respectively in 2016–2018; the GDE of Yancheng was all above 0.9 from 2009 to 2014 and dropped to 0.631, 0.792, 0.682 and 0.634 respectively in 2015–2018. The above results showed that the changing trend of GDE is unstable, presenting big fluctuations in this area. In consequence, more measures should be taken to improve GDE steadily.

Table 3. GDE of 41 cities (2009–2018) in Stage I.

City	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Mean	Ranking
Shanghai	0.898	0.934	1.000	1.000	1.000	1.000	1.000	0.968	1.000	1.000	0.980	I
Nanjing	1.000	1.000	1.000	1.000	1.000	1.000	0.956	1.000	1.000	1.000	0.996	I
Wuxi	0.973	0.926	1.000	0.968	0.953	0.903	0.740	1.000	1.000	1.000	0.946	II
Xuzhou	0.783	0.721	0.615	1.000	0.622	0.741	0.666	1.000	0.824	0.965	0.794	III
Changzhou	1.000	0.956	0.889	0.938	0.925	0.923	0.695	1.000	1.000	1.000	0.933	II
Suzhou [1]	0.838	0.819	0.766	0.759	0.762	0.808	0.860	1.000	1.000	1.000	0.861	III
Nantong	1.000	0.951	0.841	1.000	0.785	0.778	0.739	0.935	0.902	0.943	0.887	II
Lian Yungang	0.839	0.766	0.681	0.636	0.654	0.580	0.549	1.000	0.660	0.721	0.709	IV
Huaian	0.694	0.632	0.587	0.581	0.614	0.636	0.547	0.736	0.689	0.832	0.655	IV
Yancheng	0.970	0.952	0.984	0.987	1.000	1.000	0.631	0.792	0.682	0.634	0.863	III
Yangzhou	0.966	0.958	0.888	0.884	0.867	0.853	0.585	0.801	0.765	0.832	0.840	III
Zhenjiang	0.859	0.857	0.854	0.806	0.804	0.900	0.664	0.920	0.833	0.830	0.833	III
Taizhou [1]	0.846	0.819	0.889	0.811	0.783	0.868	0.601	0.764	0.730	0.764	0.788	IV
Suqian	0.547	0.498	0.546	0.522	0.509	0.782	0.505	0.570	0.559	0.561	0.560	IV
Hangzhou	0.816	0.788	0.842	0.902	0.951	0.953	0.865	0.934	1.000	0.877	0.893	II
Ningbo	0.768	0.768	0.803	0.813	0.852	0.858	0.852	0.869	0.904	0.886	0.837	III
Wenzhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	I
Jiaxing	0.929	0.888	0.831	0.844	0.839	0.820	0.981	1.000	0.781	0.767	0.868	III
Huzhou	0.886	0.986	0.972	1.000	0.995	0.871	0.918	1.000	0.925	0.963	0.952	II
Shaoxing	0.954	0.976	0.988	0.947	0.840	0.789	0.714	1.000	0.827	0.773	0.881	II
Jinhua	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	I
Quzhou	1.000	0.956	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.996	I
Zhoushan	0.929	1.000	0.953	0.918	0.878	0.781	0.664	0.728	0.925	1.000	0.878	III
Taizhou [2]	0.954	0.961	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.992	I
Lishui	0.929	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.993	1.000	0.992	I
Hefei	0.948	0.837	0.750	0.650	0.690	0.688	0.708	0.666	1.000	0.979	0.792	IV
Wuhu	0.766	0.665	0.563	0.526	0.509	0.470	0.519	0.529	0.622	0.760	0.593	IV
Bengbu	0.985	0.881	0.745	0.756	0.710	0.711	0.786	0.597	0.919	0.880	0.797	III
Huainan	1.000	0.954	0.761	0.852	0.763	0.929	0.714	1.000	0.707	0.766	0.845	III
Maanshan	0.890	0.778	0.644	0.629	0.587	0.736	0.717	0.953	1.000	0.767	0.770	IV
Huaibei	0.939	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.994	I
Tongling	1.000	1.000	1.000	0.916	0.896	0.912	0.791	0.749	0.821	1.000	0.909	II
Anqing	0.625	0.652	0.650	0.699	0.706	0.706	0.865	0.674	0.840	0.805	0.722	IV
Huangshan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.846	1.000	1.000	0.985	I
Chuzhou	0.744	0.722	0.831	0.696	0.741	0.740	0.800	0.710	0.573	0.508	0.707	IV
Fuyang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.856	0.926	0.720	0.950	II
Suzhou [2]	0.817	0.834	0.686	0.678	0.737	0.713	0.621	0.736	0.634	0.883	0.734	IV
Luan	0.767	0.746	0.691	0.789	0.726	1.000	0.725	0.558	0.750	0.759	0.751	IV
Bozhou	1.000	1.000	1.000	1.000	1.000	1.000	0.992	0.718	0.847	0.834	0.939	II
Chizhou	1.000	1.000	1.000	1.000	1.000	0.995	0.918	0.647	1.000	1.000	0.956	I
Xuancheng	1.000	1.000	1.000	1.000	1.000	0.909	1.000	0.646	0.668	0.691	0.891	II
YRD	0.893	0.877	0.860	0.866	0.846	0.862	0.802	0.851	0.861	0.871	0.859	

