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Water Use Efficiency and Its Influencing Factors in China: Based on the Data Envelopment Analysis (DEA)—Tobit Model

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Abstract: Water resources are important and irreplaceable natural and economic resources. Achieving a balance between economic prosperity and protection of water resource environments is a major issue in China. This article develops a data envelopment analysis (DEA) approach with undesirable outputs by using Seiford's linear converting method to estimate water use efficiencies for 30 provinces in China, from 2008–2016,and then analyzes the influencing factors while using a DEA-Tobit model. The findings show that the overall water use efficiency of the measured Chinese provinces, when considering sewage emissions as the undesirable output, is 0.582. Thus, most regions still need improvement. 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. This study implies that factors like export dependence, technical progress, and educational value have a positive influence on water use efficiency. Further, while industrial structure has had a negative impact, government intervention has had little impact on water use efficiency. These research results will provide a scientific basis for the government to make plans for water resource development, and it may be helpful in improving regional sustainable development.

Keywords: China; water; efficiency; DEA-Tobit model; data envelopment analysis

1. Introduction

Water resources are important and strategic economic and natural resources. They form the basis of survival and development inhuman society. The world now faces a severe water resource crisis because of resource shortages and pollution. This shortage has also become a critical issue that restricts economic development. Approximately 1.8 billion people will face an absolute water shortage by 2025, and nearly two-thirds of the global population may live under water tension. From a resource distribution perspective in China, interregional precipitation has increasingly fluctuated with climate change, while rainfall in North and Northeastern China has decreased. However, a lack of water resources in the north has caused the south to become prone to flooding. The unbalanced regional distribution of water resources in China has, thus, created problems, as its structure is unreasonable and the total amount of water is insufficient. Additionally, China's water pollution became an increasingly serious problem from 2005–2016, with increases in soil erosion, water logging, and waste water emissions. China's Statistical Yearbook indicates that the total amount of waste water that is discharged from the nation in 2016 was 711 billion tons, and the total investment in environmental pollution controls accounted for 1.24% of China's GDP [1].

In view of this, documentation from the Central Water Conservancy 2011 conference first focused on water resource management, and noted the significant issue of water wastage [2]. The State Council's 2012 opinion on implementing the most stringent water resource management system clearly strengthened the utilization and development of water resources [3]. Nineteen government reports from China in 2017 proposed implementing national actions to conserve water [4]. Together, they inform the spatial pattern, industrial structures, production modes, and lifestyles required for conserving resources and protecting the environment. The implementation of such national action plans to conserve water involves strategically designing activities to substantially decrease the consumption of water resources, in order to address acute water shortages, mismanagement, and contamination in China. This indicates that the Chinese government intends to act with determination to improve the efficiency of water resources and to promote sustainable economic development.

Sustainable development has proven to be a positive factor in the governance and regulation of the water industry [5]. As the contradiction between the supply of and demand for water resources has become increasingly serious, improving water resource efficiency is an important measure to address environmental and resource problems.

Existing research focuses on optimizing water resources and improving water use efficiency without considering the effect of water resources on ecology and the environment. For this research, we therefore selected sewage emissions as the undesired output. Second, we developed a data envelopment analysis (DEA) model with poor outputs by using Seiford's linear converting method to estimate water use efficiencies for 30 provinces in China from 2008–2016. Data envelopment analysis (DEA) is a widely used method in empirical studies on water use efficiency and water supply efficiency. This method has also been used to calculate the water use efficiency in Canada [6], Kenya [7], the United States [8,9], Australia [10], Europe [11], and India [12–14]. Regarding studies on China, Ren et al. [15] analyzed water use efficiency using a two-stage DEA method. Long and Pijanowski [16] measured Chinese water use efficiency from 2003–2013. Moreover, DEA has been applied to measure water supply efficiency in Korea [17,18], Italy [19,20], America [21], and Australia [22,23].

With these efficiency values, we can understand the efficiency of water resource utilization in various regions, and note the trends in efficiency changes. A qualitative analysis of the theoretical factors that affect efficiency is followed by the Tobit model, which empirically analyzes the selected typical variables. Based on our empirical research, government policy recommendations are put forward. This paper aims to solve the problem of severe water waste, propose countermeasures to improve water use efficiency, and achieve regional sustainable development.

The rest of the paper is structured as follows: Section 2 introduces the methodology and Section 3 describes the data. Section 4 demonstrates the empirical results and discussion. Finally, Section 5 concludes the paper, and presents policy recommendations.

2. Materials and Methods

Currently, the primary methods to assess water use efficiency include the stochastic frontier, index system, and ratio analyses. DEA is an effective way to evaluate multi-input and multi-output decision-making units (DMUs) without prior identification of functional relationships, non-subjective weights, and an analysis of invalid factors in the DMU. In other words, DEA keeps the input and output of DMUs unchanged, while using the effective sample instead.

Existing research structures a DEA model with poor (undesirable) outputs to calculate efficiency [24–27]. This section first expounds on this research method, and then explains water use efficiency.

2.1. Water Use Efficiency Calculation Method

The DEA method, as developed by Charnes, Cooper, and Rhodes [28], estimates the effective frontier using a mathematical programming method, which is not an established statistical model.

