water

MDPI

Article

Assessing China's Use Efficiency of Water Resources from the Resampling Super Data Envelopment Analysis Approach

Jin-chi Hsieh [1,*], Liang-han Ma [1] and Yung-ho Chiu [2]

[1] Department of Business Administration, Taipei City University of Science and Technology, Xueyuan Rd., Beitou, Taipei 11202, Taiwan; lhma@tpcu.edu.tw

[2] Department of Economics, Soochow University, 56, Kueiyang St., Sec. 1, Taipei 10048, Taiwan; echiu@scu.edu.tw

* Correspondence: gchsieh@tpcu.edu.tw; Tel.: +886-2-28927154 (ext. 7015); Fax: +886-2-28912710

Received: 25 April 2019; Accepted: 21 May 2019; Published: 22 May 2019

check for updates

Abstract: Water resources' use efficiency is an important issue under China's rapid economic growth. This is because some provinces' economic development may be delayed due to lack of adequate water resources. Whereas, high economically developed provinces may overuse water resources in order to achieve their economic goals; while also creating a large amount of pollutants. To assess water resources' use efficiency from the resampling super data envelopment analysis (DEA) approach, our research comprehensively utilizes the following as inputs and outputs: (1) water resources: supply of water (SW), per capita water consumption (PCWC), and total water resources (TWR); (2) economic development: gross domestic product (GDP); (3) environmental issues: governance wastewater investment (GWI), wastewater discharge (WD), chemical oxygen demand (COD), and other major pollutants (OMP). The results show that Tibet, Beijing, Guangdong, Qinghai, Shandong, Sichuan, Yunnan, Tianjin, Jiangsu, and Henan have relatively good water resources' use efficiency with efficiency values larger than 1. The best efficiency is in 2015, while the worst is in 2017. Water resources' use efficiency shows significant regional differences in 2013–2017, with the best average efficiency value in southwest China (1.4355) and the worst in north China (0.2987). The results of the Wilcoxon test present that PCWC, GDP, COD, and OMP exhibit very significant differences, PN and WD have significant differences, and SW and TWR have no significant influence. These results imply that China's regional governments must formulate a better water resource strategy based on the water resource distribution of each region. Lastly, the emissions of environmental pollutants must be strictly monitored.

Keywords: water resources use efficiency; resampling; data envelopment analysis; Wilcoxon test; China

---

1. Introduction

Water pollution has worsened in almost all the rivers in Africa, Asia, and Latin America ever since the 1960s, with the greatest amount of pollutants occurring in low- and lower-middle income countries, primarily due to higher populations and economic growth and the lack of wastewater management systems. The trends in water availability and quality are accompanied by projected changes in flood and drought risks. The number of people threatened globally from floods is projected to rise from 1.2 billion in 2018 to around 1.6 billion in 2050; these phenomena will directly impact the gross domestic product (GDP) per capita of the eco-economy [1].

Limited water resources could cloud Asia's bright future. With water as an essential ingredient for economic development; it is estimated that threats to water security incur an annual cost of US$500 billion or around 1% of the world's GDP [2]. Total water resources (TWR) is contained surface water resources, ground water sources, and deducting duplicate water resources. China's TWR were not stable in the period 2010–2017, as seen in Table 1, total water supply (SW) is the same as TWR, while the total amount of wastewater discharged hit 700 billion tons in 2017. While China's gross domestic product (GDP) has increased year by year from 592,963 billion CN¥ to 820,754 billion CN¥ over the period 2013–2017, sewage treatment investment (STI) has also risen yearly from 2013–2017 by 1055, 1196, 1249, 1486, and 1728 billion CN¥ [3], respectively. From the statistical data of China's Ministry of Water Resources (MWR), total water consumption was 3207 billion m^3 and total wastewater discharge was 756 billion tons in 2017.

Table 1. China's total water resources (TWR), total water supply (SW) and gross domestic product (GDP) in periods 2010–2017.

Variables	2010	2011	2012	2013	2014	2015	2016	2017
TWR (billion m^3)	30,906	23,257	29,529	27,958	27,267	27,963	32,466	28,761
SW (billion m^3)	6022	6107	6131	6183	6095	6103	6040	6043
GDP (billion CN¥)	412,119	487,940	538,580	592,963	641,281	685,993	740,061	820,754
STI (billion CN¥)	1173	972	934	1055	1196	1249	1486	1728

Source: Authors' collection.

Freshwater resources in China add up to 2.8 trillion m^3, or 6% of the global total and ranking No. 6^{th} in the world, after Brazil, Russia, Canada, the U.S., and Indonesia. China's per capita water resources, however, only stand at 2100 m^3, or 28% of the global average, making China one of the most water scarce countries in the world. The main use of water consumption is for production purposes at 89.3% in China for 2014, with primary industries accounting for 63.5%, secondary industries accounting for 22.9%, and domestic water consumption at 9.0%. China's total national water supply is 609.5 billion m^3 in 2014, surface water sources is 80.8%, ground water sources is 18.3%, and other water sources is 0.9%. Water resources differ substantially between years and are unevenly distributed in time. Sometimes precipitation and river runoff are highly concentrated within a year in China. However, there is severe pollution of water bodies. The Chinese government takes resource conservation and environmental protection as a basic policy, plays an active and significant role in facilitating rational water allocation with the management and protection of water resources; raising water resources' use efficiency and controlling rapid increase in water demand [4]. Damkjaer and Taylor utilized various indices to explore the metrics of water scarcity [5], China is considered water scarce from these indices. Therefore, water resources' use efficiency is a necessary topic for research, especially as the metrics of water scarcity become increasingly serious. Finding solutions to improve this efficiency is necessary in order to solve environmental and resource problems.

The use and management of water resources are complicated issues because it is important and necessary natural resources and economic resources that affects structural changes in the ecology and environment Conflicts may also arise between environmental sustainability and economic development. Therefore, previous research on water resources' use efficiency focused on improving equipment and technology such as: 1) wastewater treatment's technical advancement [6–8]; and utilizing economic and statistical methods to assess water resources' use efficiency through; 2) traditional statistical methods [9–11]; 3) data envelopment analysis (DEA) [12–20]; and 4) undesirable outputs [21,22]. A brief description runs as follows.