Source: Authors' work. I II III IV represents the ranking 1~10, 11~20, 21~30, 31~41, respectively. Suzhou [1] and Taizhou [1] belong to Jiangsu Province. Suzhou [2] belongs to Anhui province, and Taizhou [2] belongs to Zhejiang provinces.

In this study, 41 cities were divided into Shanghai Municipality, Jiangsu, Zhejiang and Anhui provinces by provincial level, and the GDE time series in the YRD was further analyzed, as shown in Figure 3. The GDE for the whole region was between 0.802 and 0.893 during the study period, with a zero cut-off point in 2015. Distinctively, the GDE of Shanghai Municipality rose from 2009 to 2011 and remained at the forefront almost throughout the subsequent period, the GDE of Zhejiang Province ranked second overall, and the GDE showed a trend of declining first and then rising in both Jiangsu and Anhui provinces. The foregoing results demonstrated that the GDE needs to be promoted constantly in the YRD and stabilized in Jiangsu and Anhui provinces.

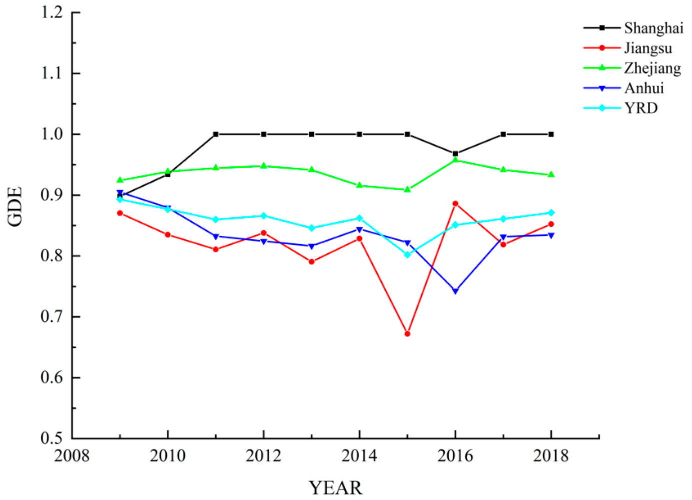


Figure 3. Time series of GDE in the YRD in Stage I.

3.2. Stage II: SFA Model

In this part, an SFA regression model was built, of which the slack value of each input variable served as the explained variable and GRP, ABD, TIP and GCA were taken as explanatory variables and an SFA regression model was built with the software Frontier 4.1 to estimate the impact of environmental variables [36]. The SFA regression results are listed in Table 4.

Table 4. The results of SFA regression.

Explanatory Variable	Slacks of Input Variables			
	AEC	IFA	EEST	EMWCE
Constant term	−177,242.07 −140,141.30	−2,391,731.60 −1,891,088.14	−49,187.69 −751.78	−816.14 −71.51
GRP	−6226.56 (−511.36) ***	−2,017,080.80 (−165,654.65) ***	−30,534.40 (−319.20) ***	385.84 (1.44) *
ABD	363,134.99 (23,017.63) ***	18,522,799.00 (1,174,083.64) ***	499,887.82 (40,106.30) ***	7736.39 (17.37) ***
TIP	−55,091.87 (−5258.59) ***	−1,120,127.10 (−106,917.67) ***	−38,150.40 (−234.72) ***	−531.48 (−11.99) ***
GCA	−328,483.35 (−21,419.04) ***	−15,710,684.00 (−1,024,428.59) ***	−455,881.82 (−19,887.36) ***	−7669.25 (−111.83) ***
γ	1.00	1.00	0.98	1.00
Log likelihood function	−561.07559	−675.04933	−529.03493	−357.3225
LR test	35.5	34.6	37.3	28.7

Notes: *, and *** indicate the significance level at 10%, 5% and 1%, respectively.

According to Table 4, the four models were subject to the LR test and the value of γ was 1 or close to 1, indicating that in the mixed error term, the management inefficiency has a much greater impact on the input slack than the stochastic error term. In the case of a negative regression coefficient, the increase of the explanatory variable reduced the slack of the input variable, narrowing the gap between the actual and ideal value of the input variable. Hence, the increase of the explanatory variable was conducive to the enhancement of GDE. On the contrary, when the regression coefficient was greater than 0, the increase of the explanatory variables was adverse to the improvement of GDE. As shown in Table 4, GRP had a significant negative relationship with AEC, IFA and EEST and a significant positive relationship with EMWCE, ABD significantly had a positive impact on the slack variables of the four inputs, and both TIP and GCA had significant negative impacts on the slack variables of the four inputs (below 1%), which are discussed in the next part.

