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Efficiency Evaluation of Water Consumption in a Chinese Province-Level Region Based on Data Envelopment Analysis

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Abstract: Due to the large volume of sewage in China, the efficiency of water consumption evaluated by the traditional model may be inaccurate. This paper evaluates the water consumption efficiency more scientifically. First, this paper uses the CCR model to evaluate the resource efficiency and environmental efficiency separately. The latter is generally lower than the former, which means the issue of water pollution is more serious than the problem of water resource consumption. Then, the water consumption efficiency is integrally evaluated by an eco-inefficiency model which focuses on undesirable outputs. The results are in good agreement with the results of the CCR model: (1) Only Beijing, Tianjin, and Shanghai are eco-efficient in terms of water consumption, water consumption efficiency in the southeastern coastal areas is higher than in the Midwest, and the overall water environment is bad; (2) China needs to focus on reducing industrial wastewater; (3) the output of water consumption has a lot of room for improvement; and (4) the output improvement schemes of all provinces have some similarities and are related to many features. So, this paper has made a clustering analysis of the improvement schemes and given detailed suggestions for improving the eco-efficiency of water consumption in China according to the clustering result.

Keywords: data envelopment analysis; water efficiency; China; output improvement; water consumption

1. Introduction

In recent years, with the rapid development of industrialization and urbanization, China's economy has experienced a period of rapid development. However, as China surpassed Japan to become the world's second-largest economy, China has also become a veritable country with huge resource consumption and environmental pollution. China's Low-Carbon Economic Development Report (2014) pointed out that at present, China's consumption of resources and various types of pollutant emissions are the highest in the world and are close to the capacity limit of their own environment [1]. In environmental issues, water environment is closely related to people's life and production. However, China is a country with a shortage of water resources per capita. In 2014, the per capita water resource was about one-quarter of the world average [2]. In addition to the shortage of water resources, China is still faced with the problem of deterioration of the water environment. With the development of economic and the improvement of people's lives, the demand for water resources is constantly increasing. Water is an indispensable necessity, which leads to the contradiction between water supply and demand. Improving the efficiency of water consumption is the key to solve this problem. Only by improving the water use efficiency can we fundamentally resolve the crisis of water resources and realize the sustainable economic and social development.

The concept of eco-efficiency first came up with the notion of "environmental efficiency" [3], proposed by Schaltegger and Sturm [4]. Despite the many definitions of eco-efficiency, Schepelmann et al. [5] pointed out that all definitions have one common theme: "Use natural resources more efficiently".

In order to comprehensively analyze eco-efficiency, we should consider both resource utilization and pollution discharge (or other non-performing outputs) [6]. Most of literature only evaluates environmental efficiency or resource efficiency. The former focuses on the environmental impact of waste discharge, while the latter focuses on resource utilization [7]. This paper integrally evaluates the water use efficiency from the perspective of the environment and resources.

Upon application, the ecological efficiency can be viewed from multiple angles, including the macro-economy (national level), small and medium-sized economy (provincial or regional region), and micro-economy (company) level [8]. Research on the application of eco-efficiency has been mostly focused on the micro-enterprise level [9–11] and the industry level. However, some scholars argue that governments can apply the concept of eco-efficiency to examine the long-run competitive advantage of a country or region [12,13]. Additionally, some countries and regions have carried out the research on eco-efficiency at the regional level [14–17]; but only focus on the regional industry level [18,19], such as regional construction industry [20,21], manufacturing industry [22], road transportation [23], and others. The evaluation of eco-efficiency at the urban and regional scales has also drawn widespread domestic interest. Although it has risen to the national level, it also focuses on a single industry, such as transportation [24], industry [25], and so on.

As mentioned in the introduction of the background, in recent years, with the rapid economic development, the domestic water environment has deteriorated day by day. In order to build a sustainable society, it is particularly important to improve the eco-efficiency of water resources. As Araral and Wang [26] pointed out, water governance has a significant impact on China's water scarcity, but further research on the relationship between governance mechanisms and performance is needed.

In terms of the eco-efficiency evaluation of water consumption, many articles focus on the enterprise level, such as the evaluation of water company efficiency [27–29]. There are also many evaluations about regional water use efficiency, but most of them only separately evaluated the agricultural use of water [30,31], industrial water consumption [32], and efficiency of domestic water use [33]. This paper simultaneously evaluates the eco-efficiency of water consumption from three major water uses to fully reflect the water consumption in China instead of evaluating the efficiency of only one aspect of water consumption.

There are many methods used to evaluate eco-efficiency. The main methods of calculation are the single ratio method and the index system method. The single ratio method is generally a single scale model of "economic output/environmental impact". Although it gives a simple ratio, it has many drawbacks. It is impossible to distinguish between different environmental impacts, and eventually, all the environments should be converted into one specific environmental impact value. Furthermore, it cannot give decision-makers the flexibility to choose, nor provide them with the optimal ratio set [34]. The indicator system approach can comprehensively reflect the level of development and coordination of social, economic, and natural subsystems. Although at present, World Business Council for Sustainable Development (WBSCD) and some scholars have put forward a series of evaluation indexes of eco-efficiency [35]. However, these methods are difficult to unify in dealing with a variety of environmental impacts. In some cases, we need to use weights to express the relationship between the environment and the economy. When studying multi-input and multi-output problems, it is necessary to give weights to synthesize different indicators into a single value, and it is very difficult to eliminate the subjective factors in the weighting process [36]. Kuosmanen and Kortelainen [23] thought that it is more reasonable to use objective weight when measuring eco-efficiency. Using the frontier approach can make up for these deficiencies. Instead of having people subjectively assign weights, one of the advantages of frontier approaches is to produce objective weights from the data. Data envelopment analysis (DEA) is a well-known frontier approach which can evaluate the effectiveness of inputs and outputs of different decision-making units [7], and there is no clear weight to aggregate indicators [6]. It measures ecological efficiency from a more integrated perspective [23]. The DEA method has shown great potential in efficiency measurement and has been widely used in ecological efficiency studies [15–17,37]. DEA is also favored in the choice of methodologies for efficiency research on water consumption [27,29].

The existing literature is useful reference work for the evaluation of regional ecological efficiency, but the following problems still need to be improved.

(1) Undesired outputs such as environmental pollutants are prominent issues in the ecological environment, but their handling is often arbitrary [6]. Dyckhoff and Allen [6] suggested that a bad output should be regarded as a classic input. Some researchers have treated bad outputs as inputs [7,14]. However, if the undesired output is regarded as an input, the final model cannot reflect the actual production process [38].

(2) Most of the literature on eco-efficiency analysis in China focuses on the industrial level. The analysis of the current situation of water resources in China based on eco-efficiency is rare. The evaluation is one-sided and cannot wholly reflect the water consumption efficiency of China at the provincial level, especially for the efficiency evaluation of water pollutants. To solve these problems, this paper adopts a new frontier approach [39] used to measure eco-inefficiency to analyze the current status of water resources in Chinese provincial regions.

(3) There are big differences among provinces in China. The government should implement different policies according to the actual situation in the region [40]. This paper will give suggestions on the provincial level.