1) Wastewater treatment's technical advancement: Wakeel and Chen [6] used the concept of the water-energy relationship to explore urban planning and management issues and proposed a processing direction for a city that does not have any large-scale wastewater recycling, and reuses policy and management systems; therefore, wastewater should be recycled to avoid energy consumption during the extraction stage. Panepinto et al. [7] focused on energy consumption to evaluate the energy efficiency of a large wastewater treatment plant in Italy, proposed an energy balance for the whole plant to be finally evaluated, and suggested some energy optimization solutions to decrease related

costs. Cano et al. [8] utilized thermal pre-treatments to recover heat from the biogas engine and found that thermal hydrolysis presents great potential to be fully integrated into a wastewater treatment plant with complete energy recovery and self-sufficiency.

2) Traditional statistical method: Wei and Guojun [9] used the regression analysis approach to assess urban water resources' utilization efficiency, and water estimation in the Hebei Province of China. Morales and Heaney [10] utilized ordinary least squares and data envelopment analysis to assess the benchmarking of non-residential water use efficiency in Austin, Texas. Long and Pijanowski [11] employed a host of spatial analyses to explore a variety of spatial correlations between water scarcity and water use efficiency from 2003 to 2013 in China, targeting local to national scales, and found that the bivariate Global Spatial Autocorrelation indicates significant positive spatial correlation between water scarcity and water use efficiency.

3) Data envelopment analysis (DEA) approach: The DEA approach is able to deal with single or multiple inputs and outputs and can discover the reasons behind efficiency and inefficiency, making it a good technique for evaluating resources and environmental efficiency [12,13]. Ali and Klein [14] used the dynamic DEA approach to assess water use efficiency and productivity of irrigation districts in southern Alberta over the period 2009–2012. Kulshrestha and Mittal [15] employed DEA for assessing the relative performances of water supply utilities, suggested that the inputs and outputs should be assets, number of employees, capital, system assets, water treatment plants, staff wages, operating and management expenses, supply volumes, water quantity sold, number of connections, peak water supply, etc., and proposed that DEA measures can be widely applied in the water supply sector for the benefit of all these stakeholders. Azad et al. [16] used the non-radial DEA approach to evaluate the economic efficiency of irrigated agricultural enterprises in Australia and found that irrigated farms are comparatively more efficient in overall farm activity management, but they are not very efficient in managing water resources. Ren et al. [17] utilized the two-stage DEA approach to evaluate water resource use efficiency on a real-case study in the Gansu Province, China for 2003–2013. Gungor-Demirci et al. [18] applied two-stage DEA to assess the performances of individual districts of a California water utility for the year 2014, and proposed that DEA offers a useful way to identify the strengths and weaknesses of individual districts and to guide subsequent managerial improvement initiatives. Kamarudin and Ismail [19] evaluated the performance of water supply services in Malaysia with the DEA approach. Liao et al. [20] used DEA and the Malmquist index to evaluate the utilization efficiency of water resources in 12 western provinces of China in 1999–2008, taking GDP, fixed assets, annual water supply and the population's water usage as inputs and outputs.

4) Undesirable outputs: Environmental issues are the most critical variables in energy and water resource' use efficiencies. Under the results that improving economic growth may produce undesirable outputs, such as wastewater, CO_2, etc., these bad outputs may cause a negative trend in environmental sustainability. How to balance economic development and environmental protection is thus a very important issue. Wang et al. [21] used the Tobit model DEA approach to assess water use efficiency and its influencing factors in China over the period 2008–2016, taking the inputs of labor, capital, and water and outputs of undesirable sewage and desirable per capita GDP, and found that provinces with the highest water efficiency are located in economically developed eastern China. The spatial pattern of water use efficiency in China is consistent with the general pattern of regional economic development. Feng et al. [22] used the directional distance function DEA approach to assess the performance of wastewater treatment in China over 2011–2015, employing the inputs of capital, population, and expenses and the good output of GDP and bad output of wastewater and chemical oxygen demand (COD).

Exploring water resources' use efficiency must contain the issues of water resources' supply and demand, economic development and environmental negative impact problems, and then across multiple periods. These studies above utilize the dynamic network DEA to consider only across multiple periods or two stages [17,18,20], or use desirable and undesirable outputs to consider only economic development and environmental negative impact problem [21,22]. They do not consider the problem that the statistical confidence interval and best efficiency is equal to 1. As such, our research refers to previous literature on non-oriented slacks-based measure (SBM), super SBM DEA, and resampling super-SBM DEA approach to get actual water resources' use efficiency, rankings, and 95% confidence interval of each decision making unit (DMU) [23–25]. We also utilize 2013–2014 data to calculate water resources' use efficiency in 2014 and for the period 2013–2015, in order to calculate this efficiency for 2015 and the years 2016 and 2017. The results help us to understand the efficiency change of cross-multiple periods, which can be used as a reference for establishing a cross-period water resource use policy.

Another important contribution of this present research is that it contains economic (GDP), water resources' supply and demand (water supply, per capita water consumption, governance wastewater investment, total water resources), and environmental variables (wastewater discharge, COD, other major pollutants) as inputs and outputs. The relationships among these variables and water resource' use efficiency can identify key issues in economic development and environmental protection. The abovementioned wastewater discharge (WD), COD, other major pollutants (OMP) are bad outputs. We refer to Hsieh et al. and Ma et al. [26,27] to adjust bad outputs, as good output variables, and utilize the maximum emission value of each bad output in all DMUs as the base; whereby the adjustment value equals (maximum value of DMUs - original emissions value of each DMU) + 1 to become good outputs. These results illustrate the relationships among rapid economic growth, water resources' use policy, and environmental degradation in China at the provincial level, thus spurring local governments to make a careful assessment of appropriate related policies when actively targeting economic development at the same time.

This research utilizes resampling super-SBM DEA to evaluate water resources' use efficiency of China provincial level in 2013–2017. We can get annual efficiency and the confidence interval (97.5, 90, 80, 75, 60, 50, 40, 25, 20, 10, 2.5%) of each DMU. The definition of water resources' use efficiency is the ratio of outputs to inputs. The variables of input and output herein are comprehensive considerations related to water resources' supply and demand, economic output, and environmental emissions, after referring to and correcting previous research [21,23–25]. These water resources' variables use to create economic growth, but also cause environmental pollution problems. Therefore, this efficiency value is a comprehensive consideration of positive and negative factors, and is also an important contribution of this research. These efficiencies are relative and thus they allow us to understand regional governments' water supply and demand situation, and to explore the mutual influence relationship between achieving economic growth goals and mitigating environmental pollution. For the assessment of water resources' use efficiency in the provinces and municipalities in China, we take the following DMUs: Beijing, Shanghai, Tianjin, Chongqing, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Sichuan, Fujian, Guangdong, Guangxi, Yunnan, Guizhou, Hebei, Shandong, Henan, Shanxi, Shaanxi, Gansu, Ningxia, Qinghai, Hainan, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Xinjiang, and Tibet. Their results provide very important reference information in formulating water resource use policies in China at the provincial level.