It is a useful tool to evaluate the relative efficiencies among DMUs with multiple inputs and outputs. Relative efficiency is then obtained, according to the degrees of deviation between the decision unit and the effective front surface. It should be noted that many scholars analyze efficiency with undesirable outputs using the slack-based measure-DEA (SBM) model; however, this makes it difficult to explain and understand the specific economic significance of efficiency [29]. Nevertheless, DEA can be divided into two kinds of models: non-oriented and oriented, where the orientation refers to the variable as undesirable outputs, outputs, or optimized inputs. Classically, the non-oriented model provides more reasonable results for environmental and energy research, because it enhances the ability to deal with both undesired and desirable outputs at the same time [30].

Numerous new models have been developed since the DEA method was first created. It should be noted that the classic CCR model (Charnes-Cooper-Rhodes model, developed by Charnes, Cooper, and Rhodes, and named by the abbreviations of their name) is used in this text. This model can be expressed in linear programming, and an important and effective linear programming theory is dual theory. Dual theory is easier for theoretical and economic analysis. This thesis addresses "poor" outputs with a linear transformation function method [31], as the traditional DEA-CCR model can estimate water use efficiency, whereby the poor (undesirable) output is converted into a good (desirable) output.

Suppose that there are n DMUs, denoted by $DMU_j(j = 1, 2 \ldots, n)$, and each indicates China's various provinces. Each $DMU_j(j = 1, 2 \ldots, n)$ $DMU_j(j = 1, 2, \ldots n)$ consumes m kinds of inputs to make u different good outputs and v different poor outputs. We define $x_i = (x_{1i}, x_{2i}, \ldots, x_{mi})$, $y_i^g = \left(y_{1i}^g, y_{2i}^g, \ldots, y_{ui}^g\right)$, and $y_i^b = \left(y_{1i}^b, y_{2i}^b, \ldots, y_{vi}^b\right)$ as the input, good output, and poor output vectors of the DMUs, respectively.

The production possibilities set (p) can be noted as $P = \left\{(x, y^g, y^b)\,|x \geq \lambda X, y^g \leq \lambda Y^g, y^b \leq \lambda Y^b, \lambda \geq 0\right\}$ by integrating the inefficiency postulate [32]. Further, Y^b, Y^g, and X represent the matrix of the poor output, good output, and input indices, respectively, while λ is the weighted coefficient. The undesirable output Y^b can become the desirable output Y^g by the linear transformation function $Y^g = Z - Y^b$ [31], in which the translation vector Z is large enough to let all Y^g be positive. The traditional DEA then includes these transformations to convert the poor output into an input:

$$\begin{aligned} &\underset{\rho,\lambda}{Min\rho} \\ &s.t. \sum_{j=1}^{m} \lambda_j x_j \leq \rho x_{j0}, \sum_{j=1}^{u} \lambda_j y_j^g \geq y_{j0}^g, \sum_{j=1}^{v} \lambda_j y_j^b \geq y_{j0}^b, \rho \leq 1, \lambda_j \geq 1 \end{aligned} \quad (1)$$

where ρ represents the efficiency score and DMU_0 is efficient if $\rho = 1$ [33]; y_j^b,y_j^g, and x_j represent the poor output, good output, and input, respectively; accordingly, u, v, and m record the number of variables in y_j^b,y_j^g, and x_j.

2.2. The Tobit Regression Model

The difference of water use efficiency is not only affected by input-output, but also by other environmental factors. The efficiency value has a minimum limit value of 0, which belongs to the truncated data. The ordinary linear squares regression model may be far away from the true motion with the value of the efficiency as the dependent variable. The Tobit model has been widely applied to the study of factors that affect efficiency [34,35].

Hence, we set up a Tobit regression model to test nine years of sample data in order to further understand the influence of water use efficiency. We assume water use efficiency as the explained variable, and various influencing factors as the explanatory variable.

The Tobit regression model is called the "limited dependent variable model", or the "check model". It specifically solves the problem of the regression of truncated or restricted explanatory variables [36].This model differs from the continuous pressure and the general discrete regression models, which consist of two kinds of equations. Part of the truncation does not satisfy the conditional dependent variable, while the rest is a constrained continuous equation, or the dependent variable can only be observed in the restricted form [37]. The Tobit model is described, as follows:

$$\begin{array}{l} E_i^* = \beta X_k + \varepsilon_i, k = 1, 2, \ldots, N \\ E_i = E_i^* \; if Y_i^* > 0 \\ E_i = 0 \; if Y_i^* \leq 0 \end{array} \quad (2)$$

Where E_i is the dependent variable; β is a vector of calculated parameters; ε_{it} is an independent, normal error term with a constant variance σ^2 and 0 mean; N is the sample size; and, X_k is a vector of explanatory variables [38].

2.3. Definition of Water Use Efficiency

Definitions of water use efficiency are far from uniform because of different research objectives, research needs, data characteristics, and model methods. For instance, the Alberta Water Council [39] defines water use efficiency as "the index of the relationship between the amount of water needed for a particular job and the amount of water used or appropriated". It is noteworthy that the roles of water resources differ in different departments; thus, the definition of water resource efficiency also differs. Figure 1 describes the circulation of water resources in human economic life [18].

