


## Article

# Efficiency Analysis of the Input for Water-Saving Agriculture in China

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**Abstract:** To optimize the installation distribution of water-saving techniques and improve the efficiency of water-saving agricultural inputs, we used a three-stage data envelopment analysis (DEA) model and Chinese provincial panel data from 2014 to 2016 to analyze the input efficiency of the water-saving irrigation. This study explores the efficiency derived from the efforts of water-saving initiatives in the agricultural sector in China. We present the impacts of factors such as technology, scale, diminishing marginal revenue, and crop water requirements on the research results. We found overall efficiency of water-saving irrigation is increasing nationally. The efficiency of water-saving irrigation input will significantly increase if management and organization of the input improve. Increasing the investment in areas with increasing marginal revenue would improve the local agricultural water-saving input efficiency in areas such as Hainan, Chongqing, Guizhou, Tibet, and Qinghai; although in areas with large water requirement for major crops, such as Inner Mongolia and Xinjiang, the efficiency of water-saving irrigation is generally high. Shanxi requires a large amount of water as the efficiency of agricultural water-saving input is 0.07, which is relatively lower than the average efficiency of all regions (0.39). The cultivated area index and the GDP per capita had no significant effect on the irrigation input efficiency.

**Keywords:** water-saving agriculture; Chinese provincial input efficiency; three-stage DEA model; environmental variables

## 1. Introduction

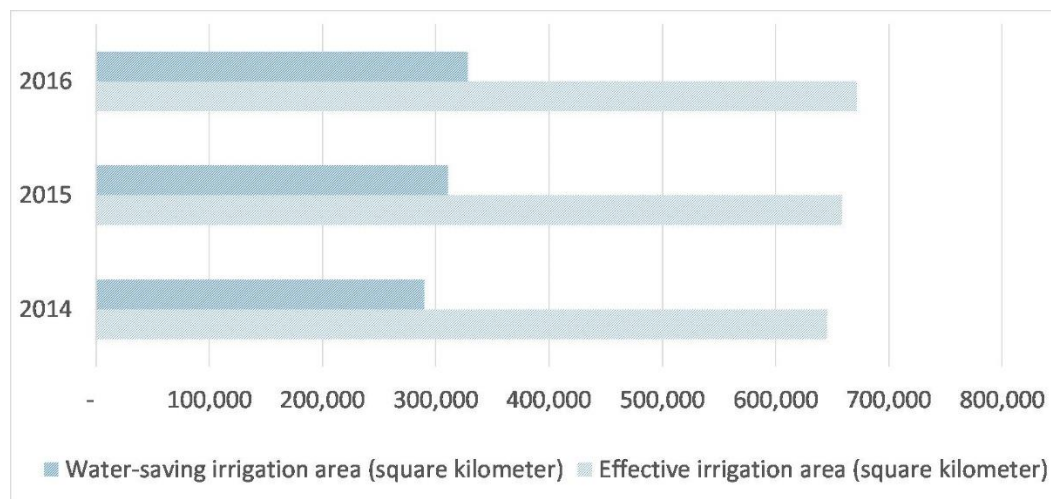
Water resource shortages have become a serious problem in China. Chinese water resources are unevenly distributed in time and space [1]. It is estimated that the per capita water resources will be reduced to one-quarter of the world average (1760 m<sup>3</sup>) by 2030, which is close to the lowest level of the countries with recognized water shortages. More than 400 of the 669 cities in China have insufficient water supply, 108 cities are seriously deprived of water, and the water shortage exceeds 6 billion m<sup>3</sup> in China annually [2]. This has affected the normal production and lives of more than 160 million people [3,4]. The amount of blue water resources in eight provinces is still unable to cover the needs of the domestic ecosystem, including in Qinghai province, which is known as the “source of rivers” [5].

According to the statistics of the Ministry of Water Resources, the agricultural sector accounts for 63.5% of the country’s total water use, of which about 90% is used for farmland irrigation. A large amount of irrigation water is wasted [6,7]. Compared with the effective use coefficient of farmland irrigation in developed countries of 0.7–0.8, this value was only 0.53 in China in 2017 [8,9], and a gap still exists between the water-saving goals proposed by the National Agricultural Water Conservation

Program (2012–2020). As such, further implementing water-saving measures for agriculture in China is crucial [10].

Although water-saving behavior will have huge ecological and social benefits, the effect of improving agricultural water-saving irrigation technology on individual farmer economic benefits is limited. The use of water-saving irrigation technology increases the opportunity cost of farmers, but the economic base of farmers in China is relatively weak. If no external stimulus exists, most farmers will not use water-saving technology. Therefore, the Chinese government has adopted the common worldwide practice of developing water-saving agriculture, providing policy support and guiding farmers toward water-saving behavior [11,12].

In recent years, the scale of China's farmland water conservancy investment has increased annually. Under the guidance of agricultural water-saving policies, the water-saving effect has also improved. According to the China Statistical Yearbook 2010–2019, the national fiscal expenditure for agriculture, forestry, and water affairs increased from 672.04 billion yuan in 2009 to 2.11 trillion yuan in 2018, which showed a growth rate of more than 213.75%. It is higher than the total expenditure growth rate of the state finance in the past 10 years (189.52%). Nevertheless, the growth rate of farmland investment effectiveness is not high. Water-saving irrigated areas and effective irrigated areas are presented in Figure 1.