2. Research Method

The DEA approach evaluates the relative efficiency of an individual DMU from the distance of each DMU to the frontier [28]. This approach follows the model developed by Charnes, Cooper & Rhodes, and modified by Banker, Charnes & Cooper [29,30]. However, these models are unable to process undesirable outputs and the best efficiency is equal to 1 in multiple DMUs. Since water resources' use efficiency is related to environmental variables, it may be affected by undesirable outputs, such as WD, COD, OMP, etc. Thus, it is necessary to get actual efficiency values when discussing water resource use polices.

The traditional DEA does not require special production functions. Thus it is difficult to have statistical inference from DEA scores. Some research used bootstrap DEA to construct confidence intervals [31], but one cannot understand the change in the situation of inputs and outputs through this method. The resampling DEA approach solves the problem of input and output values being subject to change in measurement errors, hysteretic factors, and arbitrariness in efficiency scores [23–25]. We thus use the super-SBM model of DEA-Solver-Pro to calculate water resources' use efficiency (ρ*) and the objective function as Equations (1) and (2):

$$\rho^*((x_0, y_0))^s = min_{\gamma, s^+, s^-} \frac{\frac{1}{m} \sum \frac{\overline{x}_i}{x^t_{i0}}}{\frac{1}{q} \sum_{i=1}^{q} \frac{\overline{y}_i}{y^t_{i0}}} \tag{1}$$

where $x_i(i = 1, 2, \ldots, m)$ are input variables and $y_i(i = 1, 2, \ldots, q)$ are output variables, the input excesses s^- and output shortfalls s^+ for each DMU.

Subject to

$$\begin{aligned} \overline{x} &\geq X^t\gamma \\ \overline{y} &\leq Y^t\gamma \\ \overline{x} &\geq x_0^s, \overline{y} \leq y_0^s \\ \mathrm{L} \leq \mathrm{e}\gamma &\leq \mathrm{U}, \mathrm{y} \geq 0, \gamma \geq 0 \end{aligned} \tag{2}$$

This article aims to get a triangular historical model efficiency score and its confidence interval for each DMU. We first respectively assume the downside limit, the mode, and the upside limit by a, m, and b. We employ a triangular distribution on the data as exhibited, and the observed input and output values represent mode m. Here, α and β show upside and downside error rates, and a and b can then be expressed as Equation (3).

$$\begin{aligned} a &= (1-\alpha)m \ (0 \leq \alpha \leq 1) \\ b &= (1+\beta)m \ (\beta \geq 0) \end{aligned} \tag{3}$$

The data generation process of triangular distribution (TDP) is:

$$\begin{aligned} \mathrm{TDP(x)} &= \frac{(x-a)^2}{(m-a)(b-a)} \quad (a \leq x < m) \\ &= 1 - \frac{(b-x)^2}{(b-m)(b-a)} \quad (m \leq x \leq b) \end{aligned} \tag{4}$$

We assume a uniform random number ε $(0 \leq \varepsilon \leq 1)$ and then obtain an input/output ω from:

$$\begin{aligned} \omega &= a + \sqrt{\varepsilon(m-a)(b-a)}\left(\varepsilon \leq \frac{m-a}{b-a}\right) \\ &= b - \sqrt{(1-\varepsilon)(b-m)(b-a)}\left(\varepsilon \geq \frac{m-a}{b-a}\right) \end{aligned} \tag{5}$$

The data of inputs and outputs in multiple periods take on a triangular distribution simulation as in the following steps: (I) use super-SBM DEA to obtain the efficiency score of each DMU; (II) repeat the following processes (i) and (ii) for the designated times; (i) use the data generation process to generate a set of input and output data; (ii) obtain the super efficiency score of each DMU for the resample 1000 times and record it; and (III) calculate the confidence interval (97.5, 90, 80, 75, 60, 50, 40, 25, 20, 10, 2.5%) of each DMU.

The inputs or outputs of DMU n in the past t−1 period and current t period are respectively ω_n^{t-1} and ω_n^t (t = 1, 2, ... , T) and (n =1, 2, ... , N). The upside variation rate α_n^t and downside variation rate β_n^t in period t are in the following equation:

$$\alpha_n^t\left(or\ \beta_n^t\right) = \frac{\omega_n^{t-1} - \omega_n^t}{\omega_n^t} \tag{6}$$

The upside and downside distributions are $\left\{\alpha_n^t\right\}$ and $\left\{\beta_n^t\right\}$ for all DMUs. From the distribution data, their median values are respectively α_M^t and β_M^t. These values show the downside error rate (DER) and upside error rate (UER) of inputs and outputs in period t. Previous literature review has rarely applied resampling DEA approach to the assessment of water resources' use performance, Mehrotra and Sharma applied to assess the performance of multiple variables in a changing climate, proposed changes in the dependence attributes are ascertained by resampling of the historical ranks into what these might resemble in the future, and the approach is not limited in terms of the number of variables, grid points in space, and the time scale considered [32]. We execute the same process between all pairs of inputs, outputs and input versus output in resampling, inappropriate samples with unbalanced inputs and outputs are excluded from resampling in the resampling super-SBM DEA of this research. This approach uses historical data to determine downside and upside error rates, and utilizes optimal weights of multiple periods historical data to evaluate efficiency. The variables of input and output are subject to change for several reasons, e.g., measurement errors, hysteretic factors, arbitrariness and so on in DEA approach. Therefore, DEA efficiency scores need to be examined by considering these factors. Resampling approach based on these variations is necessary for gauging the confidence interval of DEA scores. We also set downside error rate percentage (DER%) and upside error rate percentage (UER%) to find out the reasons for the poor efficiency across periods in all data of input and output in this research, this is a very important contribution. These results provide valuable reference of China' provincial levels in formulating policies for future water resources' use. This approach is suitable to research the performance of energy, environment and water resources' use that may be affected by different periods.