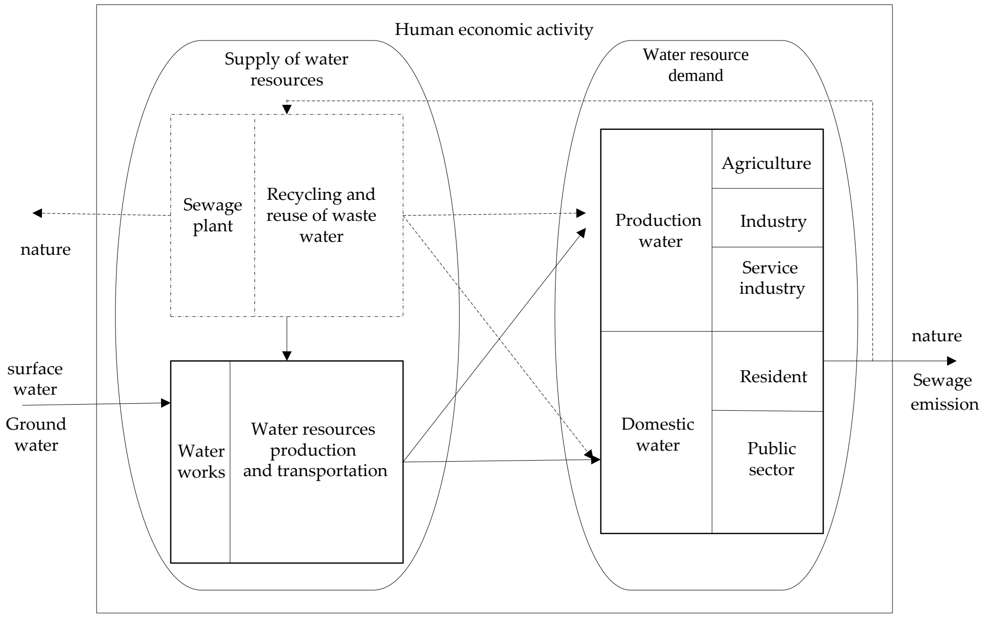

Figure 1. Circular flows of water resources.

The demand for water resources includes life and production water; industrial water use, which covers China's primary, secondary, and tertiary industries; and, domestic water, which includes water resources to support residents' lives and the public sector's water demands. The water resource supply perspective primarily includes two sectors: water works and sewage treatment. From the perspective of the water cycle, the development and utilization of water resources have changed the relationship between rivers and lakes, surface and groundwater environments, and rearrangement and transformation mechanisms, which are all, in turn, responsible for water resource production and transportation, sewage treatment, and recycling. Therefore, we posit that water use efficiency is the ratio of water resources to input and output. We follow the Alberta Water Council's (2007) definition of efficiency and the circulation of water resources above, as it conforms to Farrell's [40] definition of technical efficiency.

3. Data

According to the connotation of water use efficiency and the definition of the DEA-CCR model—combined with the rationality and accessibility of the index selection—water use efficiency is measured and analyzed from two perspectives: the input and output of water resources.

3.1. Input-Output Indicators

This section details the variables and data sources for calculating water resource efficiency. DEA is highly flexible, simple, and practical. It can evaluate a decision-making problem with multiple inputs and outputs, and it does not need to set a specific form for the production function in advance. Further, it does not need to specify the distribution of the error term; it also constructs the frontier for each period, making it more practical. Further, input-output indicators should meet the following requirements:

- The ratio cannot be considered as an indicator.
- The indicators are authentic.
- There is no difficulty in collecting index data.
- The indictors reflect a basic production relationship.

Song and Guan [41] suggested that the number of DMUs is greater than the sum of the number of inputs and outputs. The evaluation of water use efficiency is generally carried out in two dimensions: the resource dimension and the environment dimension [42]. The resource dimension mainly includes water, labor, and capital, and the environmental dimension mainly includes the discharge of the total amount of waste water, the chemical oxygen demand in the waste water, and the levels of ammonia nitrogen. On the basis of the index system of water resource efficiency constructed by some scholars [43], we choose two factors as water resource outputs—one factor as a "good" water output, and one factor as a "poor" water output. Specifically, we employ water consumption, capital, and labor as inputs; sewage as the poor (undesirable) output; and, per capita GDP as the good (desirable) output, as it has a more significant impact on water consumption. This allows for us to get closer to the expected output of water resources based on the environmental Kuznets curve theory [44,45]. Since the DEA method does not directly synthesize the data, the optimal efficiency index of the decision unit has nothing to do with the dimension selection of the input and the output index value. Table 1 illustrates the input–output index system.

Table 1. Water use efficiency evaluation index system.

Index	Indicators (Unit)
Input	Labor (10 thousand capital)
Input	Capital (100 million dollar)
Input	Water (100 million m^3)
Undesirable output	Sewage (10,000 tons)
Desirable output	Per capita GDP (dollar)

Based on the data from four municipalities, four autonomous regions, and 22 provinces in China, we can calculate the water use efficiency. Unfortunately, the autonomous regions of Tibet, Hong Kong, Macao, and Taiwan are not discussed in this paper because of data limitations. Moreover, data after 2016 and before 2008 is incomplete; hence, we used data from 2008–2016 as each province's observation sample.

