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Three-Stage Data Envelopment Analysis of Agricultural Water Use Efficiency: A Case Study of the Heihe River Basin

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Abstract: Aiming to inspect the water use-related situation in the Heihe River Basin, we used a three-stage data envelopment analysis to examine agricultural water use efficiency (WUE) and related issues in the Heihe River Basin from 2004 to 2012. This method calculates technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE). Results show that water use-related efficiency varies according to scale. TE and SE decreased in the study area, while PTE increased. This means that the effects of pure technology on improving overall technology are very limited, and scale adjustment is vitally important to the agricultural production area in the Heihe River Basin. The results provide recommendations for decision-makers to plan the efficient use of water resources in arid and semiarid areas; in addition, this method will contribute to calculations of water use-related efficiency.

Keywords: agricultural water use efficiency; three-stage data envelopment analysis; moderate scale; Heihe River Basin

1. Introduction

Water plays an important role in human life, societal development, and environmental sustainability [1–4]. According to a World Water Development report regarding serious climate change, water supply has become a major challenge, especially in arid and semiarid areas [5–7]. Currently, water shortage is the greatest problem in China, where the average water use per capita is 2200 m^3 [8]. The distribution of water resources in the country has exacerbated a water crisis in northwestern China [9]. The central government has set a target that the entire nation will be poverty-free in 2020, which would severely restrict water use [10]. The acceleration of urbanization and population growth also brings challenges to water utilization [11,12]. Increasing water use efficiency (WUE) has become a vital step toward a more sustainable world [13]. As an important maize seed production area, the Heihe agricultural production area in Gansu Province is one of the most water-stressed parts of the country [14,15]. There, agricultural water use accounts for more than 85% of total socioeconomic water consumption [16]. Low water utilization may come from inadequate water infrastructure, and water scarcity has become a major issue in this area [17].

In this paper, we focus on water use-related efficiency; furthermore, this paper must determine the definition of agricultural water use efficiency. Agricultural water use efficiency refers to the minimum water consumption which can be realized theoretically, compared to the actual water consumption with the predefined input and output levels. We identified the relevant literature based on three requirements: Firstly, these studies included water use. Secondly, the main aim of these studies was to determine water use-related efficiency; the calculated technical efficiency can be divided into two parts: the mean pure technical efficiency (PTE) and the scale efficiency (SE). Thirdly, the main conclusion or the main purpose contributed to some improvement in methodology. Various studies have focused on how to calculate and improve WUE (Table 1) [18–20]. However, this research only concentrates on how to increase water use-related efficiency [21,22]. Many studies also calculated water use on a per capita or per GDP basis [23–25]. Water resource supply studies may give a basic description of water consumption.

Table 1. Methods used to determine water use efficiency (WUE) and mean WUEs reported in recent publications.

First Author	Year	Country	Product(s)	No. Obser.	Method	Mean Water Use Efficiency
Tari et al. [21]	2016	Anatolia	wheat	22	WUE = Y/ET	1.02–1.30 kg/m^{-3}
Wei et al. [26]	2016	English/Welsh	all products	10	DEA	0.91
Wu et al. [27]	2016	China	wheat	35	WUE = Y/ET	1.80 kg/m^{-3}
Tolk [28]	2016	USA	maize	260	WUE = Y/ET	2.23 kg/m^{-3}
Kifle et al. [20]	2016	Ethiopia	potato	8	WUE = Y/ET	1.6–2.86 kg/m^{-3}
Fandika et al. [19]	2015	Agria	potato	32	WUE = Y/ET	10.3 kg/ha.mm
Gadanakis et al. [29]	2015	England	all products	66	DEA	0.51
Chen et al. [30]	2014	Zimbabwe	maize	115	WUE = Y/ET	27.5 kg/ha.mm
EI-Mageed et al. [31]	2014	China	onion	97	WUE = Y/ET	8.71 kg/m^3
Fan et al. [23]	2014	China	Wheat	86	WUE = Y/ET	0.87 kg/m^3
Pradhan et al. [32]	2014	India	Wheat	5	WUE = Y/ET	6.08 kg/ha.mm
Rana et al. [33]	2013	Spain	Chickpea	18	WUE = Y/W	1.8–5.9 kg/ha.mm
Ram et al. [34]	2013	India	Wheat	15	WUE = Y/W	148 kg/ha.cm
Xiao et al. [35]	2013	China	potato	11	WUE = Y/ET	8.6 kg/ha.mm

Note: DEA, Data Envelopment Analysis.