**Figure 1.** Water-saving irrigated and effective irrigated areas in mainland China.

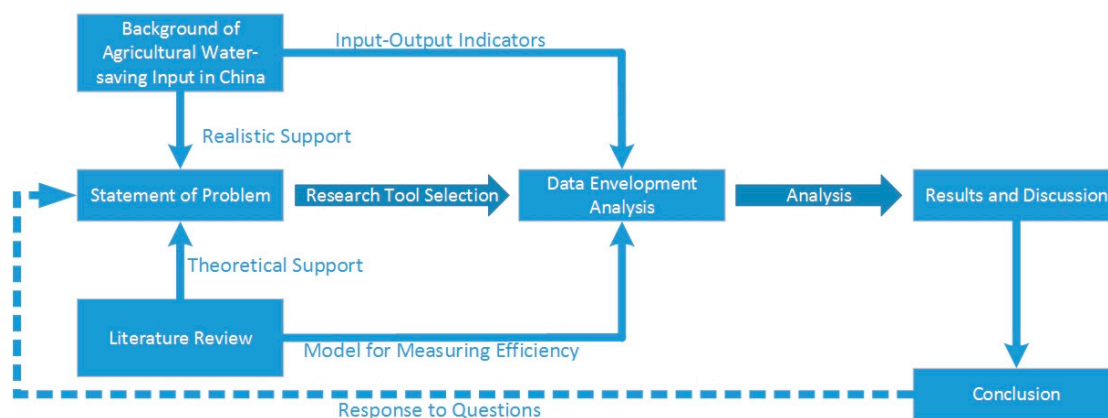
Scholars have mainly studied the agricultural water-saving input from three perspectives: A macro study on the strategic regulation of water-saving agriculture and the formulation of investment policies from the perspective of the government [13–15], analyzing and evaluating the optimization and decision-making of investment plans for water-saving agriculture projects from the perspective of social capital [16,17], and examining the behaviors of farmers who use water-saving irrigation techniques and the factors affecting their behaviors [18–20].

Scholars' research on agricultural water-saving efficiency is primarily focused on two aspects, namely influencing factors and efficiency measurement. They have studied the influencing factors of agricultural water-saving efficiency from the aspects of resources, technology, and management. Additionally, they have found that low resource prices cause low agricultural water-saving efficiency [21] and participation of farmers in irrigation management improves agricultural water-saving efficiency [22]. The clear agricultural water right and water right transfer policy not only stimulate the enthusiasm of agricultural water-saving but also promote the development of water-saving technology [23]. The improvement of irrigation technology and agricultural technology is conducive to the development of agricultural water-saving efficiency [24]. Most scholars choose to use non-parametric statistical methods such as data envelope models to conduct input–output analysis on agricultural water-saving

efficiency. The stochastic frontier production function is used to construct agricultural water efficiency models from the input–output perspective [25–27] and input-oriented Data Envelopment Analysis (DEA) to study regional differences and convergence of agricultural water use efficiency in China [28,29].

Precedents exist for the domestic input efficiency evaluation of agricultural water-saving. Some scholars have analyzed and evaluated the water-saving irrigation investment in different base years and determined the influence of investment efficiency based on principal component analysis [30–32]. Some scholars compared and analyzed the advantages of water-saving irrigation and developed an investment management system and investment management performance evaluation method for water-saving irrigation from a river [33,34]. Some scholars established certain of water-saving investment income models to study water-saving incentives in river basins and analyzed the mechanism of investment in the water rights market on the investment income of water-saving irrigation [35,36]. Most scholars analyzed the efficiency of agricultural water-saving investment from a country perspective, and research from the provincial unit perspective rarely explains the differences in environmental factors between regions [37].

In the existing research, the efficiency of agricultural water-saving input between provincial regions has not been measured well, making it impossible to analyze the influencing factors of agricultural water-saving input efficiency. It is necessary to determine the efficiency of China's agricultural water-saving input, ranking the areas where water technology improvement is needed the most. Determining the factors that affect agricultural water-saving input efficiency and trying to formulate proposals to improve the efficiency of agricultural water-saving inputs are of great significance to promote the rational use of water resources in China. The current forms of agricultural water-saving input are capital, labor, and equipment. Agricultural water-saving effects are primarily reflected in the size of water-saving irrigation areas. When the input and output indicators are clear, the DEA is a more accurate and commonly used tool for researching input efficiency analysis. The theoretical framework of this research is shown in the Figure 2.



**Figure 2.** Theoretical framework.

To solve the problem of objective factors and statistical noise, which affect the efficiency evaluation results of decision-making units, Fried [38] published Incorporating the Operating Environment into a Nonparametric Measure of Technical Efficiency and proposed a three-stage DEA model, considering the influence of environmental factors on the evaluation results in the traditional DEA. Fried [39] published Accounting for Environmental Effects and Statistical Noise in Data Envelopment Analysis, a further revision of the traditional DEA model considering environmental factors and statistical errors.

The DEA model has 4 forms, each with its own advantages and disadvantages. Form 1 is the basic sample separation method, which decomposes the sample into subsamples according to environmental factors, and is easy to understand and apply; however, it can only be used for a categorical variable and its precision is lower than that of other DEA model forms [40]. Form 2 is the one-stage DEA model, which includes environmental variables in the traditional DEA model together with input and

output factors. The one-stage DEA model is easy to interpret and apply; however, it requires prior understanding of the influence direction of the environmental variables [41]. Form 3 is the two-stage model that performs a regression evaluation on the efficiency of environmental variables, so it can accommodate continuous categorical variables without increasing decision units. This kind of DEA model does not require prior understanding of the influence direction of the environmental variables; however, if ordinary least squares (OLS) is used in the second stage, the corrected efficiency scores might be larger than 1 [39]. Form 4 is the three-stage model, which uses stochastic frontier analysis (SFA) to estimate the impact of environmental variables and the statistical noise and uses the adjusted input values in the traditional DEA model. In the three-stage DEA model, “input slack” represents the difference between the input before and after the elimination of environmental and statistical noise. Although it requires significant calculation time, this kind of model is able to capture the information contained in the input slack, which was helpful in the following analysis [42].