We used capital stock as the input to address water use efficiency, as liquidity may play an important role in the next stage. Capital stock is measured by the perpetual inventory method, which is based on research by Zhang et al. [46]. Existing studies on regional economic growth generally select the total amount of water as the water resource input index, including ecological, domestic, industrial, and agricultural water. Taking into account data availability, this paper's labor input is represented by the number of urban employed. The economic indicator of per capita GDP was converted into 2008 prices while using the producer's price index.

In researching data sets from China's Statistical Yearbook, we ultimately collected data from different Chinese provinces from 2008–2016. Table 2 lists the descriptive statistics of the input–output indicators.

Table 2. Descriptive statistics of the water use efficiency evaluation index from 2008–2016 in China.

Variable	Unit	Mean	SD	Min	Max
Labor	10 thousand capital	616.90	352.62	47.02	1973.28
Capital	100 million dollar	7039.67	6964.129	91.7044	39,045.57
Water	100 million m^3	201.03	141.97	22.33	591.29
Sewage	10,000 tons	593,035.60	189,494.10	1	910,986.90
Per capita GDP	dollar	6803.597	3603.4	1549.041	18,682.46

Note: SD, mean, max, and min indicate the standard deviation, mean value, maximum value and minimum value of 270 results of 30 provinces during 2008–2016. Data sources: China Statistical Yearbook (2009–2017).

Table 2 also reports the descriptive values of 270 input–output indicators. The maximum sewage emissions and per capita GDP were 9.11×10^9 tons and USD $18,682.46, respectively. These values were 1.536 and 2.75 times greater than their respective mean values. The descriptive statistics of the evaluation index for China's water use efficiency reveal that significant differences exist in the water use efficiency evaluation index indicators, and particularly in the sewage and per capita GDP indicators. Therefore, it can be preliminarily deduced that certain regional differences exist in China's water use efficiency.

To clarify, we combined foreign practices with the actual situation in China [33,40]. A linear data conversion function method was used to process the sewage emissions as undesirable output data. Specifically, it was assumed that the sewage emissions of province i in China for year j is W_{ij}: $W_{ij} = (W_{i1}, W_{i1}, \ldots, W_{ij})^T > 0, (i = 1, 2, \ldots, n)$. Take $\phi = max(W_{ij}) + C$, where c is a constant greater than 0 and its value here is 1. To be clear, as the total amount of waste water discharge is used as an undesired output method, we adopt the input treatment method and the directional distance function method. The undesired output in the specific production process is not always proportional to the input of labor and capital, and the distance function method is influenced by the direction vector. Drawing from Seiford and Zhu [31], Cooper et al. [47], and Han et al. [42], the linear data conversion function method is used to deal with sewage emissions in the production process, in which C is a constant more than 0. No matter the value of C, it will not change the efficiency value.

After the linear data conversion, the amount of sewage emissions can be expressed as $W_{ij}^* = -W_{ij} + \phi$. Then, W_{ij} is converted from the poor output (with smaller values as a better outcome) to the good output W_{ij}^* (with greater values as the better outcome). These can then be studied while using the DEA method.

3.2. Factors that Influence Water Resource Efficiency

A number of factors may affect water use efficiency, including sector size, economic development, population quality, environmental regulations, and scientific and technological developments, among others [48]. This paper takes water use efficiency as the dependent variable, and it selects the influence of water use efficiency as the independent variable. The following factors are selected that impact water use efficiency:

- From the points of the endogenous economic growth theory, the technological progress is the engine of one country's economic growth, and economic development is closely related to environmental protection. Thus, technological progress is an important factor in environmental performance. Production technology plays a positive role in effectively improving water environment management and decision-making. Thus, technological progress is conducive to improving water use efficiency. We determine it to be a factor of water use efficiency, and the number of invention patent applications is used as a proxy index for technological progress. Thus, the number of patent applications for inventions by X_1 is introduced, and the coefficient of X_1 is predicted to be positive.

- Government intervention will affect each Chinese province's water resource input output because of the government's influence on water usage efficiency, through environmental regulations, investment in water infrastructure, and sewage treatment, for example. Under the current worsening water environment, the government shoulders the important responsibility of water environment governance. Ma et al. [49] also considered government intervention as a factor that affects water use efficiency. As the water environment's deterioration is primarily a result of excessive pollutant emissions across industrial enterprises, we selected the complete investments in industrial pollution control, which is denoted by X_2, as the proxy index for government intervention. The coefficient of X_2 is predicted to be negative.
- Water-rich countries or regions will export water-intensive products, while water resource intensive products are imported into countries with a shortage of water resources. Trade in agricultural and industrial products that consume large amounts of water will lead to the indirect transfer of water resources [50,51]. Further, trade will influence water resource management and usage efficiency. We posit that each region would prefer to gain more profit from export commodities, and it must decrease costs by promoting water use efficiency and export dependence; specifically, the proportion of export trade to GDP is expressed as X_3, with its coefficient predicted to be positive.
- The promotion of education is conducive to improving the quality of knowledge, skills, and innovation in all aspects of the labor force. Such education can effectively reduce the waste of water resources and improve efficiency in water utilization. Therefore, the average number of schools per 100,000 people, as denoted by X_4, is a significant element that influences water use efficiency. Its effect is expected to be positive.
- According to the theory of sustainable development, the industrial structure has a direct or indirect effect on the type, scale, and cause of the formation of pollutants. Industrial structure is considered to be a key factor that influences water use efficiency [52,53]. Agricultural production uses substantial quantities of water. The agricultural irrigation mode and surface pollution all affect water use efficiency. Whether or not the other industrial development stages and models include high water consumption and pollution, industrial water use will influence a region's water resource efficiency. This index is characterized by the ratio of industrial value added to the GDP, as denoted by X_5. The coefficient of X_5 is expected to be negative.