There are many case studies that include multi-input, multi-output, and multi-decision questions [36,37]. Using data envelopment analysis (DEA) is very helpful in dealing with multi-input and multi-output questions [38,39]. DEA was proposed by Charnes et al. in 1973, and has become an efficient evaluation method [40]. This method is commonly used in water resource management [41,42]. Many researchers have been concerned with water-related issues [43,44]. Research on WUE solves water problems on different levels, linking WUE at different levels [45–47]. Based on previous studies, DEA can be more effective for analyzing water use than WUE = Y/W(ET) methods. The DEA method provides an economic calculation method that can involve different inputs and outputs. The DEA method has been used in different studies. Furthermore, various studies have summarized DEA as being the most representative methodology to evaluate efficiencies (including environmental and banking efficiencies). For example, WUE has been calculated for 31 Chinese provinces and the city of Wuhan over the period 1998–2008, and influence factors were determined [48,49]. Such research on WUE has strong effects on improving WUE. However, the DEA method assumes that inefficiency comes entirely from management, ignoring the external environment and random error [50]. We calculated WUE in the Heihe River basin using a three-stage DEA method, and found that water stress is a major problem in this area. This paper aims to determine the true reason for low water use efficiency (TE, PTE, SE).

2. Material and Methods

The Heihe River basin (Figure 1) (38°–42° N, 98°00′–101°30′ E) is the second largest inland river basin in the arid region of northwestern China, and forms a typical desert oasis zone [51]. The region extends from the northern base of the Qilian Mountains, through the Zhangye Basin in Gansu Province, to the Ejina Banner of Inner Mongolia [17,52]. However, some tributary rivers and mainstems have ceased to flow after long-term water resource exploitation. Three independent subsystems have formed in the east, middle and west parts. The east subsystem includes more than 20 rivers, including the mainstem of the Heihe and Liyuan rivers. The middle subsystem consists of the Maying and Fengle rivers. The west subsystem includes the Taolan and Hongshui rivers [53,54].