This research utilizes Wilcoxon test to explore the relationship between input and output data on water resources' use efficiency. Wilcoxon test is a nonparametric test that can determine whether two dependent samples were having the same distribution. We set data as $K_{1,i}$ and $k_{2,i}i = 1, 2, \ldots, n)$, two hypotheses are H_0: difference between the pairs follows a symmetric distribution around zero, and H_1: difference between the pairs does not follow a symmetric distribution around zero. We calculate sign function as $\text{sgn}(k_{2,i} - k_{1,i})$ and z_i as follow equation,

$$z_i = \left|k_{2,i} - k_{1,i}\right| \ (i = 1, 2, \ldots, n) \tag{7}$$

Let N_r is number of $\left|k_{2,i} - k_{1,i}\right| = 0 \ (i = 1, 2, \ldots, n)$, R_i denote the rank, starting with the smallest as 1, the test statistic ω is calculated by Equation (8).

$$\omega = \sum_{i=1}^{N_r} [sgn(k_{2,i} - k_{1,i}) \times R_i] \tag{8}$$

$$\delta_\omega = \sqrt{\frac{N_r(N_r + 1)(2N_r + 1)}{24}} \tag{9}$$

$$Z = \frac{\omega}{\delta_\omega} \tag{10}$$

$Z =$ If $|Z| > Z_{critical}$, then reject hypotheses H_0, and then utilizes p-value to explain whether it is significant, symbol " * " as slightly significant and $p < 0.05$, " ** " as significant and $p < 0.01$, " *** " as very significant and $p < 0.001$.

3. Data Analysis and Discussion

This research uses the resampling super-SBM DEA approach to evaluate water resources' use efficiency. The inputs and outputs are economics, water resources' supply & demand and negative environmental emission variables in the period 2013–2017. DEA is widely used to evaluate water use efficiency with across multiple periods [14,17,20–22], the main purpose is exploring the impact of across period, the data is still not available in 2018, so we use the data from 2013–2017 as the analytical data. The annual statistical data come from China's National Bureau of Statistics [33]. The inputs are population number (PN), supply water (SW), per capita water consumption (PCWC), and governance wastewater investment (GWI). The outputs are total water resources (TWR), gross domestic product (GDP), wastewater discharge (WD), chemical oxygen demand (COD), and other major pollutants (OMP). These data of input and output are defined as follows.

PN (unit, 10,000 people): Total people in the current period at China's provincial level; the values shown are mid-year estimates.

SW (unit, billion m^3): Total amount of water supply in the current period.

PCWC (unit, m^3): Per capita water consumption in the current period.

GWI (unit, million CN¥): Total governance wastewater investment in the current period.

GDP (unit, billion CN¥): The monetary value of all finished goods and services produced within a country's borders in the current year.

TWR (unit, billion m^3): Total water resources in the current period.

WD (unit, million tons): Total amount of wastewater discharge in the current period.

COD (unit, 10,000 tons): The chemical oxygen demand at China's provincial level in the current period.

OMP (unit, 10,000 tons): The total amounts of other major pollutants in the current period, covering the emissions of ammonia nitrogen, nitrogen, and phosphorus.

The descriptive statistics of the inputs and outputs are shown separately in Table 2. The average values of PN and GDP exhibit a growing trend year by year for 2013–2017. The environmental variables of WD, COD, and OMP decreased from 2015–2107, WD decreased from 2372 to 2257 million tons, COD decreased from 72 to 33 (10,000 tons), and OMP also decreased from 24 to 12 (10,000 tons); the wastewater treatment costs (GWI) do not increase, implying that China efforts to reduce water pollution problems are remarkable in 2015–2017. The water resources' supply and demand of SW, PCWC, and TWR are unstable in 2013–2017, indicating that there should be a more effective strategy to maintain a stable supply of water resources. These statistics represent the changes of all DMUs in different periods, and can analyze the trend of the differences between the data of multiple periods. Although the trend of each DMU may be inconsistent, the statistics data also cannot be explained and analyzed one by one, but the input and output data of each period will produce the result of the difference in efficiency with DEA approach for all DMUs, and we will analyze the impact of input and output based on the results of efficiency performance in this study, so as to put forward the reference of strategy logic in all DMUs.

This research uses the resampling super-SBM DEA approach to assess the efficiency of use of water resources at China's provincial level in 2013–2017. The results are shown in Table 3. The efficiencies of resampling DEA are in 97.5% and 2.5% confidence intervals for all DMUs. We define a variable called the confidence interval error (I-Dev), where I-Dev of each DMU is equal to the (average value of efficiency – efficiency of resampling DEA). It shows the order of efficiency value deviation through resampling 1000 times and also presents the stable order of inputs and outputs in each DMU. I-Dev is a statistically sensitive, smaller value that shows the smaller difference between the efficiency of the confidence interval and the actual efficiency. It also indicated that the input and output data are relatively stable across multiple periods. If I-Dev is relatively larger, these DMUs must adjust or control input and output data in future. Tibet has the best water resources' use efficiency in 2013–2017, but its I-Dev (0.1089) is larger, meaning that some significant changes in input and output lead to relatively high sensitivity, and so it must maintain a stable water resource management policy to keep its good water resources' use efficiency. The best I-Dev is Shanghai, but the confidence interval change is too large; its 97.5% confidence interval is 1.0341, and its 2.5% confidence interval is 0.0726, illustraing its water resources management policy is unstable and must improve. I-Dev is the problem of the stability of the input and output data of each DMU after resampling 1000 times, so the I-Dev value is independent of the efficiency by resampling super-SBM DEA approach. DEA efficiency can find differences in water resources' use performance of all DMUs in 2013–2017. The places with relatively good water resources' use efficiency are Beijing, Tianjin, Chongqing, Jiangsu, Zhejiang, Sichuan, Guangdong, Yunnan, Shandong, Henan, Qinghai, and Tibetl whose efficiency values are greater than 1, most of these DMUS also have relatively high GDP, indicating that economic development is closely related to water resources' use efficiency. Relatively poor water resources' use efficiency are Anhui, Jiangxi, Hubei, Guangxi, Hebei, Shanxi, Shaanxi, Gansu, Ningxia, Inner Mongolia, Liaoning, Jilin, Heilongjiang, and Xinjiang, whose efficiency values are less than 0.5. These DMUs must be more proactive in developing stable water resource management policies and effectively control environmental pollutants in order to improve water resources' use efficiency.

Table 2. Descriptive statistics of input and output data in 2013–2017.