The data for specific indicators of influencing factors are derived from the 2009–2017 China Statistical Yearbook [1], a collection of statistics and statistical bulletins from relevant provinces and cities. The nominal variables were then deflated—these include price factors, such as complete investments in industrial pollution controls and import and export values. Finally, panel data were collected for 2008–2016 for 30 Chinese provinces. Table 3 lists the descriptive statistics for the variables that affect water use efficiency.

Table 3. Variables' descriptive statistics.

Variable	Independent or Dependent	Unit	Mean	SD	Min	Max
Technological progress	Independent	1000pieces	4.678	7.169	0.023	40.952
Government intervention	Independent	10,000 million dollars	3.497	3.107	0.059	22.763
Education	Independent	10,000 person/per 100,000 population	0.245	0.093	0.097	0.675
Industrial structure	Independent	%	46.8	8.1	19.3	59.0
Export	Independent	%	14.6	16.0	1.4	75.4
Water use efficiency	Dependent	-	0.582	0.276	0.213	1.000

Notes: According to Equation (2), the water use efficiency is estimated. Data sources: China Statistical Yearbook (2009–2017).

4. Results and Discussion

4.1. Estimate Results for Water Resource Efficiency

We attempted to build the frontier production function based on each year's sample, and then measure water use efficiency using DEA. China's average water use efficiency is less than 1 for every year in the sample period, based on Equation (1), which implies that water use efficiency is not optimal. Thus, it is essential to decrease water resource pollution in the environment to develop water resources for a transition to a low-pollution state and to protect the environment. The mean value of water use efficiency is 0.582; therefore, gross domestic product per capita can potentially increase by 41.8% when the 30 provincial regions simultaneously improve water use efficiency.

As mentioned before, higher water resource efficiency means a more reasonable allocation of water resources. Table 4 lists the related results. Columns 2 to 10 in Table 4 illustrate the water use efficiency for 30 provincial regions in the sample period, and column 11 lists the mean efficiency for the nine measured years. We can draw the following conclusions from Table 4:

- The promotion of water use efficiency each year from 2008–2013 may be explained by the State Council's decision to expedite water conservancy reform, introduce an emissions permit system, and enhance environmental protection consciousness. However, water use efficiency deteriorated from 2015–2016, with rapid economic development and an increasing urban population.
- Water use efficiency in Tianjin, Shanghai, Qinghai, Guangdong, and Beijing all equal 1 during 2008–2016. Specifically, these provinces are in the efficiency frontier and their efficiency is ideal.
- More than half of the 30 provinces did not exhibit an optimal water use efficiency level during 2008–2016. Seven provinces (including five efficient regions) have an efficiency of 1 and a mean efficiency greater than 0.9, including Jiangsu with 0.970 and Ningxia with 0.991. Yunnan performed the poorest with 2008–2016 efficiencies at 0.213,0.218,0.218,0.240,0.251,0.267,0.271,0.281, and 0.285. Its mean efficiency in the sample period was only 0.249. Other provincial regions also did not achieve an effective input and output of water resources, according to their mean efficiencies. For example, Hebei had a mean efficiency of 0.403; Fujian's was 0.585; Liaoning's was 0.573; and, Heilongjiang's was 0.364.
- Water use efficiency exhibited a wave-like curve for Shanxi, Jilin, and Jiangsu. Specifically, Xinjiang's water use efficiency decreased from 0.470 to 0.464 (in 2008–2009); then increased from 0.464 to 0.499 (2009–2010); then decreased from 0.499 to 0.493 (2010–2011); then decreased further from0.493 to 0.487 (2011–2012), from 0.487 to 0.476 (2012–2013), from 0.476to 0.463 (2013–2014), from 0.463 to 0.424 (2014–2015), and finally, from 0.424 to 0.392 (2015–2016). Our study's results differ from existing research because of the input and output indicators of water use efficiency we elected to utilize [48,53].
- Finally, we note that water use efficiency in developed provincial regions is generally better than that in less-developed provincial regions, which is consistent with findings from previous research [48,54]. For example, the mean water use efficiency of developed provinces, like Tianjin,

Shanghai, Beijing, Guangdong, and Jiangsu, is 1.000, 1.000, 1.000, 1.000, and 0.970, respectively, however the mean water use efficiency in less-developed regions, like Gansu, Shaanxi, and Guizhou is 0.344, 0.386, and 0.301, respectively.

Table 4. Water use efficiency of 30 provinces of China during 2008–2016.