In accordance with Formulas (4)–(6), u_i the management inefficiency term was separated and calculated next, so that the measuring unit was adjusted to the same external environment and stochastic factor state, thereby adjusting the original data to obtain new input variables. The calculation process was complicated, and it was omitted herein due to the limited space.

3.3. Stage III: Actual GDE in the YRD

Table 5 lists the actual GDE in the YRD based on the adjusted input value (2009~2018). As shown in the table, the actual mean GDE was 1 in Nanjing, Wenzhou and Jinhua cities, notably superior to that in other cities. The actual mean GDE of Huai'an, Wuhu and Suqian was dramatically lower than that of other regions, which was 0.754, 0.734 and 0.705, respectively, showing poor performance. Besides, the actual mean GDE was higher than 0.98 in Huaibei, Shanghai, Tongling and Taizhou[2], being 0.999, 0.990, 0.990 and 0.982, respectively, which was better than that in other cities. The overall mean of the actual GDE of the 41 cities in the YRD was 0.908. In addition to the aforementioned cities, the actual mean GDE was lower than the overall mean (0.908) in Taizhou[1], Lianyungang, Suzhou[2], Xuzhou, Anqing, Zhenjiang, Maanshan, Zhoushan, Hefei, Jiaxing, Ningbo, Yangzhou, Yancheng, Lishui and Shaoxing, which was 0.828, 0.832, 0.850, 0.853, 0.858, 0.866, 0.871, 0.872, 0.875, 0.885, 0.887, 0.888, 0.901, 0.903 and 0.907, respectively. Meanwhile, the actual mean GDE was higher than the overall mean (0.908) in Lu'an, Chuzhou, Hangzhou, Suzhou[1], Xuancheng, Nantong, Chizhou, Quzhou, Huangshan, Huzhou, Bengbu, Huainan, Bozhou, Changzhou, Wuxi and Fuyang, which was 0.908, 0.909, 0.915, 0.918, 0.921, 0.926, 0.937, 0.938, 0.941, 0.941, 0.946, 0.953, 0.955, 0.959, 0.965 and 0.977, respectively. From the overall trend, the actual GDE of many cities dropped dramatically in 2016. For example, the actual GDE of Chizhou was 0.378 in 2016 and above 0.995 in the other years. The actual GDE of Xuancheng was 0.559 in 2016 and above 0.8 in the other years. The actual GDE of Bengbu was 0.581 in 2016 and above 0.9 in the other years. The actual GDE trend of most other cities was relatively stable. For example, the actual GDE of Huzhou exceeded 0.9 in the ten years from 2009 to 2018.

Table 5. GDE of 41 cities (2009–2018) in Stage III.

City	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Mean	Ranking
Shanghai	0.926	0.969	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.990	I
Nanjing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	I
Wuxi	0.959	0.914	0.992	0.938	0.991	0.968	0.887	1.000	1.000	1.000	0.965	I
Xuzhou	0.817	0.755	0.664	1.000	0.724	0.867	0.832	1.000	0.891	0.983	0.853	IV
Changzhou	1.000	0.923	0.914	0.935	0.994	1.000	0.820	1.000	1.000	1.000	0.959	I
Suzhou [1]	0.853	0.833	0.849	0.772	0.877	1.000	1.000	1.000	1.000	1.000	0.918	II
Nantong	1.000	0.961	0.809	1.000	0.844	0.843	0.915	0.997	0.942	0.951	0.926	II
Lian Yungang	0.915	0.824	0.848	0.736	0.793	0.839	0.705	1.000	0.864	0.853	0.838	IV
Huaian	0.767	0.681	0.704	0.681	0.749	0.828	0.715	0.677	0.842	0.896	0.754	IV
Yancheng	1.000	1.000	0.950	1.000	1.000	1.000	0.774	0.864	0.741	0.682	0.901	III
Yangzhou	0.997	0.984	0.877	0.878	0.950	0.954	0.743	0.770	0.867	0.862	0.888	III
Zhenjiang	0.928	0.903	0.864	0.808	0.868	0.908	0.756	0.833	0.912	0.875	0.866	IV
Taizhou [1]	0.881	0.840	0.851	0.816	0.873	0.906	0.766	0.696	0.818	0.837	0.828	IV
Suqian	0.616	0.552	0.757	0.638	0.683	0.978	0.765	0.562	0.775	0.728	0.705	IV
Hangzhou	0.837	0.813	0.855	0.931	1.000	1.000	0.938	0.905	1.000	0.869	0.915	III
Ningbo	0.783	0.801	0.856	0.880	0.951	0.787	0.928	0.913	1.000	0.975	0.887	III
Wenzhou	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	I
Jiaxing	0.932	0.913	0.787	0.805	0.861	0.845	1.000	1.000	0.883	0.825	0.885	III
Huzhou	0.913	0.990	0.927	0.946	0.989	0.931	0.990	0.909	0.902	0.913	0.941	II
Shaoxing	0.949	0.999	0.883	0.943	0.909	0.844	0.810	1.000	0.910	0.826	0.907	III
Jinhua	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	I