Year	Statistics	Inputs				Outputs				
		PN	SW	PCWC	GWI	GDP	TWR	WD	COD	OMP
2013	Average	4371	199	536	409	20,463	902	2243	76	24
	Maximum	10,644	588	2615	1506	62475	4416	8625	185	79
	Minimum	312	24	165	5.72	816	11	50	2.58	0.94
	StDev	2786	149	454	393	15,710	944	1844	50	19
2014	Average	4395	197	525	372	22,076	880	2310	74	24
	Maximum	10,724	591	2551	1751	67,810	4416	9051	178	79
	Minimum	318	24	161	0.90	921	10	54	2.79	1.01
	StDev	2798	149	444	376	16,988	949	1905	48	18
2015	Average	4422	197	521	382	23,315	902	2372	72	24
	Maximum	10,849	577	2478	1649	72,813	3853	9115	176	91
	Minimum	324	26	168	8.93	1026	9.2	59	2.88	1.14
	StDev	2817	148	431	416	18,219	922	1956	47	20
2016	Average	4451	195	509	349	25,164	1047	2294	34	12
	Maximum	10,999	577	2377	1585	80,855	4642	9383	96	37
	Minimum	331	26	175	0.15	1151	9.6	61	2.74	0.8
	StDev	2843	146	412	381	20,103	1055	1942	23	8.28
2017	Average	4479	195	504	246	27,327	928	2257	33	12
	Maximum	11,169	591	2281	1056	89,705	4750	8820	100	37
	Minimum	337	26	176	2.80	1311	11	72	2.5	0.78
	StDev	2867	146	598	285	23,187	1017	1851	23	8.34

Source: Authors' collection.

Principal component regression (PCR) is commonly applied in forecasting to decompose space–time fields, which by reducing both dimensionality and multicollinearity of a set of variables [34,35]. This approach aims to acquire the correction coefficient and eigenvectors of PCR in all inputs and outputs as listed in Tables 4 and 5. We find the key variables of the impacts of inputs and outputs on water resources' use efficiency and find that the main key variables are the environmental variables WD, COD, and OMP. The economic and environmental variables of GDP, WD, COD, and OMP have a significantly positive correlation with other variables, and their slope values are also relatively large. The largest eigenvector of PCR is WD (0.94), and its proportion is very high up to 54.23%, it indicates that most DMUs in China must work to reduce WD in the future. Eigenvectors and proportion of PN, GDP, COD and OMP are relatively large, these results may cause negative I-Dev DMUs, accounting for 23 or 74.19% in Table 3. These results show that undesirable emissions have a significant impact on water resources' use efficiency. Therefore, water resource management strategies must be used to reduce undesired emissions in China in the future.

Table 3. Results of water resources' use efficiency in China with resampling data envelopment analysis (DEA).

DMU	DEA	97.50%	90%	80%	75%	50%	25%	20%	10%	2.50%	Average	Rank	I-Dev
Beijing	1.17	1.53	1.42	1.31	1.28	1.17	1.09	1.08	1.07	1.06	1.20	4	−0.033
Shanghai	1.00	1.03	1.02	1.02	1.01	1.00	0.14	0.12	0.09	0.07	0.67	15	0.334
Tianjin	1.21	1.38	1.30	1.25	1.24	1.22	1.21	1.21	1.21	1.20	1.24	3	−0.025
Chongqing	1.02	1.25	1.16	1.10	1.08	1.02	1.00	0.79	0.73	0.66	0.99	11	0.033
Jiangsu	1.05	1.07	1.06	1.06	1.05	1.05	1.04	1.03	1.03	1.02	1.04	10	0.003
Zhejiang	1.01	1.03	1.03	1.02	1.02	1.01	0.79	0.76	0.71	0.66	0.93	13	0.074
Anhui	0.31	0.41	0.38	0.35	0.35	0.31	0.28	0.28	0.26	0.25	0.32	24	−0.006
Jiangxi	0.32	0.41	0.38	0.36	0.35	0.32	0.30	0.29	0.28	0.27	0.33	23	−0.007
Hubei	0.49	0.71	0.62	0.57	0.55	0.49	0.45	0.44	0.42	0.39	0.51	18	−0.024
Hunan	0.62	1.03	1.01	0.82	0.74	0.63	0.56	0.55	0.51	0.47	0.69	14	−0.063
Sichuan	1.05	1.11	1.09	1.08	1.07	1.05	1.04	1.03	1.02	1.01	1.06	9	−0.004
Fujian	0.61	1.01	1.00	0.75	0.71	0.62	0.55	0.54	0.50	0.46	0.66	16	−0.046
Guangdong	1.09	1.13	1.12	1.11	1.11	1.10	1.09	1.09	1.08	1.07	1.10	6	−0.005
Guangxi	0.43	0.66	0.56	0.51	0.49	0.43	0.38	0.37	0.33	0.31	0.44	20	−0.016
Yunnan	1.09	1.12	1.11	1.10	1.10	1.08	1.07	1.07	1.06	1.04	1.08	7	0.003
Guizhou	0.57	1.00	1.00	1.00	0.66	0.57	0.53	0.52	0.50	0.47	0.66	17	−0.086
Hebei	0.33	0.51	0.43	0.38	0.37	0.33	0.30	0.30	0.28	0.26	0.35	22	−0.015
Shandong	1.11	1.13	1.12	1.12	1.12	1.11	1.10	1.10	1.10	1.09	1.11	5	0.001
Henan	1.03	1.07	1.06	1.05	1.05	1.03	1.01	1.00	0.65	0.58	0.97	12	0.060
Shanxi	0.41	0.47	0.44	0.43	0.42	0.41	0.39	0.39	0.37	0.36	0.42	21	−0.010
Shaanxi	0.47	1.00	0.52	0.50	0.50	0.47	0.46	0.45	0.44	0.43	0.49	19	−0.021
Gansu	0.21	0.39	0.27	0.25	0.24	0.22	0.21	0.20	0.19	0.18	0.24	27	−0.030
Ningxia	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.011	0.01	31	−0.003
Qinghai	1.24	1.27	1.26	1.26	1.26	1.25	1.24	1.24	1.24	1.23	1.25	2	−0.005
Hainan	1.08	1.16	1.13	1.11	1.10	1.08	1.04	1.04	1.03	1.01	1.08	8	0.002
Inner Mongolia	0.16	0.29	0.20	0.18	0.18	0.17	0.15	0.15	0.14	0.14	0.18	29	−0.020
Liaoning	0.28	0.37	0.33	0.31	0.30	0.28	0.27	0.26	0.25	0.24	0.29	26	−0.013
Jilin	0.30	0.37	0.34	0.33	0.32	0.30	0.29	0.28	0.27	0.26	0.31	25	−0.004
Heilongjiang	0.19	0.21	0.20	0.20	0.19	0.19	0.18	0.18	0.17	0.16	0.19	28	−0.001
Xinjiang	0.14	0.16	0.15	0.14	0.14	0.14	0.13	0.13	0.12	0.12	0.14	30	−0.001
Tibet	2.63	3.85	3.39	3.11	2.98	2.64	2.40	2.35	2.24	2.09	2.74	1	−0.109

Source: Authors' collection.