Province	2008	2009	2010	2011	2012	2013	2014	2015	2016	Mean
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hebei	0.327	0.342	0.361	0.429	0.436	0.463	0.440	0.428	0.406	0.403
Shanxi	0.358	0.329	0.348	0.361	0.365	0.356	0.339	0.327	0.305	0.343
Inner Mongolia	0.556	0.602	0.630	0.710	0.726	0.696	0.691	0.671	0.649	0.659
Liaoning	0.452	0.486	0.518	0.614	0.638	0.659	0.674	0.659	0.457	0.573
Jilin	0.378	0.406	0.421	0.475	0.487	0.488	0.489	0.487	0.465	0.455
Heilongjiang	0.350	0.333	0.330	0.376	0.393	0.389	0.381	0.372	0.349	0.364
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	0.871	0.947	1.000	1.000	1.000	0.987	0.939	0.995	0.988	0.970
Zhejiang	0.703	0.754	0.813	0.896	0.860	0.843	0.824	0.856	0.840	0.821
Anhui	0.216	0.234	0.263	0.340	0.346	0.375	0.378	0.386	0.368	0.323
Fujian	0.445	0.477	0.489	0.621	0.600	0.647	0.656	0.672	0.656	0.585
Jiangxi	0.252	0.265	0.287	0.341	0.337	0.355	0.358	0.372	0.375	0.327
Shandong	0.567	0.627	0.687	0.716	0.744	0.759	0.763	0.812	0.713	0.710
Henan	0.295	0.316	0.346	0.386	0.391	0.403	0.411	0.410	0.384	0.371
Hubei	0.301	0.330	0.357	0.430	0.455	0.490	0.504	0.527	0.500	0.433
Hunan	0.273	0.295	0.316	0.377	0.409	0.445	0.452	0.468	0.453	0.388
Guangdong	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Guangxi	0.295	0.288	0.318	0.344	0.354	0.355	0.354	0.364	0.353	0.336
Hainan	0.886	0.899	0.894	0.896	0.896	0.884	0.896	0.899	0.912	0.896
Chongqing	0.355	0.374	0.374	0.418	0.430	0.449	0.467	0.497	0.543	0.434
Sichuan	0.225	0.241	0.257	0.319	0.335	0.361	0.376	0.385	0.386	0.321
Guizhou	0.269	0.285	0.285	0.292	0.305	0.310	0.318	0.328	0.321	0.301
Yunnan	0.213	0.218	0.218	0.240	0.251	0.267	0.271	0.281	0.285	0.249
Shaanxi	0.283	0.306	0.334	0.387	0.411	0.429	0.444	0.447	0.437	0.386
Gansu	0.359	0.356	0.353	0.361	0.358	0.349	0.340	0.317	0.303	0.344
Qinghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Ningxia	0.937	1.000	1.000	1.000	1.000	1.000	0.991	0.993	1.000	0.991
Xinjiang	0.470	0.464	0.499	0.493	0.487	0.476	0.463	0.424	0.392	0.463
Mean	0.521	0.539	0.557	0.594	0.600	0.608	0.607	0.613	0.595	0.582

4.2. Regional Differences

We also studied water efficiency on a relatively larger scale by dividing China into three major areas—east, central, and west—in accordance with the People's Republic of China's national division standard. Table 5 illustrates the three areas and their constituent regions. As this table indicates, the western, central, and eastern areas contain 11, 8, and 11 provincial regions, respectively.

The eastern part of China is located on the coast, with favorable climate conditions, a strong industrial foundation with science and technology, and an abundant, high-quality labor force. Many potential economic opportunities exist for the region's development. In contrast, the central and western regions are primarily landlocked and underdeveloped, with a poor-quality environment and inconvenient traffic. This has led to long-term occlusion and slow economic development. We clearly demonstrate the water use efficiency of these three areas and their regions by arranging their average efficiency from 2008–2016 in Table 5.

The results from Table 5 are as follows:

- During 2008–2016, China's water use efficiency was distributed in such a way that the east had the highest efficiency, followed by the west, while the middle was the lowest. From the geometric mean, water resource development in the eastern region is better than that in the central and western regions.
- Water use efficiency in these three areas—and specifically, in Tianjin, Beijing, Guangdong, and Shanghai in the east—all reached 1. This demonstrates that water use efficiency in these

four provinces was optimal, becoming the benchmark for other provinces. Of the 11 provinces, four (Shandong, Jiangsu, Hainan, and Zhejiang) had an average water use efficiency value that was between 0.70 and 1.00, while two (Fujian and Liaoning) had average water use efficiency values between 0.50 and 0.80, with Hebei exhibiting the lowest efficiency.

- Among the eight districts in the central area, Jilin had the highest value, which was less than Beijing and Qinghai—the places with the highest water use efficiency in the east and west, respectively.
- In the western area, Qinghai was ahead in water use efficiency and achieved technical effectiveness, which was possibly because of the strict water resource management system implemented by its provincial government. However, Yunnan's value lags behind the other provinces. The efficiency of the three areas overall is less than 0.60.

Table 5. Water use efficiency in three regions of China (2008–2016).