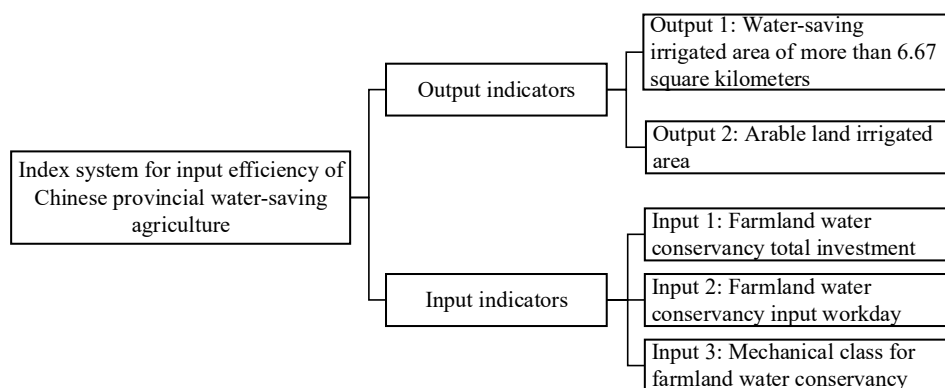
To address these research gaps, we used a three-stage DEA model to study the investment efficiency of national water-saving irrigation that considers the influence of objective factors and random statistical errors between different provinces on the efficiency of production units. We analyzed the scale effect of input from different regions and the impact of crop irrigation requirement on the efficiency of the water-saving irrigation input. Unlike the previous quantitative study of a single region, the calculation results of this research rank the agricultural water-saving irrigation input efficiency in 31 provinces in mainland China while depicting the changing trend of China’s agricultural water-saving irrigation input efficiency. In addition, it analyzes the factors that affect input efficiency and attempts to discover ways to improve areas with low input efficiency.

## 2. Materials and Methods

### 2.1. Indicator Selection and Data Source

The purpose of this article is to explore the relationship between the efficiency of water-saving input between different provinces. All 31 provincial regions in mainland China were selected as the research objects. Due to the limitation of the area for obtaining statistical data, this study does not include areas such as Taiwan, Hong Kong, Macau, and the South China Sea Islands.

In response to the irrigation water crisis, the Chinese government implemented water-saving technological transformation through agricultural irrigation infrastructure of methods such as the old ditch pumping station throughout the country, thereby transitioning irrigation behavior from traditional irrigation to water-saving irrigation. At present, the input in agricultural water-saving not only includes funds but also the input of human resources and materials. Therefore, we chose the input indicators considering three aspects: labor, material, and funds. According to the statistics of the indicators, we used three indicators: farmland water conservancy total input, farmland water conservancy input workday, and mechanical class for farmland water conservancy to represent agricultural water-saving inputs. In terms of the agricultural water-saving output, separating the portion of the grain output that has been increased due to water-saving irrigation is difficult. Additionally, the grain output is considerably affected by natural factors. The arable land irrigated area and water-saving irrigated area of more than 6.67 square kilometers were used as the output indexes of water-saving irrigation. The index system used to determine the efficiency of Chinese provincial water-saving agriculture is shown in Figure 3.



**Figure 3.** Index system used to determine the input efficiency of Chinese provincial water-saving agriculture.

As our research scope was 31 provinces in the Chinese mainland, their environmental factors such as climatic conditions, planting area, and economic development in different regions may affect the analysis results of the input efficiency. The assumption that the factors affecting the efficiency of agricultural water-saving input are the gross domestic product (GDP) per capita and cultivated land area is reasonable.

The State Council of China promulgated a policy to reconstruct the supporting facilities in irrigation districts and develop agricultural water-saving irrigation in 2013. Considering the time lag of the provincial data released by the Ministry of Water Resources, we used 2014–2016 as the study interval. To ensure the reliability of the analytical data, the data sources were the 2015–2017 China Statistical Yearbook, China Water Conservancy Statistical Yearbook and the National Water Development Statistics Bulletin.

## 2.2. Three-Stage DEA Model

### 2.2.1. Stage 1: Traditional DEA Model Analysis of the Original Input and Output Values

The first stage uses the initial input–output data of the decision-making units (DMUs) for traditional DEA analysis. In the literature related to the three-stage DEA model, the input-oriented model with variable scale return is mostly used as the first-stage calculation model, which is consistent with the model hypothesis. Therefore, we used the Banker, Charnes, and Cooper model (BCC) model. The dual form of the input-oriented linear programming model of one of the decision-making units can be expressed as [42]:

$$\begin{aligned}
 & \min \theta \\
 & \text{s.t.} \begin{cases} X_{ij0} \geq \sum_{j=1}^n X_{ij} \lambda_j \\ Y_{rj0} \geq \sum_{j=1}^n Y_{rj} \lambda_j \\ \sum_{j=1}^n \lambda_j = 1 \\ \lambda_j \geq 0 \\ j = 1, 2, 3, \dots, n \\ i = 1, 2, 3, \dots, m \\ r = 1, 2, \dots, s \end{cases} \quad (1)
 \end{aligned}$$

where  $\theta$  demonstrates the comprehensive input efficiency value of each DMU;  $X_{ij}$  and  $Y_{rj}$  are the  $i$ th and  $r$ th output of the  $j$ th DMU, respectively;  $m$ ,  $s$ , and  $n$  represent the number of input variables, output variables, and DMUs, respectively; and  $\lambda_j$  represents the  $j$  dimensional weight vector of DMU  $j$ .