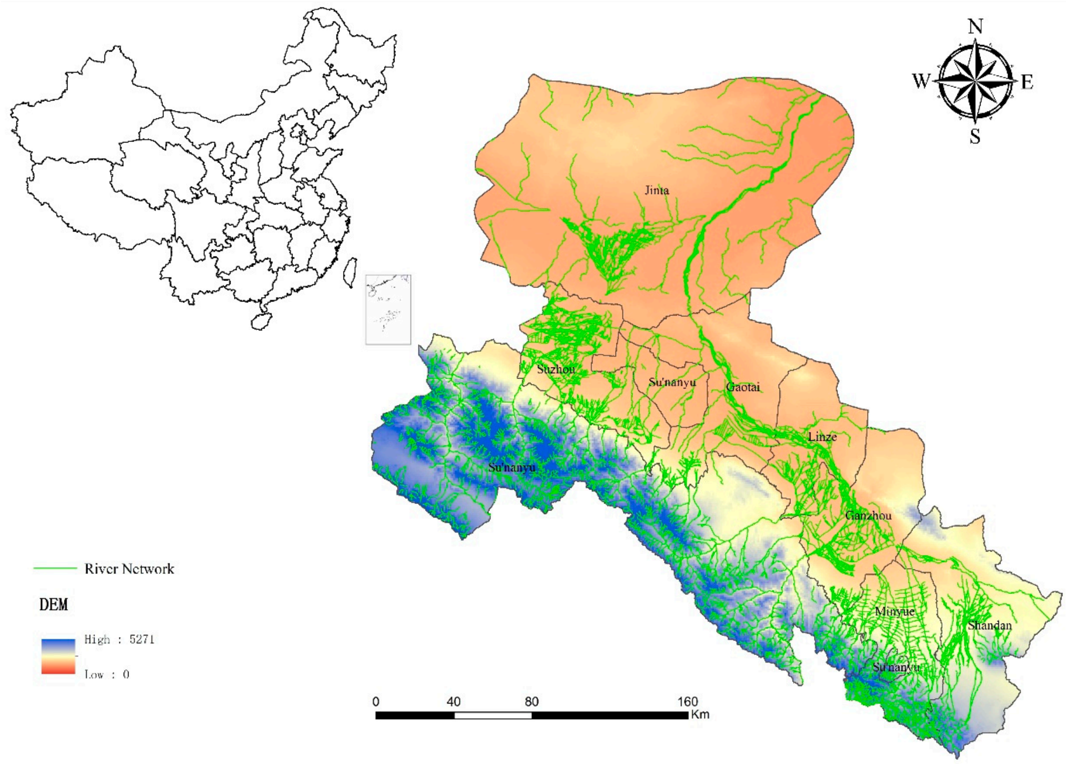


Figure 1. Agricultural production area in the Heihe River region.

The study area includes oasis agriculture zones in the middle and downstream regions of the Heihe River in Gansu, and has been a local major agriculture development zone for many years [29]. It consists of Ganzhou and Suzhou districts; Gaotai, Shandan, Minle, Linze, and Jinta counties; and Sunan Yugur Autonomous County. A very important issue in this area is how to improve WUE. Thus, this paper mainly focuses on WUE using data from the Heihe River basin. Economic development in the basin largely depends on agricultural production, which is highly water-consuming. Statistics show that agriculture consumes the largest proportion of water resources in the basin, reaching about 92.31% of the total, of which irrigation water accounted for 89.73%, in 2011 (Figure 2). The water diversion policy has been complemented in the Heihe River Basin since 2000, which constrains water use for agricultural production in the middle reaches. Thus, it is urgent to improve the agricultural water use efficiency in this area. The study area is located in Gansu Province, and here the agricultural production is quite similar; maize comprises up to 85% of crops grown, alongside vegetables and other crops. Vegetable crops are used for daily food, while maize is produced for sale as well as food.

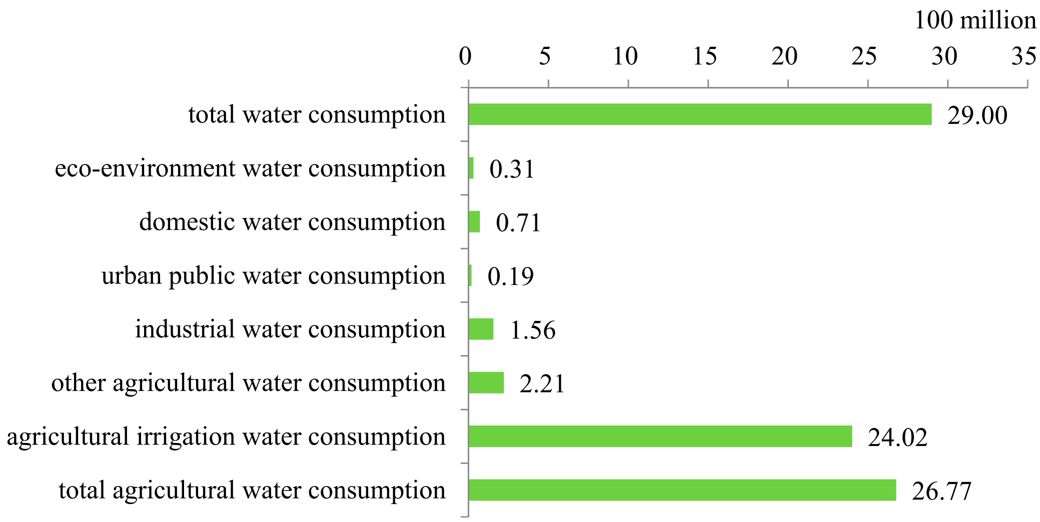


Figure 2. The water consumption of different sectors in the Heihe River Basin in 2011.

Based on the hypotheses and data availability, we collected data from the period 2004–2012 related to agricultural production from six counties and two districts in the midstream and downstream agriculture zones of the Heihe River basin. Except for data related to agricultural water use, all data were taken from Zhangye and Jiuquan statistical yearbooks. We used the DEA method to calculate technical efficiency. The inputs included labor force, investment in fixed assets, and planting; these variables all came from the Zhangye and Jiuquan statistical yearbooks. We did not include fertilizers, agrochemicals, etc., as input variables. Agricultural water resource quantity data were collected from the Center for Chinese Agricultural Policy, Chinese Academy of Sciences (Table 2).

Table 2. Basic input–output information in the Heihe agricultural production area.