This paper aims to use data envelopment analysis to evaluate the water consumption efficiency at the Chinese province-level and to develop an improvement scheme for undesired outputs such as sewage. Finally, based on the result of clustering the improvement schemes and characteristics of regions, this paper gives detailed suggestions on how to improve the efficiency of water use. The present work is organized as follows. The model will be introduced in the next section. The third section presents the source of data and the selection of the index. Furthermore, this paper analyzes the situation of China's water resources in 2014, especially the pollution discharge, and gives appropriate suggestions for promoting the recycling of water resources and social sustainable development. The fourth section is the full text summary.

2. Materials and Methods

2.1. Traditional DEA Model: CCR Model

The non-parametric frontier model, also known as data envelopment analysis (DEA), uses linear programming to integrate multiple inputs and outputs of a decision-making unit (DMU) into a relative efficiency score [41]. A viable production plan or set of technologies is a portfolio of inputs and outputs surrounded by borders. It is considered to be efficient if a DMU is on this boundary [42,43]. If a DMU is not on the border, the distance to the border represents the degree of inefficiency. There are many kinds of DEA models, like Xie et al. [44], etc. The basic DEA model is the CCR model (Model proposed by Charnes A. & Cooper W.W. & Rhodes E. [41]):

$$
\begin{aligned}
& Max \frac{\sum\limits_{r=1}^{s} u_r y_{rj_0}}{\sum\limits_{i=1}^{m} v_i x_{ij_0}} \\
& s.t. \frac{\sum\limits_{r=1}^{s} u_r y_{rj}}{\sum\limits_{i=1}^{m} v_i x_{ij}} \leq 1 \\
& v \geq 0, u \geq 0, j = 1, 2, \cdots, n
\end{aligned} \tag{1}
$$

where x_{ij} is the amount of input i consumed by DMU_j (the jth DMU), y_{rj} is the amount of output r produced by DMU_j, v_i is the weight of the input i, u_r is the weight of the output r, n is the total number of DMUs (The plural form of DMU), m is the total number of inputs, s is the total number of outputs, and o is the evaluated unit for an optimization run.

The original CCR model is based on fractional programming. But t can be transformed into the equivalent linear programming form. Its dual programming is:

$$
\begin{aligned}
& Min\ \theta \\
& s.t.\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io},\ i = 1, \cdots, m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro},\ r = 1, \cdots, s \\
& \lambda_j \geq 0,\ j = 1, 2, \cdots, n
\end{aligned} \tag{2}
$$

where θ is the relative efficiency score and λ_j is the unknown variable. The CCR model calculates the efficiency score by comparing DMU_j to a DMU on the efficient frontier. DMU_j is called the DEA efficient if the optimal solution θ^* of the objective function of model (2) $\theta^* = 1$. It can be considered that the higher the efficiency score θ, the more effective the DMU is.

2.2. A New DEA Model for Measuring Inefficiency

The eco-efficiency measured by the traditional DEA model will increase with the increase of undesired outputs [39]. So, the existing models may identify eco-inefficient DMUs with a large amount of undesirable outputs as eco-efficient. The more undesirable outputs the DMU produces, the easier it may be for the DMU to be eco-efficient. This is contrary to the original intention of eco-efficiency evaluation. This paper evaluates the eco-efficiency of the water consumption for each provincial region. In reality, the eco-efficiency of water consumption should decrease rather than increase with the increase of wastewater discharge. In order to get reliable evaluation results, this paper adopts an improved frontier model proposed by Chen and Delmas [39]. This model allows DMUs to choose their own direction of improvement to achieve effective boundaries, which is called the eco-inefficiency model (o is the unit to be evaluated):

$$
\begin{aligned}
& \theta_o^{Chen} = Max \frac{1}{s} \left\{ \sum_{t=1}^{k} \frac{g_t^y}{y_{to}} + \sum_{r=k+1}^{s} \frac{g_r^u}{u_{ro}} \right\}, \\
& s.t.\ \textstyle\sum_{j \in N} \lambda_j x_{ij} \leq x_{io}, for\ \mathrm{i} = 1, \ldots, m, \\
& \textstyle\sum_{j \in N} \lambda_j y_{tj} \geq y_{to} + g_t^y, for\ t = 1, \ldots, k, \\
& \textstyle\sum_{j \in N} \lambda_j y_{rj} \leq u_{ro} - g_r^u, for\ r = k+1, \ldots, s, \\
& \lambda_j, g_t^y, g_r^u \geq 0, for\ all\ j, r, t,
\end{aligned} \tag{3}
$$

where $(x_{1j}, \ldots, x_{mj})$, $(y_{1j}, \ldots, y_{kj})$, and $(u_{k+1,j}, \ldots, u_{sj})$ are the input, desirable output, and unexpected output vector of DMU_j; λ_j is the weight of DMU_j; g_t^y is the amount of increase in desirable output t; and g_r^u is the amount of decrease in unexpected output r. g_t^y and g_r^u represent the improvement in the amount of output that can be made by the DMU_j to achieve its benchmark target on the efficiency frontier. y_{to} and u_{ro} are the observed desirable and unexpected output value of DMU_o, respectively.

N is the total number of DMUs, m is the total number of inputs, and s is the total number of outputs including k kinds of desirable outputs and s-k kinds of bad outputs.

The objective function value θ indicates the overall degree of output inefficiency. θ of model (3) is considered as an inefficiency score in this paper. θ equals the average amount of output improvement divided by the y_{to} and u_{ro}. For example, the score of 0.5 means that the evaluated unit can raise the ideal output by 50% and reduce the unwanted output by 50% on average. In theory, the inefficiency score θ ranges from zero to infinity, but in practice, the improvement of the desirable output is often less than the desirable output. So, we have $g_t^y / y_{to} \leq 1$. Similarly, it may be the case that $g_r^u / u_{ro} \leq 1$. So, the score may have an upper bound of 1. A score θ of 0 means that the evaluated unit is on the efficiency frontier and has no output slacks, so the unit is DEA efficient. If the score θ is positive, the higher the score, the lower efficient the evaluated unit is. The eco-inefficiency score θ provides an aggregate measure of the relative efficiency of DMUs. After solving model (3), this paper can identify the effective target that the evaluated DMU can emulate. Specifically, the benchmark target for DMU_o is $(x_{io}, y_{to} + g_t^{y*}, u_{ro} - g_r^{u*})$ for all i, t, r, where (g_t^{y*}, g_r^{u*}) is the optimal solution to the model. In this paper, (g_t^{y*}, g_r^{u*}) is called the improvement of the output, which is the improvement that the DMU needs to make to be DEA efficient. If the DMU's inefficiency score is 0, it is eco-efficient. The higher the inefficiency score, the lower efficient the evaluated DMU is.

2.3. The Features of the New DEA Model for Measuring Inefficiency

Some literature uses the DEA approach to evaluate the efficiency of undesired outputs. Vlontzos and Pardalos used DEA Window analysis to make a long-term evaluation of environmental efficiency and used Artificial Neural Networks (ANNs) to make predictions about future outputs like carbon emissions [45,46]. For a better explain about all dimension agricultural sustainability, they also developed a synthetic Eco-(in)efficiency indicator to evaluate sustainability variations for a specific period [47].