Table 5. *Cont.*

City	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Mean	Ranking
Quzhou	0.986	0.947	0.905	0.960	0.961	0.975	0.912	1.000	0.846	0.883	0.938	II
Zhoushan	0.843	0.942	0.961	0.898	0.910	0.929	0.799	0.490	0.952	1.000	0.872	IV
Taizhou [2]	0.940	0.966	0.983	0.940	1.000	1.000	1.000	0.986	1.000	1.000	0.982	I
Lishui	0.846	1.000	0.922	0.909	1.000	0.968	1.000	0.668	0.865	0.851	0.903	III
Hefei	0.987	0.879	0.837	0.741	0.777	0.831	0.898	0.804	1.000	1.000	0.875	III
Wuhu	0.849	0.755	0.798	0.626	0.717	0.890	0.668	0.588	0.664	0.787	0.734	IV
Bengbu	1.000	0.938	0.967	1.000	0.980	1.000	0.991	0.581	1.000	1.000	0.946	II
Huainan	1.000	0.925	0.937	1.000	0.930	0.938	0.897	1.000	0.926	0.974	0.953	II
Maanshan	1.000	0.787	0.818	0.723	0.811	0.878	0.793	0.961	1.000	0.937	0.871	IV
Huaibei	1.000	1.000	0.992	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999	I
Tongling	1.000	1.000	1.000	0.915	1.000	1.000	1.000	1.000	0.981	1.000	0.990	I
Anqing	0.674	0.723	0.840	0.863	0.889	0.964	1.000	0.655	0.978	0.995	0.858	IV
Huangshan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.422	0.995	0.993	0.941	II
Chuzhou	0.984	0.917	0.867	0.998	0.990	0.974	0.988	0.784	0.822	0.769	0.909	III
Fuyang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.882	0.978	0.905	0.977	I
Suzhou [2]	0.906	0.918	0.843	0.870	0.892	0.936	0.875	0.654	0.791	0.812	0.850	IV
Luan	0.901	0.824	0.855	0.977	0.921	1.000	0.999	0.600	1.000	1.000	0.908	III
Bozhou	1.000	1.000	1.000	1.000	1.000	1.000	0.965	0.580	1.000	1.000	0.955	II
Chizhou	1.000	1.000	1.000	1.000	1.000	0.995	1.000	0.378	1.000	1.000	0.937	II
Xuancheng	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.559	0.849	0.801	0.921	II
YRD	0.924	0.906	0.900	0.906	0.923	0.946	0.906	0.822	0.927	0.922	0.908	

Source: Authors' work. I, II, III and IV represent the ranking of 1~10, 11~20, 21~30 and 31~41, respectively. Suzhou [1] and Taizhou [1] belong to Jiangsu Province. Suzhou [2] belongs to Anhui province, and Taizhou [2] belongs to Zhejiang provinces.

Figure 4 illustrates the time series of the actual GDE in the YRD. According to Figure 4, the GDE in the YRD generally tends stable, with the highest level of 0.946 in 2014 and the lowest level of 0.822 in 2016, presenting a downward trend from 2014 to 2016. The actual GDE had been kept at 1 in Shanghai Municipality since it rose from 0.926 in 2009 to 1 in 2011, which fluctuated continuously in Jiangsu, Zhejiang and Anhui provinces from 2009 to 2018. Among them, the actual GDE of Jiangsu and Anhui provinces dropped sharply in 2015 and 2016, respectively. On the whole, the fluctuation range of GDE in Zhejiang Province was relatively small, and the GDE of Jiangsu Province was at the lowest level during 2009–2018. The above results indicated that although the influence of external environmental factors is removed, there are still regional differences in the actual GDE of cities in the YRD.