Area	Agricultural Production Value		Agricultural Water Use		Agricultural Labor Force		Investment in Fixed Assets		Planting Area	
	Mean (10,000 RMB)	SD	Mean (10,000 m^3)	SD	Mean (Persons)	SD	Mean (10,000 RMB)	SD	Mean (10,000 mu)	SD
Ganzhou	643,861	325,438	45,922	6207	324,450	7630	283,162	193,488	53.32	3.35
Gaotai	181,451	95,429	20,825	4331	134,339	2468	82,237	56,833	24.58	4.09
Shandan	198,042	81,274	38,181	4251	145,261	11,858	84,225	69,571	35.35	3.1
Minle	169,723	76,394	59,464	6583	210,166	4269	79,446	67,843	58.34	2.26
Linze	183,019	95,153	17,824	3360	125,418	691	89,841	66,615	19.74	2.72
Sunan	90,214	69,316	4436	1737	25,402	559	136,437	121,882	4.82	1.21
Jinta	227,202	157,286	40,030	2667	113,544	2978	136,232	167,775	26.08	4.62
Suzhou	681,796	550,635	69,911	14,718	225,060	8308	518,352	504,639	46.86	1.6

2.1. Environmental Variables

Environmental variables refer to the influence factors of WUE, and these variables do not change over short periods. Thus, the variables are also called external variables. Based on prior research [46–48], we used local development, natural water endowment, and industrial structure as environmental variables. Specifically, we used per capita GDP to represent local development, which reflects government finance investment and expense capabilities. Generally, with economic development, there is more investment in infrastructure and WUE increases. We used water possession per person to represent the natural water endowment. Generally, if local people possess more water, their means of water consumption and water conservation consciousness weaken, and WUE declines. We used the proportion of primary industry to GDP to represent industrial structure. If this structure is more rational, the configuration of water consumption is more reasonable and therefore water resource efficiency is greater.

2.2. Methods

DEA is based on the concept of local efficiency. There may be several units awaiting evaluation, and each unit is a separate decision-making unit (DMU). According to calculations, we can determine whether the unit is efficient [55]. The calculation of DMU is within the interval (0, 1), with values closer to 1 indicating greater efficiency. If the efficiency is equal to 1, the DMU is the most efficient compared to other DMUs [56]. Efficiency comparison can be based on DEA. The method of a three-stage DEA is thus: the first stage uses a DEA method to calculate three related technologies; the second stage peels off the redundancy of input–output variables; while the third stage uses DEA to calculate the new efficiency. In the second stage, the stochastic frontier analysis (SFA) calculation uses redundancy as a variable [57–60]. Thus, a three-stage DEA is comprised of both DEA (first and third stages) and SFA (second stage) methods. Nonparametric techniques (DEA) provide a robust framework, and parametric techniques (SFA) are used to describe parametric function.

In the first stage, aimed at calculating the WUE given a fixed output, we used the BCC (Banker, Charnes and Cooper) input-oriented DEA model. DEA was used to measure agricultural WUE. With the goal of analyzing how to improve WUE with a fixed water supply amount, we used input-oriented DEA. When the efficiency value equals 1, the decision unit is on the production frontier, and the actual production value has no difference to the possible maximum value. An efficiency value <1 implies that there is still room for improvement for the decision unit. When the value of the efficiency reached 1, the WUE of the decision unit was higher. Supposing that there are N (= 1, 2, 3, ..., 8) decision units with I (= 1, 2, 3, ...) factors in T (= 1, 2, 3, ...) time periods, then J (= 1, 2, 3, ...) types of outputs are generated. For the input–output index, we used X and Y to represent input and output. Then, the input–output index of N counties (which equaled the decision unit) during various periods was designated $x_{i,n}^t$ and $y_{i,n}^t$. If we set $x_i = (x_{1n}, x_{2n}, \ldots, x_{In})$ and $y_j = (y_{1n}, y_{2n}, \ldots, y_{Jn})$, the model is specified as follows.

$$\begin{cases} \min\theta = V_D \\ \sum\limits_{n=1}^{8} \lambda_j X_i + S^- = \theta X_0 \\ \sum\limits_{n=1}^{8} \lambda_j Y_j + S^+ = Y_0 \\ \lambda_j \geq 0, N = 1, \ldots, 8 \\ S^- \geq 0, S^+ \geq 0 \end{cases} \tag{1}$$

Here, $\theta(0 < \theta < 1)$ is the comprehensive technical scale efficiency, λ_j is the weighting variable, $S^-(S^- \geq 0)$ is the slack variable, $S^+(S^+ \geq 0)$ is the surplus variable, and ε is the Archimedes infinitesimal. The above equation is the DEA model based on constant scale returns; if $\theta = 1$, it means that the county attained the optimal water use situation on the frontier.