Model (3) has the following advantages. First, its invalid index can be compared with the UINP (undesirable output as input) [48] and the SZ model (Supplier, city, state, country) [38]. The UINP model (Supplier, city, state, country) and the SZ model assume that the evaluated unit can reach the efficiency frontier by changing its undesired and ideal output proportionally. However, this assumption is impractical in many cases because there is no guarantee that the evaluated unit can increase its efficiency by reducing the bad output and increasing the expected output proportionally. Model (3) allows the evaluated unit to choose the direction of improvement that maximizes its potential for improvement so as to increase efficiency rather than reach an efficiency frontier in a fixed direction. The flexibility of model (3) follows a basic notion of effective frontier: Every point on the effective frontier is efficient, so different production combinations of different points on the effective frontier should be equally attractive to inefficient units. The second is that model (3) maximizes the objective function to ensure that the evaluated unit has a point on the efficiency frontier as the benchmark target. The benchmark target must be efficient regardless of the type of disposability assumption. This makes the evaluation results more accurate. However, other inefficiency measures may make dominate points, rather than the efficient point, the benchmark target [49–51].

Based on the above advantages and data availability, this paper only evaluates the water use efficiency of 31 provinces in China in 2014. It is worth noting that the new DEA model (3) is used for a "static" efficiency analysis instead of dynamically evaluating water use efficiency over a longer time period.

3. Results and Discussion

3.1. Input and Output Indicators

The selection of indicators is of crucial importance to the efficiency evaluation. Otherwise, the validity and reliability of the results will be seriously compromised. The input and output indicators selected by previous literature in the evaluation of water efficiency are similar (Table 1).

Table 1. Index of previous literature.

Author	Input	Output
Zhang et al. [14]	Water resource Energy	Pollutant emission Value-added of industry
Hu et al. [52]	Labor employment Capital stock Residential use water Productive use water	GDP [a] - - -
Bian et al. [53]	Labor Capital Fresh water	GDP Waste water -
Xie et al. [32]	Labor Capital stock Coal Petrol	COD NH_4 Industrial value-added -

[a] GDP: Gross Domestic Product

Most pieces of literature choose water consumption, labor force, and fixed assets as inputs. The output of water consumption is generally measured by economic indicators, such as GDP, industrial added-value, and so on. If this paper focused on assessing the environmental impact of water consumption, the amount of pollutants may be chosen as the output, such as the amount of wastewater, chemical oxygen demand (COD), or NH_4 emissions. It is worth noting that they often use the overall amount of water as the input. However, this paper will subdivide the water consumption.

In China, water consumption is divided into domestic water, industrial water, and agricultural water. Due to the vast territory of China, the reserves of water resources vary greatly and the industrial structure is also different in each provincial region. This has led to different situations of water consumption and wastewater discharge among the regions. Combining the different situations of provinces, this paper will give a scientific and systemetic program to improve the efficiency of water use. Targeted emissions reductions are urgently needed instead of an ambiguous scheme. The model (3) can not only provide valid and reliable efficiency scores, but also provide detailed improvements for various undesirable outputs to be eco-efficient. This is in line with our purposes. Therefore, this paper evaluates the water consumption efficiency from three aspects, which are life, industry, and agriculture. Then, this paper formulates the scheme of reduction for water pollutant emission.

Referring to Table 1 and taking into account the availability of data, this paper selects the domestic water consumption, industrial water consumption, agricultural water consumption, total fixed assets, and labor force as input indicators. These indicators comprehensively reflect the regional water supply capacity, thereby affecting its water use efficiency. The eco-efficiency evaluation of water resources should include environmental efficiency and economic efficiency. This paper takes the regional GDP as the desirable output indicator. Since the amount of agricultural wastewater is difficult to obtain directly and COD is an important indicator of water pollution, this paper takes the COD emissions of living, industrial, and agricultural wastewater as the undesirable output indicators which reflect the impact on the water environment. The data comes from China Statistical Yearbook 2015. Table 2 shows the descriptive statistics of the input-output data of 31 provinces (Includes 31 DMUs).

Table 2. Summary of input and output indicators.

Category	Variable	Abbr.	Units	Mean	Std.Dev.	Min	Max
Input	Household Water Use	H	100 million cu.m	24.7	19.2	1.1	96.1
	Industry Water Use	I	100 million cu.m	43.8	47.5	1.7	238.0
	Agriculture Water Use	A	100 million cu.m	124.8	112.5	8.2	551.0
	Fixed Assets	F	100 million yuan	16,314.6	10,543.7	1069.2	42,495.6
	Labor Force	P	No.	4395.0	2797.8	318.0	10,724.0
Undesirable Output	COD of Household	HCOD	ton	278,836.8	190,660.0	17,905.0	864,345.0
	COD of Industry	ICOD	ton	100,436.2	59,845.8	907.0	235,501.0
	COD of Agriculture	ACOD	ton	355,609.8	324,784.4	5389.0	1260,559.0
Desirable Output	Regional GDP	GDP	100 million yuan	22,075.8	16,987.7	920.8	67,809.9

Data excluding Hong Kong, Macao, and Taiwan regions. Since Table 2 shows the units of each variable, the unit of each variable will not be described repeatedly in the following figures, tables, and text.

3.2. Status of Water Consumption in Provincial Regions

Let us roughly describe the water usage in all provincial regions of China and the output from water use. According to the method of classical geographical division, each province is divided into several big regions such as North, Northeast, East, South, Southwest, and Northwest. The status of water use in provincial regions of China is shown in Figure 1.

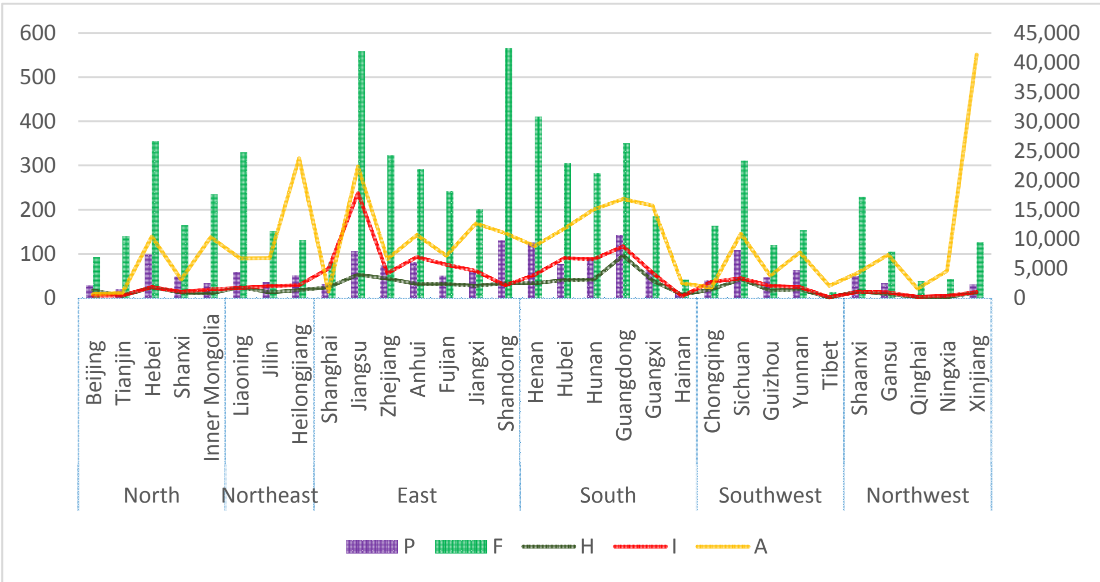

Figure 1. Water consumption in provincial regions.