The DEA-BCC model calculates the overall technical efficiency (TE), which is affected by the scale efficiency (SE) and pure technical efficiency (PTE). The relationship between these three values are expressed as [42]:

$$TE = SE \times PTE. \quad (2)$$

The efficiency evaluation results of the management unit are affected by management inefficiency, environmental factors, and statistical noise, so the last two factors need to be further separated from the results.

### 2.2.2. Stage 2: Statistical Noise and Exotic Environment Factors Separated from Results

The overall input efficiencies of each DMU can be calculated in the first stage. However, the input slacks of all DMUs are influenced by the management inefficiency, environmental factors, and statistical noise, so their effects on the results have to be eliminated in the second stage.

Fried [29] used SFA is to effectively separate environmental factors and statistical noise. This method is superior to simply using Tobit regression to separate environmental factors in the presence of statistical noise. The SFA regression function is constructed as [42]:

$$S_{ni} = f(Z_i; \beta_n) + v_{ni} + \mu_{ni} \quad (3)$$

where  $i = 1, 2, 3, \dots, I$  and  $n = 1, 2, 3, \dots, N$ ;  $S_{ni}$  is the slack variable of the  $n$ th input of the  $i$ th DMU;  $Z_i$  is the environmental variable;  $\beta_n$  is the coefficient of the environmental variable;  $v_{ni} + \mu_{ni}$  are the mixed errors;  $v_{ni}$  is the random noise;  $v \sim N(0, \sigma_v^2)$  is the influence of random interference factors on input slack variables;  $\mu_{ni}$  is the management inefficiency; and  $\mu \sim N^+(0, \sigma_\mu^2)$  is the influence of management factors on input slack variables.

To eliminate the influences of environmental factors and statistical noise, the input of decision-making units with better environmental conditions and statistical random variables is increased in the formula, as shown in Equation [42] (4):

$$X_{ni}^A = X_{ni} + [\max(f(Z_i; \beta_n)) - f(Z_i; \beta_n)] + [\max(v_{ni}) - v_{ni}] \quad (4)$$

where  $i = 1, 2, 3, \dots, I$  and  $n = 1, 2, 3, \dots, N$ ;  $X_{ni}$  is the original input;  $X_{ni}^A$  is the adjusted input;  $\max(f(Z_i; \beta_n)) - f(Z_i; \beta_n)$  is the adjustments to environment variables; and  $\max(v_{ni}) - v_{ni}$  is the elimination of the random errors in statistical noise.

### 2.2.3. Stage 3: Adjustment of the Efficiency Value

The original input of the first stage is substituted with the adjusted input data in stage 2, and then the DEA-BCC model is used again. The new efficiency value is the real efficiency that excludes exterior environmental factors and statistical noise.

## 2.3. Calculation of Irrigation Requirement Index

Irrigation requirement index ( $IR/ET_c$ ) is the ratio of irrigation requirement ( $IR$ ) to crop water requirement ( $ET_c$ ), and it reflects the degree of dependence of crop growth on irrigation in different regions [43].

$IR$  equals the difference between  $ET_c$  and effective rainfall during the growing period ( $P_e$ ) [44], as shown in Equation (5):

$$IR = ET_c - P_e \quad (5)$$

Presently, the formulas for calculating effective rainfall of various crops must determine parameters suitable for local soil quality, crops, and other conditions. Studies have shown that the calculation



method of effective crop rainfall is related to the selection of the calculation period length, and the accuracy can meet the research needs [45].

$$P_e = \begin{cases} P & P \leq ET_c \\ ET_c & P > ET_c \end{cases} \quad (6)$$

$ET_c$  is calculated as shown in Equation [46] (7):

$$ET_c = ET_0 \times K_c \quad (7)$$

Reference evapotranspiration ( $ET_0$ ) is potential transpiration rate of standard reference crop, which is calculated by using the Penman–Monteith method recommended by the Food and Agriculture Organization (FAO) of the United Nations [46].

Coefficient ( $K_c$ ) is the ratio of the potential evapotranspiration of a certain crop to  $ET_0$ . It reflects the difference between various crops and reference crops. The crop coefficient of several crops under standard conditions can be found in FAO-56.

### 3. Results and Discussion

The result is reflected in the comprehensive technical efficiency, pure technical efficiency, and scale efficiency. The slack variable of the input variable of the decision-making unit of the first stage was introduced into the SFA analysis model to analyze whether the factors significantly influenced efficiency judgment. The regression results are shown in Table 1.

**Table 1.** The regression results of the stochastic frontier analysis (SFA) model.

Year	Slacks Explanatory Variable	Input 1	Input 2	Input 3
2014	Constant term	(1035.5579)	4081.4798	0.007481262
	GDP per capita	0.00976548	(0.27090702)	2.5154086
	Cultivated area	0.00451017	69.011447	(0.41631877)
	$\sigma_i^2$	9,325,325.6	389,895,890	5,171,073.9
	$\gamma_i$	0.99999968	0.99999999	0.99999999
	likelihood ratio test	26.560963	14.248312	26.560963
2015	Constant term	(10.844754)	4865.9359	(1177.4461)
	GDP per capita	0.00036329	(0.28123225)	0.012144941
	Cultivated area	0.00038983	97.924711	(0.000455359)
	$\sigma_i^2$	18,050.657	413,829,350	9,919,867.8
	$\gamma_i$	0.99999999	0.99999999	0.99999999
	likelihood ratio test	8.894564	15.640943	24.943002
2016	Constant term	(6.7862996)	4597.7498	(1203.8865)
	GDP per capita	$7.0433 \times 10^{-5}$	(0.27747648)	0.012064749
	Cultivated area	0.00021407	68.236315	(0.002089515)
	$\sigma_i^2$	16093.141	417683040	9998899.5
	$\gamma_i$	0.99999999	0.99999999	0.99999999
	likelihood ratio test	14.16323	14.551437	26.015291