In the second stage, the traditional DEA could not identify whether inefficiency in the first stage of decision-making was caused by management inefficiency or external factors and random errors. Thus, in the second stage, the SFA model was used to eliminate environmental and random error factors, obtaining the input relaxation variable caused by management inefficiency. According to the model concept, the following SFA regression function was constructed.

$$S_{ni} = f(z_i; \beta_n) + \nu_{ni} + \mu_{ni}; i = 1, 2, \ldots, I; n = 1, 2, \ldots, N \tag{2}$$

where S_{ni} is the relaxation value of the nth item of the ith decision-making unit; S_i is the environmental variable and β_n is its coefficient; $\nu_{ni} + \mu_{ni}$ is a mixed error term and ν_{ni} is random interference; and μ_{ni} represents management inefficiency. Among these terms, $\nu \sim N(0, \sigma_\nu^2)$ is the random interference term, symbolizing the influence of that interference on the relaxation variable; and μ is management inefficiency, showing the impact of management factors on the relaxation variables. We suppose that μ follows a normal distribution at zero cutoff, which is $\mu \sim N^+(0, \sigma_\mu^2)$. The equation for separating random error from mixing error is

$$\hat{E}[\nu_{ni}/\mu_{ni}+\nu_{ni}] = S_{ni} - f(z_i;\beta_n) - \hat{E}[\mu_{ni}/\mu_{ni}+\nu_{ni}]; i = 1,2,\ldots,I; n = 1,2,\ldots,N \quad (3)$$

According to relevant research, the equation is

$$\hat{E}[\nu_{ni}/\mu_{ni}+\nu_{ni}] = \sigma^*[\frac{\phi(\lambda\frac{\varepsilon}{\sigma})}{\Phi(\lambda\frac{\varepsilon}{\sigma})} + (\lambda\frac{\varepsilon}{\sigma})] \quad (4)$$

Now,

$$\sigma^* = \frac{\sigma_\mu\sigma_\nu}{\sigma}, \sigma = \sqrt{\sigma_\mu^2+\sigma_\nu^2},\ \lambda = \frac{\sigma_\mu}{\sigma_\nu},\ \varepsilon = \mu_{ni}+\nu_{ni}; i = 1,2,\ldots,I; n = 1,2,\ldots,N \quad (5)$$

The second stage uses SFA methods to eliminate the influence of efficiency from environmental and random factors. To adjust all decision-making units in the same external environment, the equation is adjusted as

$$X_{ni}^A = X_{ni} + [\max f(z_i;\hat{\beta}_n) - f(z_i;\hat{\beta}_n)] + [\max(\nu_{ni}) - \nu_{ni}], i = 1,2,\ldots,I; n = 1,2,\ldots,N \quad (6)$$

Here, X_{ni}^A stands for the adjusted inputs and X_{ni} the unadjusted inputs;$[\max f(z_i;\hat{\beta}_n) - f(z_i;\hat{\beta}_n)]$ is used to adjust the external environmental factors; $[\max(\nu_{ni}) - \nu_{ni}]$ is for putting all decision-making units on the same level.

The third stage uses the adjusted input factors to calculate WUE. The exclusion of the external environment and random error factor makes the efficiency value more objective and accurate.

The calculated technical efficiency can be divided into two parts: mean pure technical efficiency and scale efficiency. The TE under the variate return scale (VRS) (PTE) presents the efficiency without considering the scale, and the TE_{VRS} could change in the short-term. SE represents the scale of the agricultural farm, which could not change easily in the short-term.