The amount of domestic and industrial water consumption in all provincial regions is similar, except for Jiangsu, where the industrial water consumption is obviously greater than the domestic water consumption. The consumption of agricultural water is generally large, especially in Heilongjiang, Jiangsu, and Xinjiang. Overall, provinces with large water consumption are concentrated in the southeastern part of China. In these provinces, the economy is more developed, investment in fixed assets is higher, the population density is larger, and water consumption is also correspondingly increased.

Figure 2 shows the output of water consumption in each provincial region. By comparison, it can be found that although the consumption of living water and industrial is similar, the domestic wastewater discharge is significantly greater than industrial wastewater. In areas with a high population density and high GDP, the gap is even more pronounced. China is a big agricultural country which consumes the largest amount of water resources and correspondingly pollutes water severely. In northeastern and southern parts of China, where major crops are cultivated, agricultural water use is relatively large. Correspondingly, the amount of agricultural wastewater is also very large. The agricultural effluents in the northeast are generally greater than those in the south. In terms of the desirable output, the GDP in the southeast is higher, while in the west, it is lower.

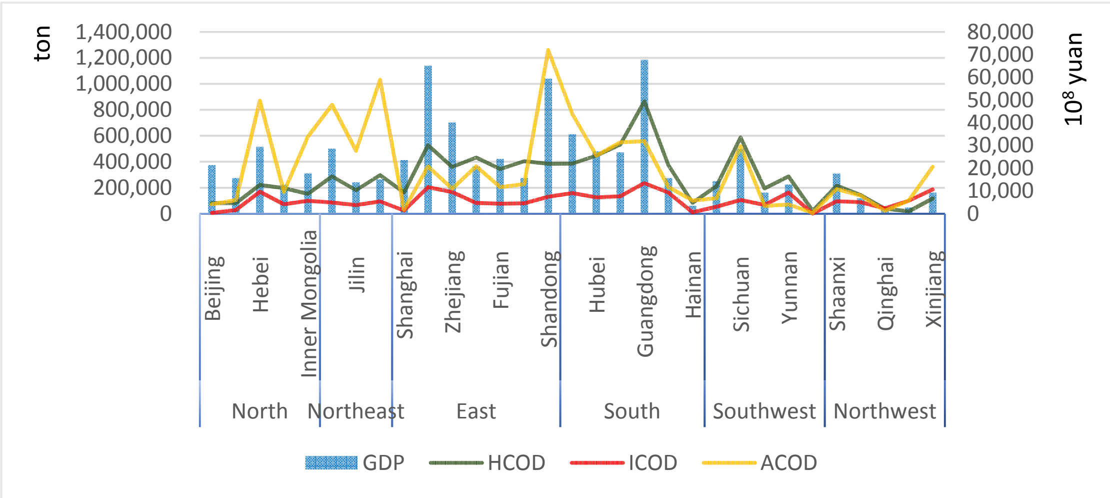

Figure 2. Output of water consumption.

3.3. *Resource Efficiency and Environmental Efficiency*

This paper takes three kinds of water consumption, labor force, and fixed assets as the inputs and GDP as the output. Model (2) can be solved to calculate the resource efficiency of each provincial region (see column 2 in Table 3). This paper takes three pollutants as the input and GDP as the output to calculate the environmental efficiency (see column 4 in Table 3). Model (3) is solved to obtain the value of eco-inefficiency in each provincial region, as shown in the fifth column. It is the opposite to the score of resource and environmental efficiency. The higher the score, the lower the eco-efficiency. Only Beijing and Shanghai are both efficient in resources, environment, and ecology. This paper turns the three efficiency values into rankings (see column 3, 5, and 7 in Table 3). In most provincial regions, the rankings based on the three types of efficiency are roughly the same. Resource efficiency rankings of Jilin and Heilongjiang are clearly ahead of their other two efficiency rankings. This means that they have a high utilization rate of water resources. Resource efficiency rankings of Guizhou and Tibet are significantly behind the other two rankings. It indicates that they need to pay attention to water conservation. Environmental efficiency of Gansu ranks low. It needs to focus on waste water reduction. The rankings of the three kinds of efficiencies in Sichuan, Ningxia, and Xinjiang are quite different.

Table 3. Resource efficiency and environmental efficiency (CCR model) and eco-inefficiency (model 3).

Region	Res.Eff	Res.Rank	Envi.Eff	Envi.Rank	Eco-Ineff	Eco.Rank
Beijing	1.0000	1	1.0000	1	0.0000	1
Tianjin	1.0000	1	0.7532	2	0.0000	1
Hebei	0.6001	10	0.5103	7	0.5837	9
Shanxi	0.5421	15	0.2528	21	0.6335	16
Inner Mongolia	0.6843	6	0.4477	9	0.5446	6
Liaoning	0.6387	7	0.3838	10	0.6084	12
Jilin	0.6031	9	0.2929	17	0.6605	19
Heilongjiang	0.5985	11	0.1949	25	0.7681	24
Shanghai	1.0000	1	1.0000	1	0.0000	1
Jiangsu	0.8046	2	0.5405	6	0.4574	4
Zhejiang	0.7252	5	0.5513	5	0.4489	3
Anhui	0.4176	25	0.1901	26	0.7632	23
Fujian	0.6256	8	0.3296	13	0.5959	11
Jiangxi	0.4056	26	0.1878	27	0.8066	27
Shandong	0.8019	3	0.5946	3	0.4017	2
Henan	0.5722	12	0.3488	12	0.6303	15
Hubei	0.4710	19	0.2360	22	0.7310	20
Hunan	0.4731	18	0.1955	24	0.7816	26
Guangdong	0.7623	4	0.3554	11	0.5611	8
Guangxi	0.3454	29	0.2050	23	0.8907	28
Hainan	0.3900	28	0.1614	30	0.9016	29
Chongqing	0.4920	16	0.3240	14	0.6103	13
Sichuan	0.4754	17	0.1874	28	0.7567	22
Guizhou	0.3968	27	0.2897	18	0.6402	18
Yunnan	0.4507	21	0.2886	19	0.6121	14
Tibet	0.4443	23	0.4868	8	0.4918	5
Shaanxi	0.5617	14	0.3152	15	0.5866	10
Gansu	0.4453	22	0.1828	29	0.7485	21
Qinghai	0.4437	24	0.2837	20	0.6371	17
Ningxia	0.5618	13	0.5923	4	0.5465	7
Xinjiang	0.4550	20	0.3044	16	0.7692	25

[a] Res.Eff: Resource Efficiency [b] Res.Rank: Resource Rank [c] Envi.Eff: Environmental Efficiency. [d] Envi.Rank: Resource Rank [e] Eco-Ineff: Eco-inefficiency Scores. [f] Eco.Rank: Eco-inefficiency Scores Rank

The correlation between resource efficiency and environmental efficiency can be seen in Figure 3. It can be seen that environmental efficiency is generally lower than resource efficiency. The two are positively related. In areas with a high resource efficiency, the environmental efficiency is also high.