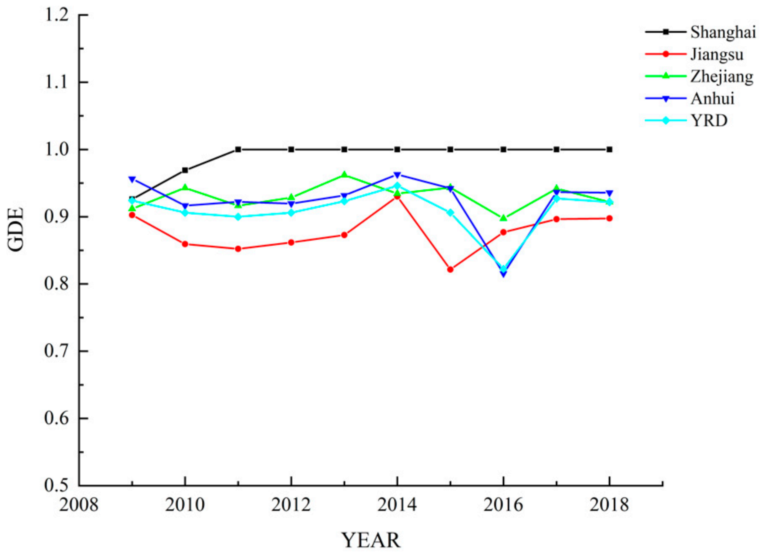


Figure 4. Time series of GDE in the YRD in Stage III.

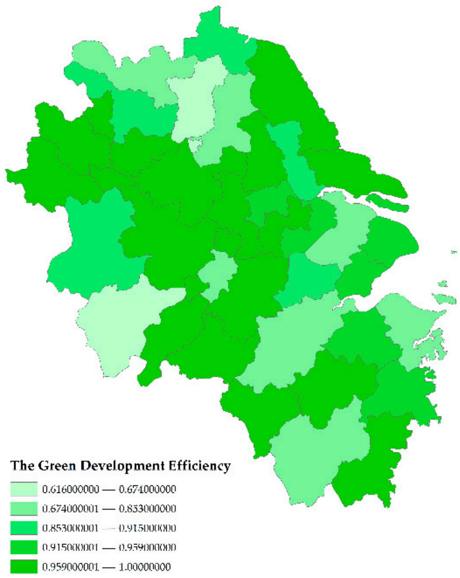
4. Discussion

4.1. GDE Analysis in the YRD

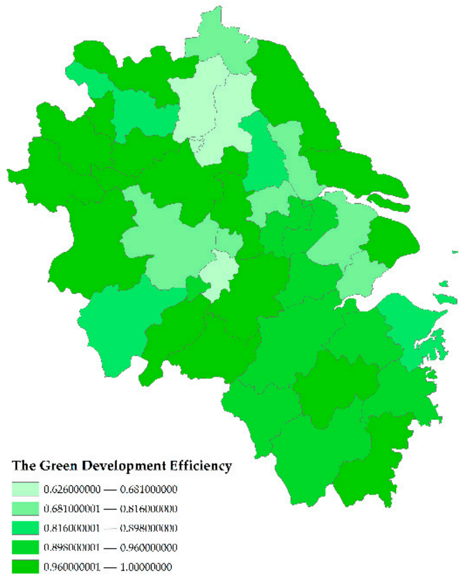
As shown in Figure 4, the actual mean GDE of the YRD was 0.908 (2009~2018). After adjustment, the GDE of the YRD in Sage III was obviously higher than that in Stage I, which testified that objective environmental factors cause people to underestimate GDE. Comparing the initial GDE (Table 3) and the actual GDE (Table 5) in the YRD, except for Chizhou, Huangshan, Huzhou, Quzhou, Taizhou[2] and Zhoushan, the GDE was enhanced upon the removal of external environmental factors and the mixed error term. From 2009 to 2018, the mean GDE of 41 cities in the YRD was 0.859 when external factors were taken into account, which was increased to 0.908 when external environmental factors were excluded. In stage III, the GDE of Nanjing, Jinhua and Wenzhou cities reached the optimal level, while only Jinhua and Wenzhou cities maintained this efficiency level in Stage I, which showed that external environmental factors negatively affected the GDE of Nanjing City. Consequently, there is substantial potential to improve the external environment.

Since it was a national strategy of China to integrate the YRD, the development of the YRD has been constantly concerned by all walks of life. In this case, the ecological environment is also one of the inevitable problems in the development process, and the main causes of excessive resource consumption and environmental pollution can be explored by virtue of effective environmental efficiency measurement, so as to improve environmental governance policies. There are many GDE calculation methods, of which the use of the three-stage DEA model enables obtains more objective and accurate efficiency by separating environmental variables such as management inefficiency and statistical noise. Before the environmental interference factors were excluded, that is, in Stage I of this study, the obtained GDE in the YRD showed a trend of falling first and then rising, and the zero cut-off point appeared in 2015. Wang et al. (2019) measured the GDE in the YRD from 2005 to 2015 using the Super-SBM model and concluded that there was a downward trend, thus predicting that the efficiency would increase after 2015 [37], which was verified in this study. Nevertheless, when the environmental factors and stochastic disturbance were removed, that is, when the actual GDE was obtained, no matter from the perspective of the entire region or the four provinces, the GDE in the entire time series was improved to a certain extent compared with that in Stage I, indicating that objective factors may cause people to underestimate the GDE. Consistent with the results herein, Guo et al. (2018) also came to the conclusion that the mean environmental efficiency of the central, eastern and western regions, as well as the whole country, was underestimated during the three-stage measurement of environmental efficiency in China [38].