3. Results

3.1. Agricultural Water Use Efficiency in the First Stage

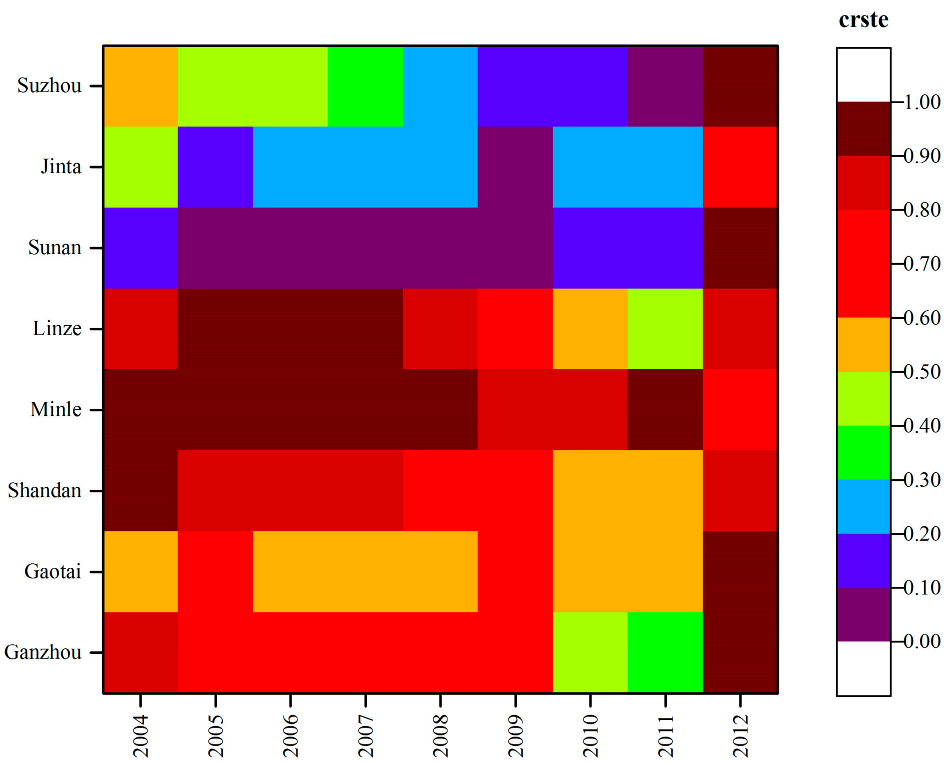
The results reveal disparities between different areas regarding agricultural water-related efficiency. On average, from 2004 to 2012 (Table 3), the comprehensive efficiency in these areas varied substantially. The comprehensive efficiency of Minle was the highest, with a mean of 0.92. The efficiency of Sunan was the lowest, with a mean of only 0.19. From the standpoint of pure technical efficiency (PTE), the difference between counties was greatly reduced. Sunan had the highest PTE, over twice that of Suzhou. Regarding the scale of efficiency, Minle's technical efficiency was five times greater than Sunan's scale efficiency.

Table 3. First stage average agricultural water use efficiency from 2004 to 2012.

Location	TE	PTE	Scale
Ganzhou	0.65	0.67	0.98
Gaotai	0.63	0.82	0.78
Shandan	0.75	0.76	0.98
Minle	0.92	0.92	1.00
Linze	0.81	0.88	0.91
Sunan	0.19	0.95	0.20
Jinta	0.29	0.55	0.51
Suzhou	0.38	0.42	0.87