East	Score	Central	Score	West	Score
Guangdong	1.000	Henan	0.371	Sichuan	0.321
Hebei	0.404	Hunan	0.388	Guangxi	0.371
Shandong	0.710	Anhui	0.323	Yunnan	0.249
Jiangsu	0.980	Hubei	0.433	Guizhou	0.301
Liaoning	0.573	Jiangxi	0.324	Shaanxi	0.386
Zhejiang	0.821	Heilongjiang	0.364	Chongqing	0.434
Fujian	0.585	Shanxi	0.343	Gansu	0.347
Hainan	0.866	Jilin	0.455	Xinjiang	0.482
Shanghai	1.000			Inner Mongolia	0.659
Tianjin	1.000			Ningxia	0.993
Beijing	1.000			Qinghai	1.000
mean	0.813		0.375		0.504
Geometric mean	0.780		0.372		0.452

Figure 2 illustrates the entire country's mean water use efficiencies, and the three areas for each year, from 2008–2016. This figure allows for us to safely conclude that from an area perspective, the eastern region has the highest average efficiency, while the central region has the lowest average efficiency. Furthermore, we know that the eastern area's average water use efficiency is higher than the entire country's in each year in the sample period.

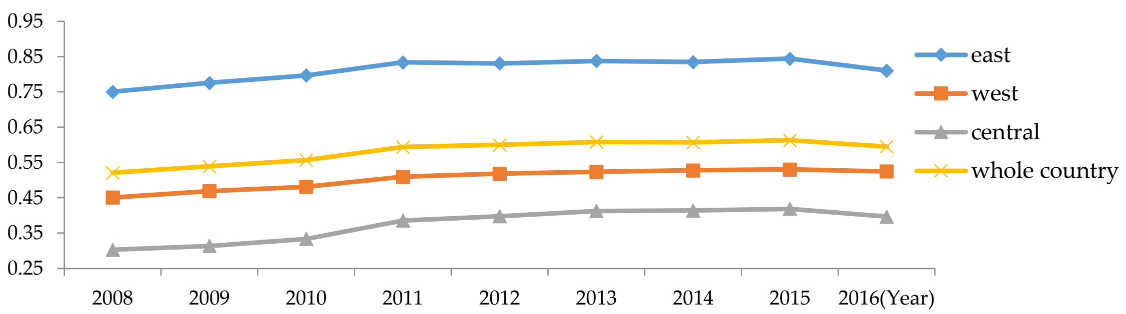

Figure 2. China's average water use efficiencies.

4.3. Water Resource Efficiency Types

Based on the basic principle of spatial differentiation, the water resource efficiency of 30 provinces, autonomous regions, and municipalities directly under the central government of China is divided into four categories while using the natural breakpoint method. Then, we analyzed the spatial distribution pattern.

The mean value of water use efficiency from 2008–2016 for the 30 provincial regions can be classified into four major categories. I: optimal efficiency (0.710 < water use efficiency $\leq$ 1.000), which is the most effective mode of water resource development; II: high efficiency (0.463 < water use efficiency $\leq$ 0.710), which indicates that the allocation of water resources is reasonable, but not technically effective; III: medium efficiency (0.371 < water use efficiency $\leq$ 0.463), which reflects that water resource development is at a mean level; and, IV: poor efficiency (water use efficiency $\leq$ 0.371), which demonstrates that water resource development is not effective.

Figure 3 illustrates water use efficiency across China, and it reveals that most of the Chinese provinces' water use efficiency is in the IV category. This indicates the overall spatial differences: the eastern coastal areas have high water use efficiency, while the central and western regions have relatively low water use efficiency. The performance characteristics of this gradient decline from the coastal to inland areas.

Figure 3. Spatial distribution of water use efficiency in China during 2008–2016.

Provinces in the I level—including Tianjin, Beijing, Shanghai, Zhejiang, Guangdong, Jiangsu, Hainan, Qinghai, and Ningxia—have made substantial efforts toward protecting water resources and implementing water ecology environmental controls. Most of the provinces are categorized as levels I or IV, and the provinces in the III level are distributed around the II-level provinces. This indicates that the provinces with strong water resource sustainable development have an important radiating role in their neighboring areas. Water use efficiency in the IV-level provinces is primarily distributed in the western region, including Guangxi, Gansu, Guizhou, Yunnan, and Sichuan. These provinces are affected by natural geographical conditions, with an uneven spatial and temporal distribution of water resources. Owing to population growth and economic development, both water consumption and demand are increasing, while water resources are in short supply. Further, there has been an acute waste of water resources. Both natural and man-made influences have created a prominent contradiction between the supply of, and demand for, water resources, thus leading to dire shortages of ecological, industrial, agricultural, and urban water.

In summary, the spatial pattern of water use efficiency in China is consistent with the general pattern of regional economic development. This indicates a general trend toward considering the eastern and coastal areas as critical to high-efficiency growth, which gradually diminishes toward inland areas. Therefore, we further analyzed the extent of these differences in the region and the mechanism of the influencing factors.

Each calculated index and impacting factor could play an important role in sustainable water resource development. Thus, the following empirical analysis explores the level of use of Chinese water resources in order to enable a low-carbon economy in China.