Table 4. Correlation matrix of principal component regression (PCR) in China's provinces for the period 2013–2017.

	PN	SW	PCWC	GWI	GDP	TWR	WD	COD	OMP
PN	1								
SW	0.58	1							
PCWC	0.28	0.52	1						
GWI	0.49	0.41	0.03	1					
GDP	0.84	0.55	0.23	0.63	1				
TWR	0.09	0.18	0.19	0.01	0.03	1			
WD	0.89	0.59	0.21	0.62	0.94	0.19	1		
COD	0.74	0.56	0.06	0.41	0.56	0.07	0.67	1	
OMP	0.76	0.48	0.11	0.41	0.59	0.11	0.66	0.94	1

Source: Authors' collection.

Table 5. Eigenvectors of PCR in all variables.

	PN	SW	PCWC	GWI	GDP	TWR	WD	COD	OMP
Eigenvector	0.93	0.66	0.16	0.66	0.90	0.05	0.94	0.84	0.84
Proportion (%)	17.29	1.00	0.54	1.47	10.16	0.24	54.23	9.52	5.54

Source: Authors' collection.

This research uses 2013–2014 data to resample 2014 water resources' use efficiency, the 2013–2015 data to resample 2015, and so on. Table 6 lists the results, which can help us understand the change in cross-period water resources' use efficiency. The results show that the best annual water resources' use efficiency is 2015 and the worst is 2017. Some DMUs have relatively unstable efficiency across time periods, such as Chongqing being significantly worse in 2013 and 2015, Guizhou in 2017, and Inner Mongolia in 2016–2017, while Fujian is significantly better in 2016, Guangxi in 2015, Hebei in 2015, Henan in 2017, and Jilin in 2016. These results denote these DMUs must develop more stable water management strategies and more active environmental monitoring mechanisms.

Table 6. Water resources' use efficiency during 2013–2017.

DMUs	2013	2014	2015	2016	2017	Average
Beijing	1.06	1.60	1.72	1.07	1.17	1.32
Shanghai	1.03	1.00	1.00	1.00	1.00	1.01
Tianjin	1.32	1.28	1.25	1.33	1.21	1.28
Chongqing	0.64	0.99	0.53	1.00	1.02	0.84
Jiangsu	1.04	1.05	1.05	1.04	1.05	1.05
Zhejiang	1.01	1.02	1.05	1.02	1.01	1.02
Anhui	0.32	0.33	0.35	0.35	0.31	0.33
Jiangxi	0.32	0.38	0.49	0.43	0.32	0.39
Hubei	0.47	0.49	0.57	0.60	0.49	0.52
Hunan	0.38	0.52	0.69	0.65	0.62	0.57
Sichuan	1.11	1.11	1.06	1.04	1.05	1.07
Fujian	0.45	0.49	0.55	0.99	0.61	0.62
Guangdong	1.12	1.08	1.11	1.14	1.09	1.11
Guangxi	0.34	0.36	1.00	0.47	0.43	0.52
Yunnan	1.04	1.00	1.04	1.06	1.09	1.05
Guizhou	1.00	1.06	1.09	1.00	0.57	0.94
Hebei	0.29	0.21	1.03	0.58	0.33	0.49
Shandong	1.11	1.09	1.11	1.11	1.11	1.10
Henan	0.30	0.41	0.46	0.56	1.03	0.55
Shanxi	0.37	0.41	0.39	0.39	0.41	0.40
Shaanxi	0.44	0.47	0.45	0.43	0.47	0.45
Gansu	0.22	0.20	0.32	0.15	0.21	0.22
Ningxia	0.01	0.01	0.01	0.01	0.01	0.01
Qinghai	1.25	1.21	1.21	1.23	1.24	1.23
Hainan	2.17	2.51	1.32	1.00	1.08	1.62
Inner Mongolia	1.00	1.00	0.99	0.27	0.16	0.69
Liaoning	1.00	0.38	0.43	0.39	0.28	0.50
Jilin	0.43	0.47	0.27	1.20	0.30	0.53
Heilongjiang	0.21	0.23	0.14	0.21	0.19	0.20
Xinjiang	0.16	0.14	0.14	0.15	0.14	0.14
Tibet	1.49	1.61	2.02	2.96	2.63	2.14
Mean	0.75	0.78	0.80	0.80	0.73	0.77

Source: Authors' collection.

The resampling DEA approach is different from other DEA methods in that it can get important information of the upside error rate (UER) and downside error rate (DER). We set UER% (or DER%) equal to [(DMU's number of UER or DER) / 31] ×100%. These results help us understand the deviation trend of all variables that have undergone 1000 times of resampling, as shown in Table 7. WD increases significantly from 19.35% to 61.29% over 2014–2017. From the various analysis results, we found that the most critical issue of water resources' use efficiency was how to reduce undesired emissions. This is the most important reference indicator when governments formulate water resource management strategies in China.

Table 7. Downside error rate percentage (DER%) and upside error rate (UER%) of all variables with resampling DEA in 2014–2017.

Variable	Classification	2014	2015	2016	2017
PN	DER%	96.77	91.80	89.25	86.99
	UER%	3.23	8.20	10.75	13.01
SW	DER%	35.48	45.16	39.78	43.55
	UER%	64.52	54.84	60.22	56.45
PCWC	DER%	25.81	35.48	27.96	34.68
	UER%	74.19	64.52	72.04	65.32
GWI	DER%	35.48	48.39	39.78	31.45
	UER%	64.52	51.61	60.22	68.55
GDP	DER%	100	98.39	96.77	94.35
	UER%	0	1.61	3.23	5.65
TWR	DER%	48.39	51.61	72.83	55.65
	UER%	51.61	48.39	27.17	44.35
WD	DER%	19.35	20.97	56.99	61.29
	UER%	80.65	79.03	43.01	38.71
COD	DER%	90.32	95.16	100	94.35
	UER%	6.68	4.84	0	5.65
OMP	DER%	35.48	70.97	92.47	84.68
	UER%	64.52	29.03	7.53	15.32

Source: Authors' collection.