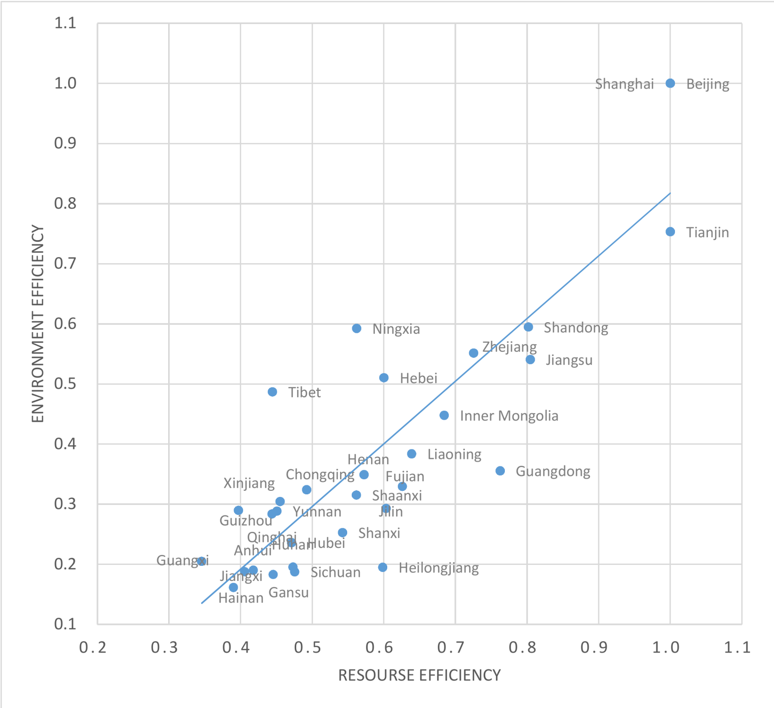

Figure 3. Relationship between environmental efficiency and resource efficiency.

Only Beijing and Shanghai are efficient in both the environmental and resource efficiency of water. Tianjin is efficient in terms of water resources, with a slightly lower environmental efficiency of water. Most provinces are concentrated in the lower left of Figure 3. Their environmental efficiency and resource efficiency of water are both low. The environmental efficiency of water in Tibet, Ningxia, and Hebei is higher than their resources efficiency of water. These provinces have a small population and laggard social development. The damage of the water environment is relatively low. But backward production facilities result in a lower resource efficiency of water. Resource efficiency in Guangdong and Heilongjiang is significantly higher than environmental efficiency. Guangdong has a large population and Heilongjiang is a gathering place for heavy industry in China. These factors put tremendous pressure on the water environment. Zhejiang, Jiangsu, and Shandong present a similar situation. They have a higher resource efficiency of water without an ideal environmental efficiency. High social development will lead to the higher resource efficiency of water consumption. Population and production patterns will have a greater impact on the environmental efficiency of water consumption.

3.4. Eco-Inefficiency of Regional Water Resource

Model (3) is solved to get the eco-efficiency values of water consumption in various provincial regions of China. Appendix A (Table A1) shows the improvement of the unexpected output and expected output that each provincial region can make to achieve eco-efficiency. This paper uses the spatial distribution map to represent the regional water consumption efficiency (Figure 4).

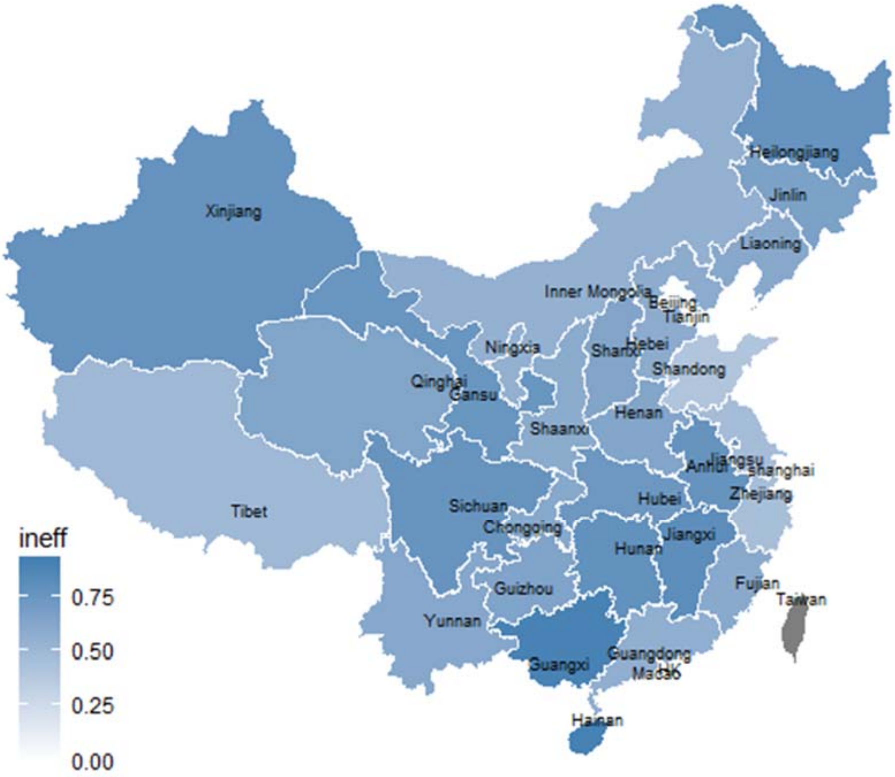

Figure 4. Eco-efficiencies of 31 provinces in China (A darker color indicates a lower eco-efficiency).

It can be found that only Beijing, Tianjin, and Shanghai were eco-efficient in terms of water consumption in 2014 ($\theta = 0$). Guangxi and Hainan were the worst. Overall, the southeast and coastal areas were more eco-efficient in terms of the water consumption, while the Midwest and the north were less eco-efficient. The scores of eco-inefficiency in terms of the water consumption of the remaining areas were almost between 0.5 and 0.9. This showed that the overall environment of water resources in China was not optimistic. In most areas, the water environment was polluted seriously and the economic effect of water consumption was low, which lead to the eco-inefficiency of water consumption.

Through $HD = HCOD^{-}/HCOD$, $GI = GDP^{+}/GDP$ ($HCOD^{-}$: The reduction of HCOD; GDP^{+}: The increment of GDP), we can get the extent of output change (like HD, GI) that each provincial region should make to be eco-efficient in terms of the water consumption (see Appendix B (Table A2)). At the national level, the average reduction in COD emissions from domestic and agricultural wastewater was similar, with values of 51.27% and 54.17% respectively. The COD emission of industrial wastewater needed to be reduced by 78.68% on average. Compared with the other two, the degree of industrial COD emission reduction was the largest. Therefore, all provincial regions should pay attention to the reduction of industrial wastewater emission. In terms of GDP growth, the country needed to increase its GDP by 50% on average to be eco-efficient.