According to the regression results of the SFA model, the likelihood ratio test values of the unilateral error of the regressions for the three input slacks with two environment variables are all under the threshold value of the mixed  $\chi^2$  distribution examination and above the 10% confidence level, implying that the regression model was not robust enough. The hypothesis that no inefficiency item exists is supported.

### 3.1. Comprehensive Technical Efficiency of the Agricultural Water-Saving Inputs

The comprehensive technical efficiency represents the ability of the DMU to convert inputs into outputs. The comprehensive technical efficiency of provincial input for water-saving agriculture is shown in Table 2.

**Table 2.** The comprehensive technical efficiency of provincial input for water-saving agriculture.

Region	2014	2015	2016	Region	2014	2015	2016
Beijing	0.234	0.098	0.232	Hubei	0.277	0.302	0.301
Tianjin	1.000	0.785	0.902	Hunan	0.084	0.093	0.107
Hebei	0.961	0.340	0.535	Guangdong	1.000	1.000	1.000
Shanxi	0.070	0.069	0.068	Guangxi	0.089	0.090	0.071
Inner Mongolia	1.000	1.000	1.000	Hainan	0.068	0.057	0.180
Liaoning	0.105	0.131	0.126	Chongqing	0.020	0.021	0.017
Jilin	1.000	0.578	0.506	Sichuan	0.404	0.399	0.562
Heilongjiang	1.000	1.000	0.686	Guizhou	0.044	0.031	0.028
Shanghai	1.000	1.000	1.000	Yunnan	0.115	0.146	0.207
Jiangsu	0.190	0.182	0.186	Tibet	0.213	0.177	0.245
Zhejiang	1.000	1.000	1.000	Shaanxi	0.207	0.309	0.365
Anhui	0.442	0.539	0.431	Gansu	0.247	0.203	0.198
Fujian	0.139	0.119	0.098	Qinghai	0.114	0.140	0.140
Jiangxi	0.061	0.054	0.049	Ningxia	0.419	0.418	0.389
Shandong	0.097	0.105	0.102	Xinjiang	1.000	1.000	1.000
Henan	0.177	0.219	0.223	China Mainland	0.412	0.374	0.386

The comprehensive technical efficiency of the national average agricultural water-saving input was 0.412 in 2014, followed by a slight decline in 2015, and the value rebounded to 0.386 in 2016. The use efficiency of China's water festival irrigation investment rebounded slightly, showing that the current input efficiency of agricultural water-saving is increases, but room for improvement remains in the management efficiency of agricultural water use reduction in China.

From a regional perspective, the Inner Mongolia Autonomous Region and the provinces of Shanghai, Zhejiang, Guangdong, and Xinjiang were at the forefront of technical efficiency. Heilongjiang province had a high overall efficiency in 2014 and 2015, but exhibited a small decline in 2016. Tianjin was more efficient in 2014 and showed a slight rebound after a slight decline in 2015. Jilin displayed a downward trend after high efficiency in 2014. The six regions of Guizhou, Chongqing, Jiangxi, Shanxi, Hainan, and Guangxi showed lower comprehensive technology efficiency than other regions. Among them, the efficiency of Hainan in 2016 significantly improved compared with the previous two years, whereas the input efficiency of the other five regions did not change much in three years, so they can share the good ideas and practices of high-efficiency provinces based on the actual situation in the region.

### 3.2. Pure Technical Efficiency of Agricultural Water-Saving Inputs

Pure technical efficiency is a measure of the impact of non-scale factors, such as management and technology, on the output of water-saving irrigation inputs of each DMU. The pure technical efficiency of agricultural water-saving input is shown in Table 3.

Different from the scale efficiency, pure technical efficiency measures the investment of decision-making units from a technical perspective. Under the condition of constant scale, DMU with higher pure technical efficiency has higher comprehensive efficiency. In the study of input efficiency for water-saving agriculture, technical efficiency refers to the level of management and organizational [47].



**Table 3.** The pure technical efficiency of the provincial input for water-saving agriculture.

Region	2014	2015	2016	Region	2014	2015	2016
Beijing	0.295	0.254	0.344	Hubei	0.279	0.303	0.303
Tianjin	1.000	0.805	0.917	Hunan	0.099	0.109	0.120
Hebei	1.000	0.388	0.568	Guangdong	1.000	1.000	1.000
Shanxi	0.112	0.117	0.106	Guangxi	0.117	0.126	0.102
Inner Mongolia	1.000	1.000	1.000	Hainan	0.252	0.270	0.301
Liaoning	0.126	0.195	0.183	Chongqing	0.103	0.104	0.082
Jilin	1.000	0.623	0.565	Sichuan	0.439	0.406	0.647
Heilongjiang	1.000	1.000	0.793	Guizhou	0.120	0.087	0.075
Shanghai	1.000	1.000	1.000	Yunnan	0.127	0.149	0.208
Jiangsu	0.192	0.191	0.189	Tibet	1.000	1.000	1.000
Zhejiang	1.000	1.000	1.000	Shaanxi	0.215	0.330	0.366
Anhui	0.459	0.541	0.431	Gansu	0.270	0.239	0.235
Fujian	0.288	0.274	0.218	Qinghai	0.446	0.528	0.514
Jiangxi	0.080	0.081	0.074	Ningxia	0.510	0.526	0.523
Shandong	0.103	0.112	0.109	Xinjiang	1.000	1.000	1.000
Henan	0.178	0.221	0.226	China Mainland	0.478	0.451	0.458

In 2014, the pure technical efficiency of the national average agricultural water-saving input was 0.478, which was the first to decline in 2015 and 2016, and then it rebounded. This shows that the input efficiency of agricultural water-saving in China was growing currently, and the efficiency of use of capital, human, and material resources needs to be further improved.