This research divides China into seven regions: Municipality, North China (North), Northeast China (Northeast), East China (East), South Central China (South Central), Southwest China (Southwest), and Northwest China (Northwest), with the name of the DMUs in the regions shown in Table 8. The results of regional differences in water resources' use efficiency are in Table 9. The best average value of water resources' use efficiency is Southwest, as its efficiency values are increasing year by year in 2013–2017. In order, the best is Municipality, South Central, East, Northwest, and Northeast, with North as the worst. The most obvious change of North is in 2015–2017, where its efficiency values are respectively 0.23, 0.58, and 0.17. This region is relatively poor, and it must have more effective water resources' use strategies to balance economic development and environmental protection.

Table 8. The regional division information of various provinces in China.

Region	Name
Municipality	Beijing, Shanghai, Tianjin, Chongqing
North	Hebei, Shanxi, Inner Mongolia
Northeast	Liaoning, Jilin, Heilongjiang
East	Jiangsu, Zhejiang, Anhui, Jiangxi, Fujian, Shandong
South Central	Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan
Southwest	Sichuan, Guizhou, Yunnan, Tibet
Northwest	Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang

Source: Authors' collection.

Table 9. Regional difference of water resources' use efficiency in China.

Region	2013	2014	2015	2016	2017	Average
Municipality	1.04	1.29	1.26	1.11	1.08	1.16
North	0.26	0.21	0.53	0.32	0.19	0.30
Northeast	0.42	0.32	0.23	0.58	0.17	0.34
East	0.74	0.78	0.83	0.81	0.76	0.78
South Central	0.86	1.01	0.91	0.65	0.83	0.85
Southwest	1.10	1.31	1.56	1.56	1.64	1.44
Northwest	0.38	0.38	0.38	0.35	0.39	0.38

Source: Authors' collection.

This research comprehensively explores the relationship between input and output variables on water resources' use efficiency. As a result, we utilized the Wilcoxon test to check the variables of input and output. The results are in Table 10. The higher a classification indicates a larger than average value, except for others; these results show a significant difference in PN and WD, whose p-value < 0.01**, and prove hypothesis (H_0) to establish for the difference between the pairs, it indicates that Higher PN shows better water resources' use efficiency, and Higher WD shows poor efficiency in China within 2013–2017. PN is difficult to have a specific improvement strategy, but reducing WD must be monitored and controlled with a more active environmental strategy now and in the future; there are very significant differences in PCWC, GDP, COD, and OMP with p-value < 0.001***, and prove hypothesis (H_0) to establish the difference between the pairs. Higher PCWC, COD and OMP show poor efficiency; and Higher GDP shows better efficiency, indicating that there is a big impact between economic growth and environmental issues in China over 2013–2017. Therefore, future water resource management policies must reduce the impact of environmental degradation on the basis of stable economic growth in China.

Table 10. The Wilcoxon test on all test items.

Test Items	Classification	Mean Score	*p*-Value
PN	Higher Others	0.58 0.43	0.0092**
SW	Higher Others	0.45 0.53	0.1781
PCWC	Higher Others	0.28 0.57	0.0006***
GWI	Higher Others	0.45 0.51	0.1875
GDP	Higher Others	0.68 0.37	< 0.0001***
TWR	Higher Others	0.56 0.46	0.1092
WD	Higher Others	0.43 0.63	0.008**
COD	Higher Others	0.43 0.95	< 0.0001***
OMP	Higher Others	0.39 0.86	< 0.0001***

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. Source: Authors' collection.

4. Conclusions and Policy Implications

Water resources' use efficiency is related to economic development, water resources' supply & demand, and environmental problems. This research comprehensively considers these factors and uses resampling super non-oriented slack-based measure (SBM) data envelopment analysis (DEA) to evaluate water resources' use efficiency in China over 2013–2017. The actual water resources' use efficiency from resampling super DEA are in the 97.5% and 2.5 % confidence intervals for all decision-making units (DMUs). The environmental variables of wastewater discharge (WD), chemical oxygen demand (COD), and other major pollutants (OMP) are the most critical factors affecting water resources' use efficiency. The local governments must therefore work to reduce the emissions of pollutants in China. The regional impact of water resources' use efficiency is very distinct in China - the best is Southwest, followed by Municipality, South Central, East, Northwest, and Northeast, and the worst is North. North, Northeast, and Northwest are obviously relatively poor, and hence they must have more effective water resources' use strategies to balance economic development and environmental protection.

In summary, we recommend the national government in China adjust their future water resources' use policy to reduce undesired emissions. At the provincial level, these governments must simultaneously balance economic development, water resource utilization, and environmental protection in order to increase water resources' use efficiency in the future. Those that have to pay greater attention to this are Ningxia, Xinjiang, Inner Mongolia, Heilongjiang, Gansu, Liaoning, Jilin, Anhui, Jiangxi, Hebei, Shanxi, Guangxi, Shanghai, Hubei, Guizhou, and Fujian.

Author Contributions: Conceptualization, J.-c.H., L.-h.M. and Y.-h.C.; Methodology, J.-c.H., L.-h.M. and Y.-h.C.; Software, Y.-h.C.; Validation, J.-c.H., L.-h.M. and Y.-h.C.; Formal Analysis, J.-c.H. and Y.-h.C.; Investigation, Y.-h.C.; Resources, L.-h.M.; Data Curation, J.-c.H., L.-h.M. and Y.-h.C.; Writing—Original Draft Preparation, J.-c.H., L.-h.M. and Y.-h.C.;Writing—Review and Editing, J.-c.H. and Y.-h.C.; Visualization, J.-c.H.; Supervision, Y.-h.C.; Project Administration, J.-c.H., L.-h.M. and Y.-h.C.; Funding Acquisition, J.-c.H., L.-h.M. and Y.-h.C.

Funding: This research received no external funding.

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

Abbreviations

Abbreviation	Full text
DEA	data envelopment analysis
PN	population number
SW	supply of water
PCWC	per capita water consumption
TWR	total water resources
GDP	gross domestic product
GWI	governance wastewater investment
WD	wastewater discharge
COD	chemical oxygen demand
OMP	other major pollutants
DMU	decision making unit
SBM	slacks-based measure
DER	downside error rate
UER	upside error rate
I-DEV	the confidence interval error
PCR	Principal component regression

References

1. The United Nations World Water Development Report. *Nature-Based Solutions for Water*; The United Nations Educational, Scientific and Cultural Organization: Paris, France, 2018.