In addition, combining the decrease of unexpected output and the increase of expected output, it can be seen that regions that needed to significantly increase their GDP were less likely to reduce COD emissions from wastewater, while areas that needed to act "vigorously" to reduce emissions did not need to increase GDP too much to be eco-efficiency in water consumption. This is much closer to the real word. Reducing wastewater emissions may hinder economic development, so there will not be too much demand for economic development while focusing on emission reductions. This indicates that according to the results of this model (3), it is reasonable to give some guidance to increase or decrease the output of each provincial region to make it eco-efficienct in terms of water consumption.

3.5. Cluster Analysis

This paper calculates the proportion for the extent of each output improvement (Table A3) to analyze which output improvement the provincial region should focus on. Due to the similarities in the proportions of the output improvement in each provincial region, this paper clusters the data of Appendix C and classifies provincial regions into nine clusters using the average linkage clustering method. The algorithm of hierarchical clustering is as follows:

(1) Define each observation (row or unit) as a cluster;
(2) Calculate the distance between each cluster and other clusters;
(3) Combine the two clusters with the shortest distance into one, and the number of clusters will decrease by one;
(4) Repeat steps (2) and (3) until the clusters containing all the observations are combined into a single cluster.

In hierarchical clustering algorithms, the main difference is that they have different definitions of distances between two clusters (step (2)). This paper uses the average linkage clustering method, which calculates the average distance between a point in one cluster and a point in another cluster.

The result is shown in Figure 5. According to the clustering results, this paper puts together provincial regions with similar output improvement schemes. Based on the data of Table A3, Figure 6 can clearly and directly show the output improvement schemes in all provincial regions.

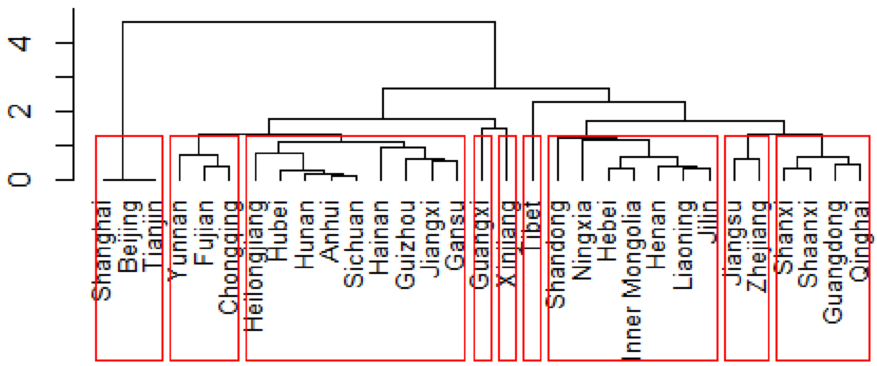

Figure 5. Result of average linkage clustering.

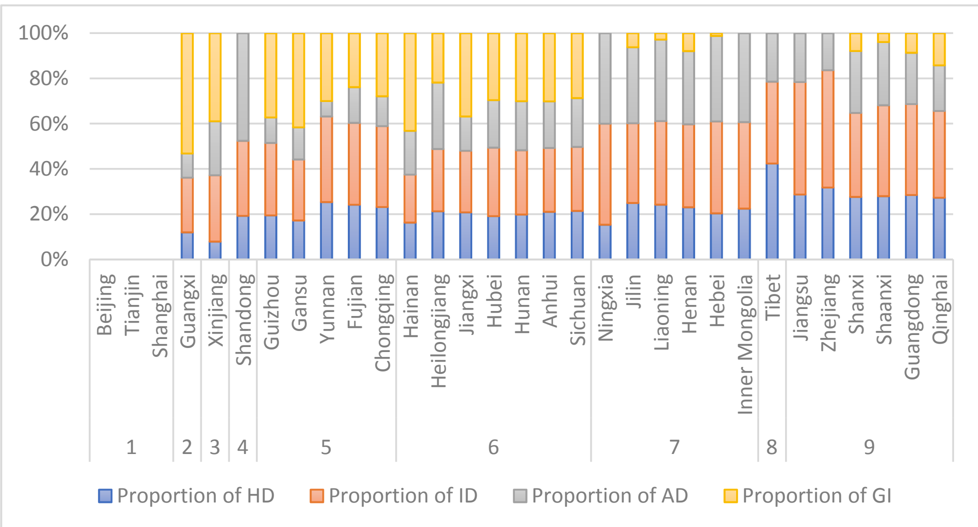

Figure 6. The proportion of output improvement.

If the proportion of changes in the undesirable output is greater, the region may need to pay more attention to the emission reduction to be eco-efficient in terms of water resources. If the proportion of the improvement in the expected output is larger, it means the value brought about by the water consumption is too low in this region, and more attention should be paid to improving the GDP than reducing emissions.

3.6. Some Suggestions

By solving model (3), the output improvement of the water use for 31 provincial-level regions can be obtained. As can be seen in Appendix A, each region's output improvement is different, but there are similarities among some improvements. In practical applications, if the government proposes different improvement for each provincial-level regions, the implementation of the policy will also have greater difficulties. Additionally, it is not convincing to give policy recommendations only from the results of the DEA model. Sometimes it is necessary to give advice based on the development background of the region, which makes the policy more reasonable and acceptable. So, this paper clusters improvement results derived from the DEA model and tries to group together regions with similar output improvements. The clustering result shows that output improvement has a certain geographical connection. For example, areas with similar improvement schemes are often tied together (see Figure 7), which is inseparable with the local resources and environment and is line with China's national conditions and some endemic development policies. Cluster analysis combines the data results with the actual situation well, which facilitates the analysis of the reasons behind the model giving such output improvements. Then, combined with the regional characteristics, a more targeted output improvement scheme is proposed, which also facilitates the implementation of the policy.

Table 4 shows the average improvement in the output for each cluster. According to Table 4, this paper can formulate output improvement schemes for nine clusters of regions. It can also be found that there is a geographical connection between the nine types of regions. Figure 7 shows the spatial distribution.

Table 4. The average extent of output improvement in nine clusters.

Cluster	HD	ID	AD	GI
1	0.00%	0.00%	0.00%	0.00%
2	42.74%	86.00%	38.05%	189.48%
3	24.26%	90.25%	73.42%	119.76%
4	30.98%	53.28%	76.42%	0.00%
5	55.55%	85.75%	31.61%	83.65%
6	62.67%	85.42%	66.58%	100.13%
7	52.17%	91.89%	86.54%	7.67%
8	83.36%	71.20%	42.16%	0.00%
9	63.11%	93.41%	50.98%	14.14%

Figure 7. The spatial distribution of the clustering result.

Combining the regional natural environment, this paper gives policy recommendations based on the clustering results for each cluster of province-level regions in China.

The first cluster includes Beijing, Tianjin, and Shanghai, which are eco-efficient regions of water consumption and do not need to be improved in terms of the GDP.

The second cluster is Guangxi, which has many rivers and is rich in water resources. It mainly develops industry and tourism. However, the data shows that the gross product value is too low. It needs to nearly double the expected output and reduce 90% of industrial wastewater discharges. This means that industrial water pollution in Guangxi is too high and the output value brought about by water consumption is too low.