4.4. Influencing Factors

The multiple linear regression model is established, as shown in Equation (3). The dependent variable is water use efficiency and the independent variables are selective factors:

$$TECH_{it} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon_{it} \quad (3)$$

where *TECHit* expresses the water use efficiency value of province i in year t, and β_i (i = 1,2, . . . ,5) by the undetermined coefficients of influencing factors [55]. The Tobit model's parameters were obtained using Stata 13.0 software (StataCorpLLC4905LakewayDrive College Station, TX77845-4512USA, https://www.stata.com/company/contact/), and Table 6 displays the results. Variable X_2 did not pass the significance test and the other variables' regression coefficients are consistent with expectations.

First, the technical progress for variable X_1 positively impacts water use efficiency; this relationship is significant. Table 6 reveals that, with every 1% increase in the number of patent applications for inventions, water use efficiency improves by 0.008%. With the improvement of technological progress, water supply and purification capacities also increase, and this intensifies the positive impact on environmental efficiency. Therefore, the faster technology progresses, the higher the water use efficiency. The eastern area exhibits significant technological progress and high water use efficiency, which also confirms the analysis results.

- For variable X_2, government intervention has a negative relationship with water use efficiency. The greater the number of completed investments in industrial pollution controls, the more wastewater occurs. The higher the output of sewage emissions, the lower the water use efficiency. The regression coefficient did not pass the 10% significance test, with government intervention having a non-significant effect on water use efficiency. The government can use tax collection to compare with the external uneconomical consumption tax, or give subsidies relative to external economic value, in order to achieve effective allocation of resources in the future [56].
- For variable X_3, Tianjin, Shanghai, Beijing, Jiangsu, and Zhejiang have higher export dependence and a higher water use efficiency. In order to produce more for exporting, those regions with higher export dependence should continuously improve their water use efficiency.

- For variable X_4, education has a significant, positive effect on water use efficiency; that is, the higher the residents' educational level, the more significance that environmental protection has to residents, and the more dissatisfied they will be with the current environmental situation. This will increase the urgency in improving this situation, as the improvement of knowledge and cultural levels create a better understanding of the dire situation of water resources and the environment in China.
- Finally, the industrial structure in variable X_5 negatively impacts water use efficiency, as the regression coefficient did pass the 10% significance test, and the structure's effect on water use efficiency was significant. This negative relationship is possibly related to industrial enterprises not having widely used water-saving technology. China's industrial structure must be adjusted and optimized to some extent, as most industries in China consume high amounts of energy and water resources, and they emit pollution.

Table 6. Tobit regression analysis of factors affecting water use efficiency.

Variable	Coefficient	Std.Err	t	$P > \|t\|$
X_1	0.008**	0.004	2.18	0.030
X_2	−0.008	0.006	−1.46	0.146
X_3	0.113***	0.015	7.61	0.000
X_4	0.799***	0.227	3.51	0.001
X_5	−0.383*	0.231	−1.66	0.099
CONS	0.438***	0.122	3.59	0.000

Note: *,**,***represent significance level at 10%,5%, and 1%, respectively.

5. Conclusions

This paper evaluated water use efficiency by taking sewage emissions as an undesirable output in China's 30 provincial regions from 2008–2016.To this effect, we incorporated a DEA model with Seiford's linear transformation method. We then analyzed the influencing factors that are based on a Tobit model.

Both the overall water use efficiency and that of most of the provincial regions still have room for improvement. The time series demonstrates that water use efficiency in 2008–2016 did not substantially change, and the overall level is poor. The trends in the three regions—Eastern, Central, and Western China—are essentially the same, and Beijing, Guangdong, Shanghai, Jiangsu, and Tianjin display relatively high water use efficiency. Water use efficiency in the western and central regions, including Jiangxi, Shanxi, Gansu, Yunnan, and Xinjiang, is relatively low. Significant differences and gradient development trends exist between China's western, central, and eastern water use efficiencies. Regarding influential factors, education, export dependence, and technological progress positively impact water use efficiency, while the industrial structure has a significantly negative influence. While the relationship between government intervention and water use efficiency is not obvious, the results point to some suggestions that should be considered to effectively promote overall water use efficiency and water resource management in these Chinese provinces.

First, water use efficiency must be improved in economically disadvantaged provinces by studying advanced water resource management from Chinese regions with higher water use efficiency. For the eastern region, one could study the potential of water-saving by improving the capacity of sewage treatment and the reuse of water, increasing the publicity of environmental protection, and promoting the development of a water-saving society. As technology develops, the central and western regions could strengthen environmental monitoring, establish an evaluation system and a penalization mechanism for water resource use, and promote the improvement of water use efficiency.

Second, sewage emissions must decrease in some regions; except for Shanghai, Tianjin, Beijing, Shandong, and Guangdong, waste water treatment in Chinese provinces must be improved. The theory of virtual water provides a new perspective on water resource security [57,58]. In addition, based on international water resources management experience, we should build a water resource governance structure combining unified management and inter-ministerial consultation [59]. Finally, in considering the factors that influence water use efficiency, improving residents' educational levels, increasing export trade, and enhancing competencies in developing technological innovations will help to promote water use efficiency. Each region should improve its industrial water resource management by developing standards for water quotas, and strengthening the water management and technological innovation in high water-consuming industries based on their actual water resource consumption and availability.

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