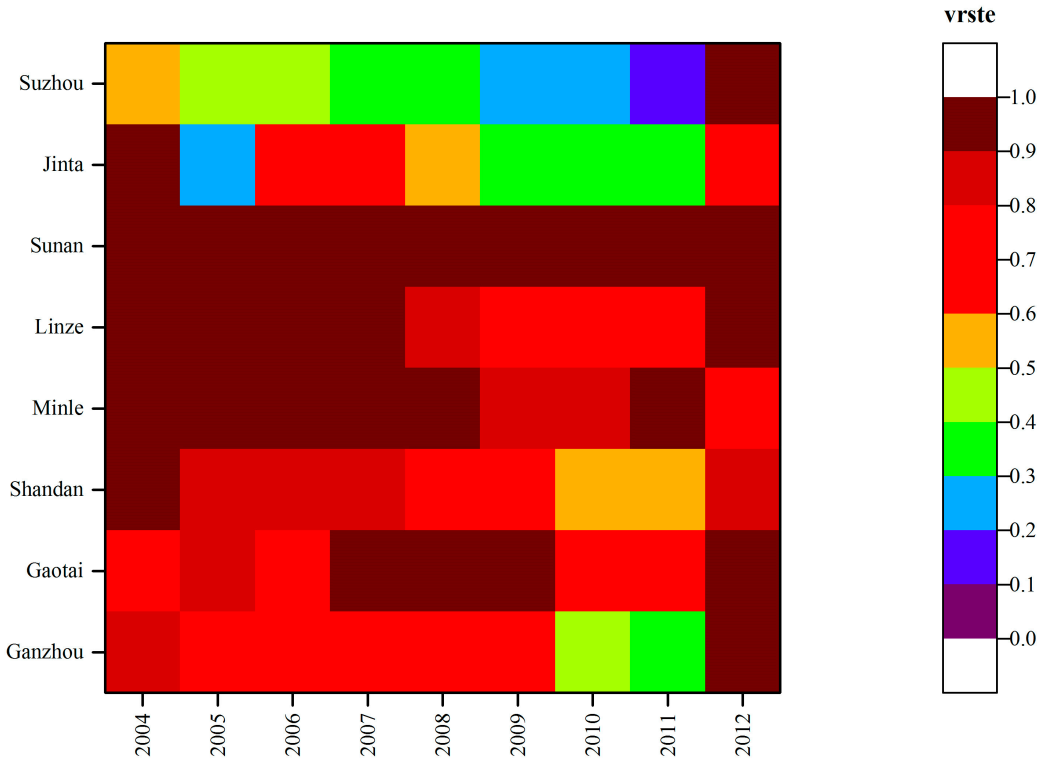
Note: TE means technical efficiency; PTE means pure technical efficiency.

Regarding county-scale time difference (Figure 3), in 2004, the technical efficiency of Shandan and Minle was located on the frontier, which is equal to 1 (Figure 3a); while the technical efficiency of Jinta was the lowest. The pure technical efficiencies of Shandan, Minle, Sunan, and Jinta were equal to 1 (Figure 3b). The scale efficiencies of Shandan and Minle were also equal to 1 (Figure 3c). By 2012, the technical efficiency of Minle was equal to 1, and the pure technical efficiencies of Ganzhou, Sunan and Suzhou were equal to 1. The scale efficiencies of Ganzhou, Shandan, Minle, Sunan and Suzhou were equal to 1. The main reason for the changes is that the various efficiencies measured by our approach represent a relatively comparative concept. Between 2004 and 2012, the agricultural production area of the Heihe River basin substantially increased. In particular, agricultural production land reclamation entered a period of rapid development. Thus, the scale efficiency has increased, especially beginning in 2012. In addition to the five counties above, scale efficiency of the other counties was above 0.91 (Figure 3c), indicating that the scale of efficiency to enhance the space was smaller. The technical efficiency of Minle was on the frontier. Since the 12th Five-year Plan, Minle has been committed to transforming traditional to modern agriculture, and its industrial structure improved considerably, leading to an intensive and professional mode of agricultural production and management. Because of improvement in organization and socialization, the agricultural water resource efficiency of Minle also increased.



(**a**)