The third cluster is Xinjiang, which is a minority nationality with a sparse population. Therefore, it requires less emission reduction of domestic wastewater. Xinjiang is rich in mineral resources and is the leading force in the mining development of China. However, its remote location has led to its backward development of economy and technology. Xinjiang province needs to adjust the industrial structure. It can weed out high energy consuming and polluting industrial equipment to significantly reduce industrial wastewater discharge. Xinjiang is also the largest grain base in the northwest provincial region. The main production is cotton. Animal husbandry and forestry horticulture are more developed. However, the dry climate has led to it being the largest province in China for agricultural water use, so it needs to pay more attention to the reduction of agricultural wastewater.

The fourth cluster is Shandong, which is the second largest province in terms of population. As one of the fastest growing provinces in China, GDP has been ranked third in the country since 2007. Shandong does not need to make improvements in the gross domestic product. It is noteworthy that the amount of water resources per capita in Shandong Province is extremely low, with only 14.9% (less than 1/6) of the national average, which is 4.0% (1/25) of the world's per capita. It belongs to a serious water shortage area with a per capita possession of less than 500 cm^3. Water saving is especially important. Water pollution brings more pressure to Shandong. However, Shandong is a major agricultural province in China. The added value of agriculture ranks first in China for a long period of time, and the agricultural water consumption is very large. Therefore, the main obstacle to improving water efficiency in Shandong is to save agricultural water and reduce emissions. In terms of methods, water-saving technologies can greatly improve the economic benefits of agricultural water use [54]. Water recovery (water reclamation) can produce more economic benefits and environmental benefits for provinces that suffer from significant water resource shortages and pollution [55]. In addition, although Shandong has a huge population, the efforts that are needed to reduce domestic water use are minor. This means that the efficiency of domestic water use is higher in Shandong than in other provinces. Shandong has developed education and citizens are of high quality. Additionally, higher education has a greater impact on domestic water use efficiency [33]. This is a reference for other provinces to improve the efficiency of domestic water consumption: Increase public awareness of water conservation through effective publicity. At the moment, there is a lack of correct understanding of water pollution and water resources status. Many people are not conscious of saving water and improving water use efficiency in the process of water use. Therefore, the government can enhance public awareness of water conservation through publicity and guide water-saving practices correctly at the same time.

The fifth cluster is the area located in southwestern and northwestern China and includes Fujian. The land is barren and less suitable for agriculture. This cluster can slightly reduce agricultural wastewater discharge and should focus on reducing industrial wastewater discharge and increasing the expected output, like GDP.

The sixth cluster is concentrated in central and western China, including Heilongjiang. These areas have a large population and a balanced development in all aspects. They should give priority to raising the GDP and reducing the industrial wastewater discharge. Moreover, they should reduce 60% of life and agricultural waste water.

Provincial regions of the seventh cluster are located in northeast China. Northeast is China's heavy industry base with an earlier started economy. These regions need to pay attention to industrial wastewater reduction. The fertile black soil in Northeast makes Heilongjiang and Jilin provinces the major agricultural provinces. Table 4 shows that their agricultural wastewater needs to be reduced by 86.54%, the highest in China. However, compared to domestic and industrial water, agricultural water is not controllable and independent. This cluster also has climate and cost uncertainty. In China, the agricultural water consumption of unit output value is huge. The flow of rain water or irrigation water through the surface of farmland is the main source of agricultural wastewater. Farm runoff mainly contains nitrogen, phosphorus, pesticides, and other pollutants. Therefore, improving crop cultivation techniques and reducing the use of chemical fertilizers and pesticides are the main methods used to reduce the emission of agricultural wastewater. Zhong et al. [56] believe that reducing irrigation has great potential for solving the problem of water shortage in China, especially in provinces with high irrigational subsidies such as Guangdong, Shandong, and Jilin. In order to prevent the agricultural economy from being damaged, the government should gradually reduce irrigation subsidies.

The eighth cluster is Tibet. Due to the barren land in Tibet, it is not suitable for crop growth. The consumption of agricultural water and the pollution caused by it are relatively small. Tibet needs to reduce agricultural discharge by 40%. Since Tibet's economy and technology develop slowly, not much pressure will be put on boosting GDP in the short term. Its industrial technology is relatively backward. Tibet should make more effort to reduce industrial waste water. Combined with the actual situation in Tibet, focusing on reducing domestic wastewater can make it more rapidly efficient in terms of water consumption. The government can actively promote the use of water-saving appliances. Efficient water-saving appliances can significantly reduce the domestic water consumption of residents and raise residents' awareness of water conservation [57].

Provincial regions in the ninth cluster are located in the northwestern part of China and some southeast coastal areas. The features of southeastern provinces are advanced economies and technology. They are the bases for high-tech light industry. Therefore, industrial water consumption is high. The industrial water consumption in Jiangsu ranks first in China (Figure 1). Although the amount of industrial water is larger, the actual consumption is not much. The general industrial water consumption is about 0.5~10% of its total water consumption, that is, more than 90% of the water can still be reused after proper treatment. Increasing the reuse rate of industrial water is the main way to save industrial water. Specific measures to reduce the water demand of industrial production are changing the production process, taking water-saving or even anhydrous technologies and choosing a reasonable industrial layout. It is also possible to improve the efficiency of industrial water by increasing revenue and reducing expenditure. The industrial level of the northwest is backward, but rich mineral resources make it suitable for the development of heavy industry. The main reasons for the low water consumption efficiency are the large amount of sewage discharged and the low unit output of water. They can reform the production process to save water and increase the output. Cleaner production strategies should be implemented to reduce pollution.

4. Conclusions

In view of the shortcomings of the traditional model in efficiency evaluation, this paper adopts the improved frontier model for a better evaluation of the unexpected output. Its advantage is that it can make the evaluated unit free to choose its own improvement program to be eco-efficient. This paper uses this model to evaluate the eco-efficiency of water consumption in China in 2014. In reducing wastewater discharge and increasing the desired output, the guidance given by the model results is more suitable for each provincial region to be eco-efficient in terms of water consumption. It can be seen that except for a few economically developed provincial regions, the overall water environment in China is not optimistic. The industrial wastewater urgently needs to be reduced among the three major discharges of waste water. In some provinces, the emission reduction and the GDP increase should be carried out simultaneously. Based on the results of the model, this paper emphatically analyzes the wastewater discharge in all provincial regions of China and the effort that each province should make to be eco-efficient in terms of water consumption. Then, this paper gives some countermeasures, hoping to improve regional water consumption efficiency in China. However, this paper does not make a dynamic evaluation of China's overall water consumption efficiency. It only evaluates the efficiency in 2014. As mentioned above, the situation of each Chinese province-level region is quite different. To make the results of the evaluation more fair and convincing, weights can also be considered.

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

Appendix A

Table A1. The amount of output and its improvement in each region.