In the efficiency evaluation, the pure technical efficiency of agricultural water-saving input was found to be one, indicating that the input management of the DMU is efficient. Nationally, Inner Mongolia, Shanghai, Zhejiang, Guangdong, Tibet, and Xinjiang were at the forefront of efficiency in the assessment year. The pure technical efficiency of Heilongjiang was relatively high in 2014 and 2015 and decreased in 2016. Hebei and Tianjin showed a small rebound in 2016 after an efficiency decline in 2015. Shanxi, Jiangxi, Shandong, Hunan, Guangxi, Chongqing, Guizhou, and Yunnan showed low technical efficiency. Except for Yunnan's pure technical efficiency showing an upward trend, the remaining three low-efficiency provinces remained at a relatively low level of pure technical efficiency over the three years.

### 3.3. Scale Efficiency of the Agricultural Water-Saving Inputs

With a certain level of management and technology, the input efficiency is affected by the scale of input. Scale efficiency reflects the ratio of the actual input scale to the optimal input scale. The scale efficiency of the average agricultural water-saving input in mainland China is generally higher than the pure technical efficiency, at about 0.78 for the assessment period, as shown in Table 4. This means that the agricultural water-saving input is relatively high; however, room for further improvement remains. Subsidies can be adopted for different places according to actual needs.

From a national perspective, Inner Mongolia, Shanghai, Zhejiang, Guangdong, and Xinjiang were at the forefront of scale efficiency. Most provinces had a high level of input, and there is relatively low scale efficiency in Hainan, Chongqing, Guizhou, Tibet, and Qinghai. Among them, Hainan's scale efficiency considerably improved in 2016. Considering the scale of remuneration, the scale returns of Hebei, Jilin, Heilongjiang, and Sichuan decreased in 2016, while other provinces had an increasing return to scale or a constant return to scale. The redeployment of agricultural water-saving inputs between provinces may have contributed to an increase in the overall efficiency.

**Table 4.** The scale efficiency of provincial input for water-saving agriculture.

Region	2014	2015	2016	Region	2014	2015	2016
Beijing	0.793	0.385	0.674	Hubei	0.993	0.995	0.994
Tianjin	1.000	0.974	0.983	Hunan	0.849	0.856	0.892
Hebei	0.961	0.875	0.941	Guangdong	1.000	1.000	1.000
Shanxi	0.622	0.589	0.641	Guangxi	0.761	0.712	0.692
Inner Mongolia	1.000	1.000	1.000	Hainan	0.269	0.209	0.598
Liaoning	0.829	0.669	0.689	Chongqing	0.192	0.198	0.206
Jilin	1.000	0.928	0.897	Sichuan	0.921	0.982	0.869
Heilongjiang	1.000	1.000	0.864	Guizhou	0.370	0.355	0.371
Shanghai	1.000	1.000	1.000	Yunnan	0.906	0.984	0.998
Jiangsu	0.990	0.956	0.981	Tibet	0.213	0.177	0.245
Zhejiang	1.000	1.000	1.000	Shaanxi	0.963	0.937	0.997
Anhui	0.962	0.996	1.000	Gansu	0.915	0.851	0.845
Fujian	0.484	0.435	0.451	Qinghai	0.257	0.266	0.273
Jiangxi	0.759	0.668	0.668	Ningxia	0.822	0.796	0.743
Shandong	0.942	0.942	0.940	Xinjiang	1.000	1.000	1.000
Henan	0.990	0.989	0.989	Mainland China	0.799	0.765	0.788

### 3.4. Marginal Revenue of the Agricultural Water-Saving Inputs

We propose that the marginal revenue of input efficiency in agricultural water-saving inputs is diminishing, which means that after a regional water-saving irrigation input produces certain effects, the efficiency of the subsequent input is less than that of the previous input efficiency. We measured scale of the agricultural water-saving inputs by the ratio of local water-saving irrigation area to cultivated land area. The marginal revenue analysis was conducted by combining the input scale saturation with the comprehensive benefits of the agricultural water-saving input.

In this study, five areas with a high water-saving input efficiency and five areas with a low water-saving efficiency were selected as the research objects to analyze the diminishing marginal benefit. The data on water-saving irrigated area and cultivated area in 2016 in 10 regions are shown in Table 5.