For further analysis, the GDE calculated in the previous parts was divided into five levels, and the GDE spatial distribution maps in the YRD in 2009, 2012, 2015 and 2018 were drawn using ArcGIS, as shown in Figure 5. Thereout, the differences in spatial distribution, as well as the spatial characteristics, were determined intuitively, and it was visibly that spatial heterogeneity existed in the GDE of the YRD and changed with time. For example, the GDE in the northeast coastal region changed from a high level at the beginning to a low level in the later period, while the GDE in the western region experienced the opposite process. In addition, the GDE was maintained at a high level in some cities in the northwest, southeast and middle of China, as well as a small area formed around Shanghai Municipality, presenting certain clustering characteristics, and the GDE there was better than that in other regions.



(**a**)



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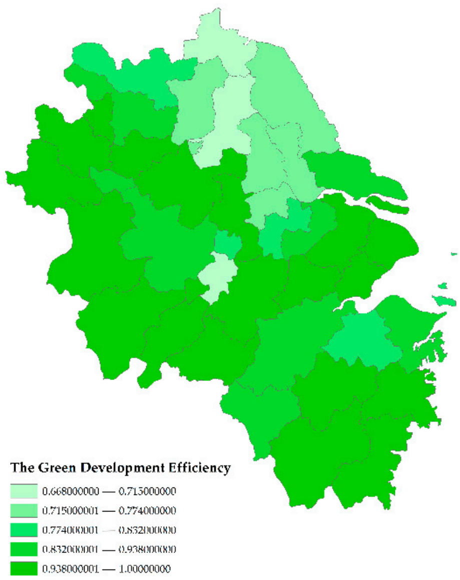

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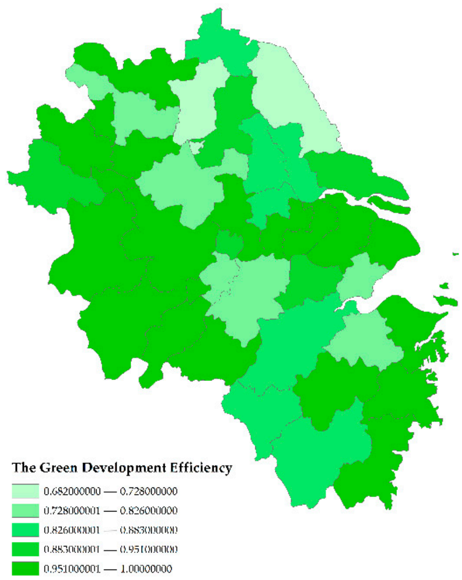

(**d**)

Figure 5. Spatial distribution maps of GDE in the YRD: (**a**) spatial distribution of GDE in 2009; (**b**) spatial distribution of GDE in 2012; (**c**) spatial distribution of GDE in 2015; (**d**) spatial distribution of GDE in 2018.

Based on the spatial distribution maps drawn from the actual GDE results, the GDE in the YRD showed certain spatial heterogeneity, not only different from the conclusion of Wang et al. (2018) who calculated that the GDE is low in the east and high in the west of the YRD [37], but also different from the conclusion of Deng et al. (2021) who found that the GDE in the eastern region is significantly higher than that in the western region [39]. In this study, it was discovered that the GDE showed high clustering characteristics to some extent in several cities in the northwest, southeast, and middle of China, as well as a small area around Shanghai Municipality. Combined with the efficiency decomposition diagram in Figure 5, the GDE tends to have high-high clustering in cities with good economic development levels and low-low clustering in cities with relatively low economic development levels. In this sense, environmental protection was better implemented in the eastern region with better economic development than in the western region. Feng et al. (2020) believed that economic development is correlated with green development, but there is not a complete positive correlation [33]. As shown in this paper, after excluding the objective factor of economic development, the GDE was high in some economically underdeveloped regions. For example, surrounded by mountains and rivers, some cities in central China such as Xuancheng, Huangshan, and Quzhou are famous for tourism and mainly develop tourism and service industries, and there are few industries characterized by high pollution, presenting high green development levels. Topography affects industries, thereby affecting local green development. Accordingly, it is necessary to comprehensively consider the factors affecting GDE from various aspects [40].

4.2. SFA Regression Analysis

In Stage II, SFA regression was performed on the input slack variables obtained in Stage I and four environmental variables, and some meaningful information was obtained.