Region	Undesirable Output						Desirable Output		Theta
	HCOD	HCOD$^-$	ICOD	ICOD$^-$	ACOD	ACOD$^-$	GDP	GDP$^+$	
Beijing	82,194	0	6050	0	72,201	0	21,330.83	0.00	0.0000
Tianjin	80,459	0	28,269	0	105,058	0	15,726.93	0.00	0.0000
Hebei	222,142	105,620	168,218	159,641	870,899	768,543	29,421.15	818.44	0.5837
Shanxi	197,074	138,088	72,385	68,043	169,091	117,276	12,761.49	2546.52	0.6335
Inner Mongolia	152,962	74,835	99,469	82,855	593,185	507,843	17,770.19	0.00	0.5446
Liaoning	287,403	169,430	85,406	76,722	838,288	734,658	28,626.58	1989.43	0.6084
Jilin	181,599	119,712	66,488	61,933	484,071	429,708	13,803.14	2257.72	0.6605
Heilongjiang	297,294	194,332	94,038	79,557	1,030,634	929,571	15,039.38	10,089.48	0.7681
Shanghai	163,438	0	24,766	0	30,331	0	23,567.70	0.00	0.0000
Jiangsu	527,877	277,072	204,361	185,900	364,090	143,778	65,088.32	0.00	0.4574
Zhejiang	360,421	205,622	166,342	154,948	192,467	56,489	40,173.03	0.00	0.4489
Anhui	432,220	277,985	81,751	70,398	364,833	229,350	20,848.75	19,177.93	0.7632
Fujian	343,224	197,857	77,631	66,931	204,819	77,125	24,055.76	13,669.68	0.5959
Jiangxi	403,951	271,474	79,691	69,940	227,721	111,350	15,714.63	18,665.65	0.8066
Shandong	385,112	119,324	130,511	69,536	1,260,559	963,373	59,426.59	0.00	0.4017
Henan	385,927	224,440	158,863	146,977	767,318	625,464	34,938.24	6970.57	0.6303
Hubei	446,947	250,165	125,811	111,327	448,078	275,220	27,379.22	23,689.30	0.7310
Hunan	532,928	330,827	133,708	118,832	549,951	372,421	27,037.32	25,411.43	0.7816
Guangdong	864,345	552,223	235,501	212,527	557,958	283,783	67,809.85	13,191.41	0.5611
Guangxi	373,957	159,813	161,863	139,206	204,676	77,872	15,672.89	29,697.65	0.8907
Hainan	83,602	49,113	10,784	8245	100,187	69,891	3500.72	5449.90	0.9016
Chongqing	212,663	120,316	53,360	46,563	119,739	38,619	14,262.60	9703.21	0.6103
Sichuan	586,861	381,376	105,322	90,197	518,638	338,135	28,536.66	24,790.41	0.7567
Guizhou	195,164	97,360	67,250	55,137	59,281	17,063	9266.39	8842.81	0.6402
Yunnan	286,925	178,165	162,472	150,411	71,448	11,971	12,814.59	9408.63	0.6121
Tibet	21,321	17,773	907	646	5389	2272	920.83	0.00	0.4918
Shaanxi	216,952	142,494	95,565	90,084	189,456	124,050	17,689.94	1633.28	0.5866
Gansu	144,082	74,280	88,586	71,475	138,930	59,194	6836.82	8516.88	0.7485
Qinghai	39,598	27,511	41,373	40,483	21,821	11,203	2303.32	833.57	0.6371
Ningxia	17,905	6000	99,821	97,481	101,191	88,482	2752.10	0.00	0.5465
Xinjiang	117,395	28,476	186,960	168,722	361,597	265,499	9273.46	11,106.20	0.7692

HCOD$^-$ means reduction of HCOD, and so on.

Appendix B

Table A2. The extent of output improvement of China in 2014.

Region	HD	ID	AD	GI
Beijing	0.00%	0.00%	0.00%	0.00%
Tianjin	0.00%	0.00%	0.00%	0.00%
Hebei	47.55%	94.90%	88.25%	2.78%
Shanxi	70.07%	94.00%	69.36%	19.95%
Inner Mongolia	48.92%	83.30%	85.61%	0.00%
Liaoning	58.95%	89.83%	87.64%	6.95%
Jilin	65.92%	93.15%	88.77%	16.36%
Heilongjiang	65.37%	84.60%	90.19%	67.09%
Shanghai	0.00%	0.00%	0.00%	0.00%
Jiangsu	52.49%	90.97%	39.49%	0.00%
Zhejiang	57.05%	93.15%	29.35%	0.00%
Anhui	64.32%	86.11%	62.86%	91.99%
Fujian	57.65%	86.22%	37.66%	56.82%
Jiangxi	67.20%	87.76%	48.90%	118.78%
Shandong	30.98%	53.28%	76.42%	0.00%
Henan	58.16%	92.52%	81.51%	19.95%
Hubei	55.97%	88.49%	61.42%	86.52%
Hunan	62.08%	88.87%	67.72%	93.99%

Table A2. *Cont.*

Region	HD	ID	AD	GI
Guangdong	63.89%	90.24%	50.86%	19.45%
Guangxi	42.74%	86.00%	38.05%	189.48%
Hainan	58.75%	76.46%	69.76%	155.68%
Chongqing	56.58%	87.26%	32.25%	68.03%
Sichuan	64.99%	85.64%	65.20%	86.87%
Guizhou	49.89%	81.99%	28.78%	95.43%
Yunnan	62.09%	92.58%	16.75%	73.42%
Tibet	83.36%	71.20%	42.16%	0.00%
Shaanxi	65.68%	94.27%	65.48%	9.23%
Gansu	51.55%	80.68%	42.61%	124.57%
Qinghai	69.47%	97.85%	51.34%	36.19%
Ningxia	33.51%	97.66%	87.44%	0.00%
Xinjiang	24.26%	90.25%	73.42%	119.76%
Mean	51.27%	78.68%	54.17%	50.30%
Std	20.87%	27.53%	27.41%	54.08%

Appendix C

Table A3. The proportion of output improvement.

Region	Proportion of HD	Proportion of ID	Proportion of AD	Proportion of GI
Beijing	0%	0%	0%	0%
Tianjin	0%	0%	0%	0%
Hebei	20%	41%	38%	1%
Shanxi	28%	37%	27%	8%
Inner Mongolia	22%	38%	39%	0%
Liaoning	24%	37%	36%	3%
Jilin	25%	35%	34%	6%
Heilongjiang	21%	28%	29%	22%
Shanghai	0%	0%	0%	0%
Jiangsu	29%	50%	22%	0%
Zhejiang	32%	52%	16%	0%
Anhui	21%	28%	21%	30%
Fujian	24%	36%	16%	24%
Jiangxi	21%	27%	15%	37%
Shandong	19%	33%	48%	0%
Henan	23%	37%	32%	8%
Hubei	19%	30%	21%	30%
Hunan	20%	28%	22%	30%
Guangdong	28%	40%	23%	9%
Guangxi	12%	24%	11%	53%
Hainan	16%	21%	19%	43%
Chongqing	23%	36%	13%	28%
Sichuan	21%	28%	22%	29%
Guizhou	19%	32%	11%	37%
Yunnan	25%	38%	7%	30%
Tibet	42%	36%	21%	0%
Shaanxi	28%	40%	28%	4%
Gansu	17%	27%	14%	42%
Qinghai	27%	38%	20%	14%
Ningxia	15%	45%	40%	0%
Xinjiang	8%	29%	24%	39%

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