2. Hu, F.; Tan, D. *Water Risk Report. No Water, No Growth—Does Asia Have Enough Water to Develop?* Chinawaterrisk.org: Hong Kong, China, 2018.
3. National Bureau of Statistics of China. *China Statistical Yearbook (2009–2017)*; China Statistical Publishing House: Beijing, China, 2018.
4. Ministry of Water Resources, the People's Republic of China. Water Resources Management and Protection in China. Available online: http://www.mwr.gov.cn (accessed on 22 May 2018).
5. Damkjaer, S.; Taylor, R. The measurement of water scarcity: Defining a meaningful indicator. *Ambio* **2017**, *46*, 513–531. [CrossRef]
6. Wakeel, M.; Chen, B. Energy consumption in urban water cycle. *Energy Procedia* **2016**, *104*, 123–128. [CrossRef]
7. Panepinto, D.; Fiore, S.; Zappone, M.; Genon, G.; Meucci, L. Evaluation of the energy efficiency of a large wastewater treatment plant in Italy. *Appl. Energy* **2016**, *161*, 404–411. [CrossRef]
8. Cano, R.; Perez-Elvira, S.I.; Fdz-Polanco, F. Energy feasibility study of sludge pretreatments: A review. *Appl. Energy* **2016**, *149*, 176–185. [CrossRef]
9. Wei, H.; Guojun, S. Evaluation of urban water resources utilization efficiency and water estimation in Hebei province. *Acta Sci. Circum.* **2018**, *38*, 2909–2918.
10. Morales, M.; Heaney, J. Benchmarking nonresidential water use efficiency using parcel-level data. *J. Water Res. Plan. Manag.* **2015**, *142*, 04015064. [CrossRef]
11. Long, K.; Pijanowski, B. Is there a relationship between water scarcity and water use efficiency in China? A national decadal assessment across spatial scales. *Land Use Policy* **2017**, *69*, 502–511. [CrossRef]
12. Mardani, A.; Edmundas, K.Z.; Dalia, S.; Ahmad, J.; Masoumeh, K. A comprehensive review of data envelopment analysis (DEA) approach in energy efficiency. *Renew. Sustain. Energy Rev.* **2017**, *70*, 1298–1322. [CrossRef]
13. Mardani, A.; Streimikiene, D.; Balezentis, T.; Saman, M.Z.M.; Nor, K.M.; Khoshnava, S.M. Data envelopment analysis in energy and environmental economics: An overview of the state-of-the-art and recent development trends. *Energies* **2018**, *11*, 2002. [CrossRef]
14. Ali, M.K.; Klein, K.K. Water use efficiency and productivity of the irrigation districts in Southern Alberta. *Water Resour. Manag.* **2014**, *28*, 2751–2766. [CrossRef]
15. Kulshrestha, M.; Mittal, A.K. Performance appraisal of water utilities using DEA approach. *Crit. Transit. Water Environ. Resour. Manag.* **2004**, 1–8. [CrossRef]
16. Azad, M.A.S.; Ancev, T.; Hernández-Sancho, F. Efficient water use for sustainable irrigation industry. *Water Resour. Manag.* **2015**, *29*, 1683–1696. [CrossRef]
17. Ren, C.; Li, R.; Guo, P. Two-stage DEA analysis of water resource use efficiency. *Sustainability* **2017**, *9*, 52. [CrossRef]
18. Gungor-Demirci, G.; Lee, J.; Keck, J. Assessing the performance of a California water utility using two-stage data envelopment analysis. *J. Water Res. Plan. Manag.* **2018**, *144*, 1943–5452. [CrossRef]
19. Kamarudin, N.; Ismail, W.R. Establishment of performance indicators for Malaysian water utilities with the presence of undesirable output. *J. Teknol.* **2016**, *78*, 99–105. [CrossRef]
20. Liao, H.C.; Dong, Y.M. Utilization efficiency of water resources in 12 western provinces of China Based on the DEA and Malmquist TFP index. *Resour. Sci.* **2011**, *2*, 1–12.
21. Wang, S.; Zhou, L.; Wang, W.; Li, X. Water use efficiency and its influencing factors in China: Based on the data envelopment analysis (DEA)-Tobit model. *Water* **2018**, *10*, 832. [CrossRef]
22. Feng, Y.; Chiu, Y.H.; Liu, F.P. Measuring the performance of wastewater treatment in China. *Appl. Sci.* **2019**, *9*, 153. [CrossRef]
23. Tone, K.A. Slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
24. Tone, K.A. Slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [CrossRef]
25. Tone, K.; Quenniche, J. DEA scores' confidence intervals with past-present and past-present-future based resampling. *Am. J. Oper. Res.* **2016**, *6*, 121–135. [CrossRef]
26. Hsieh, J.C.; Lu, C.C.; Li, Y.; Chiu, Y.H.; Xu, Y.S. Environmental assessment of European Union countries. *Energies* **2019**, *12*, 295. [CrossRef]
27. Ma, L.H.; Hsieh, J.C.; Chiu, Y.H. A study on the effects of energy and environmental efficiency at China's provincial level. *Energies* **2019**, *12*, 591. [CrossRef]

28. Farrell, M.J. The measurement of productive efficiency. *J. R. Stat. Soc.* **1957**, *120*, 253–281. [CrossRef]
29. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [CrossRef]
30. Banker, R.D.; Charnes, A.; Cooper, W.W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [CrossRef]
31. Simar, L.; Wilson, P.W. The sensitivity of efficiency scores: How to bootstrap in nonparametric frontier models. *Manag. Sci.* **1998**, *44*, 49–61. [CrossRef]
32. Mehrotra, R.; Shrama, A. A Resampling Approach for Correcting Systematic Spatiotem poral Biases for Multiple Variables in a Changing Climate. *Water Resour. Res.* **2019**, *55*, 754–770. [CrossRef]
33. China Statistics Bulletin. *China National Annual Statistical Bulletin*; National Bureau of Statistics of China: Beijing, China, 2017. Available online: http://data.stats.gov.cn (accessed on 22 May 2019).
34. Delorit, J.; Ortuia, E.C.G.; Block, P. Evaluation of model-based seasonal streamflow and water allocation forecasts for the Elqui Valley, Chile. *Hydrol. Earth Syst. Sci.* **2017**, *21*, 4711–4725. [CrossRef]
35. Wolter, K.; Timlin, M.S. El Niño/Southern Oscillation behaviour since 1871 as diagnosed in an extended multivariate ENSO index (MEI.ext). *Int. J. Climatol.* **2011**, *31*, 1074–1087. [CrossRef]