(1) GRP is negatively correlated with the slacks of electricity consumption, fixed asset investment and scientific education investment in the whole society, while it has a positive correlation with the slacks of water conservancy and environment practitioners. It indicates that the increase in GRP makes the electricity consumption, fixed asset investment and scientific education investment rationalized on the one hand, and on the other hand, it shows inefficiency in the input of water conservancy and environmental practitioners. GRP represents the local economic development level, and the classic environmental Kuznets curve shows that the quality of the environment will first decline and then rise with the development of the economy [41]. From the perspective of input, it is the rationality and waste of these different input factors that explain the complexity of the mechanism of the relationship between economic development and green development.

(2) ABD has a significant positive correlation with the slacks of the four input variables, proving that the increase in the urban construction area will increase the input slacks, which goes against the GDE. With the expansion of urban space, among the land cover types in the urban fringe area, land types with less interference from human activities such as cultivated land, forest land and orchards have been greatly reduced and replaced by high-density urban land. The impervious area in the urban center area has been increased, and the natural green area has been reduced, replaced by squares and roads covered with cement and asphalt. The increase of impervious area and the reduction of the green area have seriously caused problems for the water environment and atmospheric environment in cities [22,42]. On the contrary, in terms of geographic space, cities surrounded by mountainous terrain and famous for tourism enjoy high GDE as large-scale construction may not be applicable, such as Xuancheng, Huangshan, Quzhou and Jinhua, which is consistent to the conclusion of Li et al. (2022) [40].

(3) TIP has a negative impact on the slacks of the four input variables, that is, the higher the proportion of the tertiary industry, the more beneficial to input slack reduction and GDE improvement, which fully reveals that the optimization of industrial structure is conducive to local green development. According to the *13th Five-Year Plan for Economic and Social Development of the People's Republic of China (2016–2020)*, green development can be achieved through industrial restructuring. Many studies also support that the high proportion of the tertiary industry is conducive to the protection of the ecological environment [27,43]. Guo et al. (2020) concluded that the secondary industry is adverse to green development, which in turn supports the aforesaid statement [44]. The rise of the tertiary industry, on the one hand, compresses the secondary industry supported by a large amount of fixed capital investment, which is conducive to reducing the waste of capital input; on the other

hand, it has a strong ability to absorb labor employment and reduces the slack degree of labor equivalent. In this sense, industrial structure optimization is the appropriate path for green development.

(4) GCA is negatively correlated with the slacks of the four input variables. The increase in the urban green area supports the social fixed asset input, social electricity consumption, scientific education investment and water conservancy and environmental management personnel to reach the ideal input value, suggesting that the increase in urban green area is helpful to the rational use of energy, capital, labor and innovation input. Similar to the formulation of environmental policies and the investment in pollution control, the planning of urban green areas demonstrates the active intervention of the government in green development planning and plays an essential role in urban sustainable development [45]. Today, governments are gradually conscious that the construction of green spaces has become a vital issue for high-quality economic development [22]. Many policies have been issued by governments at all levels, such as the *Regulations of China on Urban Greening*, *Shanghai Greening Regulations*, specifying that urban greening should keep pace with urban development. In line with the study results of this paper, in the process of urban expansion, reasonable planning and investment should be carried out on the coverage of the urban green area, in a bid to prevent the expansion of urban construction area from reducing the GDE and causing a series of environmental problems.

4.3. GDE Decomposition Analysis in the YRD

To better understand the GDE in the YRD, the software DEAP 2.1 was applied to divide the actual GDE into two types, that is, the comprehensive technical efficiency (TE) was decomposed into pure technical efficiency (PTE) and scale efficiency (SE) [31]. PTE reflected the production efficiency of DMUs at certain input factors at an exact scale (usually optimal) and explained how to effectively apply green technologies to achieve maximum efficiency, and SE presented the realization degree of scale effects on green development [46].

The efficiency decomposition scatters diagram of 41 cities was drawn according to PTE and SE, which was divided into four quadrants according to the mean value to represent four categories of high-high, low-high, low-low and high-low, respectively (Figure 6). It can be seen that after the environmental factors and stochastic disturbance were eliminated, the mean PTE rose from 0.883 to 0.966, while the mean SE slightly dropped from 0.974 to 0.939. On the whole, environmental factors affected the real performance of PTE, causing GDE to be underestimated.

The high-high category contained areas with high PTE and high SE. According to the efficiency decomposition in Stage I, 13 cities were included in this category, and Shanghai, Changzhou, Tongling, Huainan, and Bozhou cities became new members of this category in Stage III, implying that the SE level of these cities was improved dramatically with consideration of the environmental disturbance factors. Among them, both PTE and SE of Nanjing, Jinhua and Wenzhou cities were 1, indicating that these cities achieved a high-efficiency level.

The high-low category contained cities with high SE and low PTE. According to the calculation results of Stage I, 10 cities were classified into this category, and the number was reduced to 8 in Stage III. Among them, Huangshan, Nantong, Huzhou and Shaoxing cities fell from the original high-high category to the high-low category, reflecting that the utilization efficiency there in the exogenous environment should be strengthened. It is necessary to invest more in green technology innovation and application, enhance the quality of green talents and raise energy utilization to improve the overall GDE locally.