**Table 5.** Agricultural water-saving situation and ranking in some areas.

Region	Water-Saving Area of the Total Cultivated Area		Agricultural Water-Saving Input Efficiency	
	Proportion	Rank of Mainland China	Value	Rank of Mainland China
Inner Mongolia	28.50%	10	1	1
Shanghai	76.10%	2	1	1
Zhejiang	54.89%	4	1	1
Guangdong	11.56%	25	1	1
Xinjiang	74.59%	3	1	1
Guangxi	23.45%	13	0.071	27
Jiangxi	17.03%	20	0.068	28
Shanxi	22.41%	16	0.049	29
Guizhou	7.14%	30	0.028	30
Chongqing	9.18%	27	0.017	31

The five regions with the largest proportions of water-saving cultivated land were Beijing, Shanghai, Xinjiang, Zhejiang, and Jiangsu, and the five regions with the smallest proportion were Tibet, Guizhou, Hubei, Hunan, and Chongqing. Among the five regions with high comprehensive efficiency of agricultural water-saving, the area with water-saving irrigation in Guangdong accounts for a small proportion of cultivated land, and the water-saving irrigation areas in the other four regions are relatively large. Of the areas where the water-saving irrigated area is relatively small, the comprehensive efficiency of agricultural water-saving is relatively low in Chongqing and Guizhou.

The results indicate that the water-saving irrigation input in 31 regions of China has not shown a significant downward trend in marginal benefits, which means that agricultural water-saving input

has not reached its maximum utility in most regions. Where the proportion of the water-saving area was high, the agricultural water-saving input was highly efficient, and where the proportion of the water-saving area was low, the agricultural water-saving input was inefficient.

### 3.5. Irrigation Water Requirement of Crops

The 31 regions in mainland China mainland are widely distributed and have different climatic conditions, so the irrigation water requirements vary amongst the different types of major local crops in different locations. The crop requirements for agricultural irrigation in different regions affect the enthusiasm toward input in water-saving irrigation and influence the agricultural water-saving input efficiency. The irrigation requirement index indicates the degree of dependence of crops on agricultural irrigation, which is related to the water requirement characteristics of crop growth and the precipitation in the local crop growth period [44,48,49], as shown in Table 6.

**Table 6.** Average irrigation requirement index for the main crops in different regions.

Region	Main Crop Species	Irrigation Requirement Index	Region	Main Crop Species	Irrigation Requirement Index
Heilongjiang; Jilin; Liaoning	Middle-season rice	0.4	Shaanxi; Gansu; Shanxi	Middle-season rice	0.7
	Spring maize	0.25		Cotton	0.65
	Spring wheat	0.34		Spring maize	0.65
Beijing; Tianjin; Hebei; Shandong; Henan	Middle-season rice	0.6		Summer maize	0.4
	Cotton	0.425		Spring wheat	0.675
	Spring maize	0.425	Sichuan; Chongqing	Late-season rice	0.3
	Summer maize	0.325		Middle-season rice	0.275
	Winter wheat	0.625		Early-season rice	0.35
Jiangsu; Zhejiang; Shanghai; Hunan; Hubei; Jiangxi; Anhui	Late-season rice	0.425		Cotton	0.15
	Middle-season rice	0.375		Spring maize	0.125
	Early-season rice	0.325		Summer maize	0.125
	Cotton	0.3		Winter wheat	0.575
	Spring maize	0.2	Yunnan; Guizhou	Late-season rice	0.3
Fujian; Guangdong; Guangxi; Hainan	Summer maize	0.35		Middle-season rice	0.375
	Late-season rice	0.4		Early-season rice	0.35
	Middle-season rice	0.35		Spring maize	0.275
	Early-season rice	0.3		Summer maize	0.15
Inner Mongolia; Ningxia	Cotton	0.2	Qinghai; Tibet	Winter wheat	0.625
	Spring maize	0.175		Spring wheat	0.625
	Summer maize	0.2	Xinjiang	Middle-season rice	0.9
	Middle-season rice	0.775		Cotton	0.9
	Spring maize	0.7		Spring maize	0.85
	Spring wheat	0.6		Summer maize	0.9
				Winter wheat	0.8
				Spring wheat	0.875

According to the regional main crop irrigation requirement index, the crop requiring the most irrigation water is rice, followed by wheat and cotton. Although cotton requires more water than wheat, due to the higher amount of precipitation in the cotton growing area, the irrigation water requirement of wheat is higher than that of cotton during the growing process. Summer maize requires little irrigation, and crops grown in the dry fields in the south and northeast require no irrigation.

The comprehensive efficiency of water-saving irrigation input in Zhejiang, Shanghai, and Guangdong was higher than other regions', but their average irrigation requirement index were 0.33, 0.33, and 0.27, respectively, lower than the average irrigation requirement index (0.43). The irrigation requirement indexes in Inner Mongolia and Xinjiang were 0.69 and 0.87, respectively, significantly higher than the average. Therefore, the efficiency of agricultural water-saving input in Inner Mongolia and Xinjiang was higher due to the large water requirement of crops; without the high agricultural water-saving input efficiency, the growth needs of local crops cannot be met. For the crop water

requirement in Zhejiang, Shanghai, and Guangdong, the developed social economy plays a role in increasing the efficiency of the agricultural water-saving input.

Overall, the efficiency of agricultural water-saving inputs in Guangxi, Jiangxi, Guizhou, and Chongqing was lower than other regions. The irrigation requirement index in these areas were lower than the regional average, indicating that crop irrigation in these areas requires less irrigation water than other regions. Notably, the irrigation requirement index of Shanxi was 0.61, which is higher than the regional average (0.48), but the agricultural water-saving input efficiency was low, indicating room for improvement.