The low-high category contained areas with low SE and high PTE. Nantong, Huzhou and Shaoxing cities, which were originally included in the high-high category in Stage I, were assigned to this category in Stage III, indicating that the SE of the three cities was overestimated. For these cities, the SE should be enhanced by increasing the green investment, conducting green transformation and strengthening green talent aggregation.

(a)

(b)

Figure 6. GDE decomposition of 41 cities: (**a**) Stage I (**b**) Stage III.

The low-low category contained areas with low PTE and low SE. Comparing Stage I with Stage III, the number of cities in this category was increased from 7 to 12, and all cities included in this category presented poor GDE. Xuzhou, Huai'an and Suqian cities were contained in the low-low category no matter whether the influence of external environmental factors and statistical noise was excluded. Most cities in this category were weak in economic foundations and dominated by traditional energy-intensive industries. In consequence, for cities in this category, it is not only necessary to advance technological innovation during green transformation, but also to consider the stimulation of scale effect. In the meantime, the priority should be given to the construction of a green economy and a sound green development foundation.

5. Conclusions

At present, green development is a considerable environmental management issue in China, aiming to improve the status of regional environmental development in light of energy saving, emission reduction and pollutant control [13]. Since the integration of the YRD was brought into the national strategy, the development of the region has received continuous attention from all sectors of society. As a result, the ecological environment is one of the inevitable issues in the development process. In this study, panel data from 2009 to 2018 of 41 cities in the YRD were selected and the three-stage DEA model was applied to calculate the objective GDE in this region. Besides, a comprehensive analysis was performed on the grounds of the empirical results. After the adjustment, the GDE in each city changed considerably, which proved that it is objective and accurate to measure GDE after eliminating environmental factors and stochastic disturbance. On this basis, the following suggestions and implications were drawn:

(1) The GDE in the YRD adjusted in Stage III was clearly higher than that in Stage I, mainly because the GDE was underestimated under the influence of objective environmental variables. The GDE levels of different cities showed heterogeneity upon the removal of external environmental factors and stochastic disturbances. The GDE developed out of balance in the four provincial administrative regions and generally behaved better in the coastal and southeastern areas than that in the central, western and northern regions in terms of spatial distribution. As a national central city, Shanghai Municipality serves as the center of the international economy, finance, trade, shipping and technological innovation in China, which is required to not only maintain high-quality development as a leader in the YRD but also to focus on the balanced development of cities in the YRD as a whole. For other regions, it is necessary to control the industrial scale, actively use foreign capital to improve production technologies, achieve clean production and reduce energy consumption.

(2) In terms of external environmental variables, the ABD reflecting urban construction has a negative impact on GDE since urban construction requires the improvement of urban governance infrastructure, which will inevitably lead to an increase in investment in pollution control. Consequently, the faster the urban construction process is, the more capital, labor, energy and resources will be required, which partly generates redundant inputs, thus reducing GDE. Moreover, industrial structure adjustment and green covered area are conducive to GDE, so it is necessary to sequentially strengthen the development of the tertiary industry, reduce the idle employees caused by labor aggregation, and improve the regional economic level while improving the capital utilization efficiency. Besides, the government should increase green investment and carry out rational layouts of urban green spaces to prevent the reduction of the green development level in the process of urban expansion and construction.

(3) The GRP reflects the local economic development level, the impact of which on GDE was not determined in this paper. In spite of this, it is believed that in the new era emphasizing high-quality development, more emphasis should be put on innovation and ecology, which are beneficial to the healthy and sustainable development of cities. In the future, the government still needs to play an active role in pollution control and urban green planning. While accelerating the process of urbanization, it is necessary to promote clean production, control pollution emissions, eliminate passive terminal control, pay attention

to the excessive consumption of resources and energy in urban construction, keep abreast of the speed of urbanization, adhere to quality-oriented policies, and create a new spatial pattern of intensive and efficient urbanization. Additionally, it is necessary to cultivate new growth points for cities, give play to regional advantages pursuant to different orientations, and realize the coordinated development of urban agglomerations, cities and industries.

Suggestions for future study: First and foremost, when measuring the GDE of 41 cities in YRD from 2009 to 2018, the time lag effect and delayed utility between inputs and outputs have been neglected to some extent. The digestion and absorption of inputs often take time to produce effective outputs, which means that green development inputs will not be converted into relevant outputs in an instant, and further verification is required. Secondly, although the influence mechanism of four objective environmental variables has been involved in this paper, there are still some unconsidered factors, such as urban resources, culture, society, etc. [22,23], and more attention can be paid to the correlations between the factors and the green ecology of cities in future studies. Last but not least, though complex, in-depth research is required to reveal the impact of economic development on urban green development.

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