According to DEA calculation results, there are six provinces with a comprehensive efficiency of less than 0.1, including Chongqing (0.02), Guizhou (0.03), Jiangxi (0.05), Shanxi (0.07), Guangxi (0.08), and Hunan (0.09). As the results of Section 3.4 reveal there is no significant downward trend in marginal benefits in China, the problem of insufficient levels of agricultural water-saving investment in these areas is widespread. Li [49] proposed that the low availability of local financial funds in agriculture is because of inadequate balancing of agricultural investment. It is of great significance to increase the proportion of local fiscal agricultural investment in public products related to agricultural production and management (such as small farmland water conservancy, research and development, and promotion of agricultural water-saving technologies), which is of great importance to improve the efficiency of agricultural water-saving investment. Therefore, it is necessary for local governments to closely consider the use and management of agricultural water-saving irrigation inputs and establish incentive and restraint mechanisms to strengthen the efficiency of local financial investment. This approach can ensure the expansion of investment scale, thereby improving agricultural water-saving investment efficiency. In addition to insufficient investment scale, the pure technical efficiency in these regions is low. Shanxi Province exhibited the highest irrigation requirement index among the six provinces, and there is an urgent need to upgrade water-saving technologies to meet the water needs of crops. Shanxi Province can learn from Gansu Province, which is also a dry farming area, to improve the efficiency of water-saving irrigation by enhancing the quality of cultivated land and increasing well water irrigation. By rationally determining the scale of planting, scientifically arranging well irrigation, and improving irrigation technology efficiency, developments to agricultural water-saving irrigation input efficiency from the perspective of improving pure technical efficiency are possible [50]. The comprehensive technical efficiency of agricultural water-saving investment in Chongqing is the lowest in the country. To improve this situation, Chongqing can learn from Sichuan Province with its similar geographical location and climatic conditions. On one hand, it actively explores agricultural credit services, establishes agricultural water-saving development funds, and broadens the sources of investment. And on the other, it is necessary to actively promote the concept of water conservation among farmers, encouraging them to actively adopt water-saving measures to improve agricultural water efficiency [51]. Guizhou, Jiangxi, Guangxi, and Hunan belong to paddy fields in southern China. Farmers' participation in agricultural water-saving irrigation is relatively poor [52]. To further enhance the efficiency of agricultural water-saving irrigation, it is essential to appropriately increase the cost of agricultural water, promote water-saving irrigation technology, and improve drainage channels [53–55]. Additionally, the reclaimed water which has been assessed quality can supplement the irrigation water, thereby the investment efficiency of agricultural water-saving irrigation will be improved [56].

#### 4. Conclusions

In this study, the three-stage DEA model was used to analyze the input efficiency and level of water-saving agriculture of the 31 provinces in mainland China. During the second stage of the model, we found that the GDP per capita and the cultivated area do not play significant roles in the efficiency determination, which means that the result of the one-stage DEA model is the real efficiency. We analyzed the efficiency of the agricultural water-saving input in 31 regions from the perspectives of pure technical efficiency, scale efficiency, scale efficiency decreasing effect, and crop water requirement. The primary conclusions are as follows:

(1) The efficiency of agricultural water-saving input in China generally is in the stage of increasing marginal revenue, and the efficiency of agricultural water-saving input increases with increasing total input. The annual average water-saving irrigation coefficient in China was 0.39, of which the pure technical efficiency was 0.46 and the scale efficiency was 0.78. Room for improvement exists in the use rate and the scale of input. However, in different regions, agricultural water-saving investment is polarized. The comprehensive technology efficiency of eight of the regions was above 0.7, and 12 regions were below 0.15.

(2) Strengthening resource and organization management in agricultural water-saving would play a significant effect on the improvement of input efficiency, while pure technical efficiency plays a major role in the improvement of input efficiency. The pure technical efficiency of agricultural water-saving was found to be 0.46 across the whole country for three years, indicating a certain gap compared with the scale efficiency of 0.78. The main factor leading to the low efficiency of integrated technology is the low level of technical efficiency. In terms of the water-saving input in agriculture, areas with low pure technical efficiency should focus on improving resource management and the technology.

(3) Further optimizing the distribution of resources and investing in subsidies in areas with increasing scale efficiency can lead to an increase in overall efficiency, but there is a diminishing effect of scale in some regions. There is a reduced scale of input in Hebei, Jilin, Heilongjiang, and Sichuan, indicating that the agricultural water-saving inputs in these regions exceed the local resource distribution capacity. It is necessary to reduce the inputs appropriately and improve the local resource distribution capacity to further improve the efficiency of agricultural water-saving investment. The distribution of resources nationwide should be optimized, and resource subsidies should be provided to areas with high technical efficiency and lack of input, so as to maximize the overall investment efficiency of all provinces.

(4) This study analyzes irrigation input efficiency from the perspective of crop irrigation requirement, comprehensively considers the region's own water requirement and the precipitation conditions of the crop location, examines the impact of agricultural water-saving irrigation requirement, further explores the necessity of water-saving irrigation, and enhances the scientific nature of the conclusion. It is discovered that the low input efficiency of water-saving irrigation in Guangxi, Jiangxi, Guizhou, and Chongqing may be related to the low local crop irrigation requirement.

(5) In the case of input and output indicators, the impact of the regional per capita GDP on the agricultural water-saving input efficiency was not obvious. The impact of the area of cultivated land on the efficiency of agricultural water-saving input was not significant.

Due to the limitation of the DEA model, this study can only rank the regional agricultural water-saving irrigation input efficiency. If the appropriate model is used to obtain the absolute value of the input efficiency, it will help expand the research content. Limited by the available data collected from China Water Conservancy Statistical Yearbook and the National Water Development Statistics Bulletin, in the future research, we will investigate and survey the input efficiency for water-saving agriculture to collect data of some sophisticated indicators such as popularity of efficient irrigation technology, average education level of farmer households. These indicators will be used to evaluate the efficiency of water-saving agricultural inputs from the characteristics of farmers in different regions.

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