Figure 3. *Cont.*



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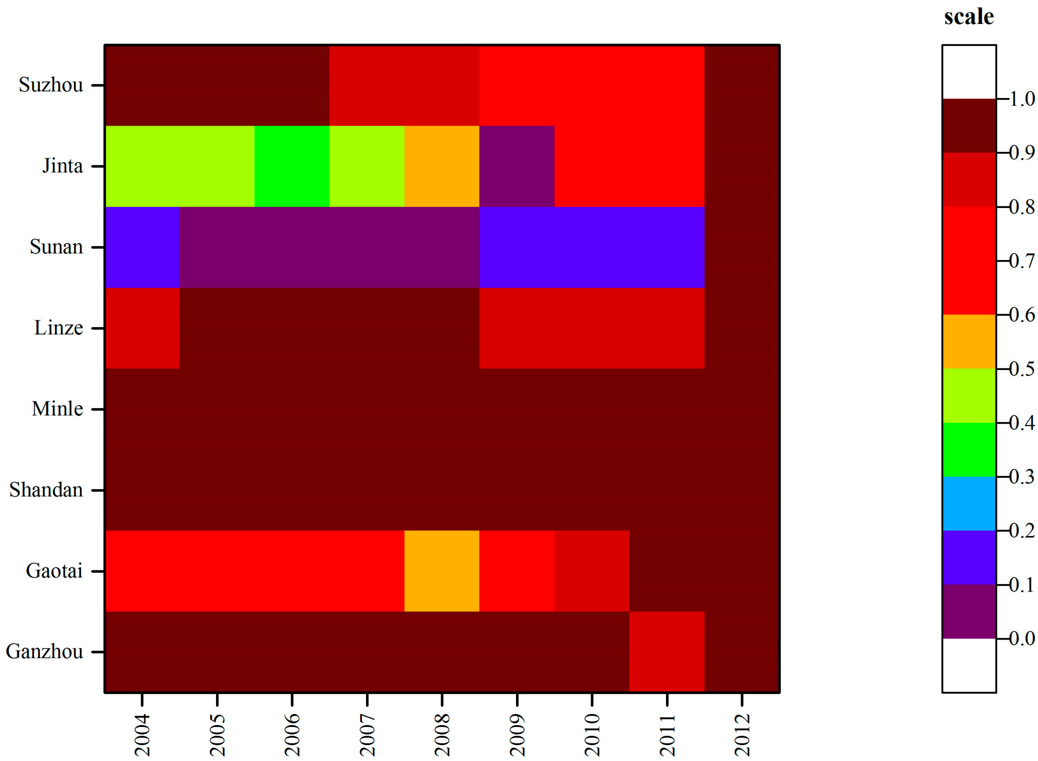

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Figure 3. Technical, pure technical, and scale efficiency in the Heihe agricultural area. (**a**) technical efficiency; (**b**) pure technical efficiency; (**c**) scale efficiency.

3.2. Agricultural Water Use Efficiency in the Second Stage

To establish the SFA equations, we used investment in fixed assets (Equation (1)), planting area (Equation (2)), agricultural labor force (Equation (3)), and agricultural water use (Equation (4)) as dependent variables; and local development, natural water endowment, and industrial structure as independent variables. To identify the effects clearly, we constructed 24 equations using progressive panel regression, and the equations according to 2012 data are listed in Table 4.

Table 4. Second stage: SFA analysis for 2012 data from the Heihe agricultural area.

Variables	Equation (1)	Equation (2)	Equation (3)	Equation (4)
Constant	24,490.60 *	0.30 *	2304.71 *	−1245.39 *
	(49,900.15)	(2.63)	(14,517.76)	(−3501.62)
local development	32.19 *	0.00 ***	8.01 ***	1.15 **
(Per capita GDP)	(6.2)	(0.00)	(1.80)	(0.44)
Water resources endowment	−93.49 *	0.02 **	57.07 *	30.41 ***
(Per capita water resources)	(110.92)	(0.01)	(32.27)	(7.78)
Industrial structure	−45,167.11 *	−2.52 *	−11,931.18 *	−4726.67 *
(The proportion of the primary industry)	(78,599.98)	(4.14)	(22,867.58)	(5515.56)
σ^2	1011.06	72.63	2216.43	128.94
γ	0.99	0.77	0.68	0.64

Figures in parentheses are standard deviations of corresponding coefficients; ***, ** and * represent 1%, 5% and 10% significance levels, respectively.

Results show that the *T*-value of the likelihood ratio of unilateral error is larger than the critical value of a mixed χ^2 distribution. Thus, the original hypothesis is rejected, indicating that the model is reasonable and suitable for regression analysis using SFA. Among them, if the value of $\gamma = \frac{\sigma_\mu^2}{\sigma_\mu^2+\sigma_v^2}$ in the variables is close to 1, the effect of inefficiency on the relaxation variable in the mixed error term is dominant, and the effect of random error on the relaxation variable is very small. In constructing the model, it is seen that input redundancy can be regarded as the opportunity cost of each region. A positive regression coefficient shows that the explanatory variable is positively correlated with the relaxation variable, indicating that an increase in the explanatory variable is not conducive to a decrease in redundancy variables. When the regression coefficient is negative, an increase of the explanatory variables reduces the relaxation variable. Thus, an increase in the explanatory variables improves the efficiency of agricultural water resource utilization.

The regression coefficient of local development for the four relaxation variables was negative throughout the significance testing. This was mainly because in more developed areas, other industries made up a larger proportion than agriculture, and the proportion of agriculture in industry was small. This caused a weak water resource scale effect.

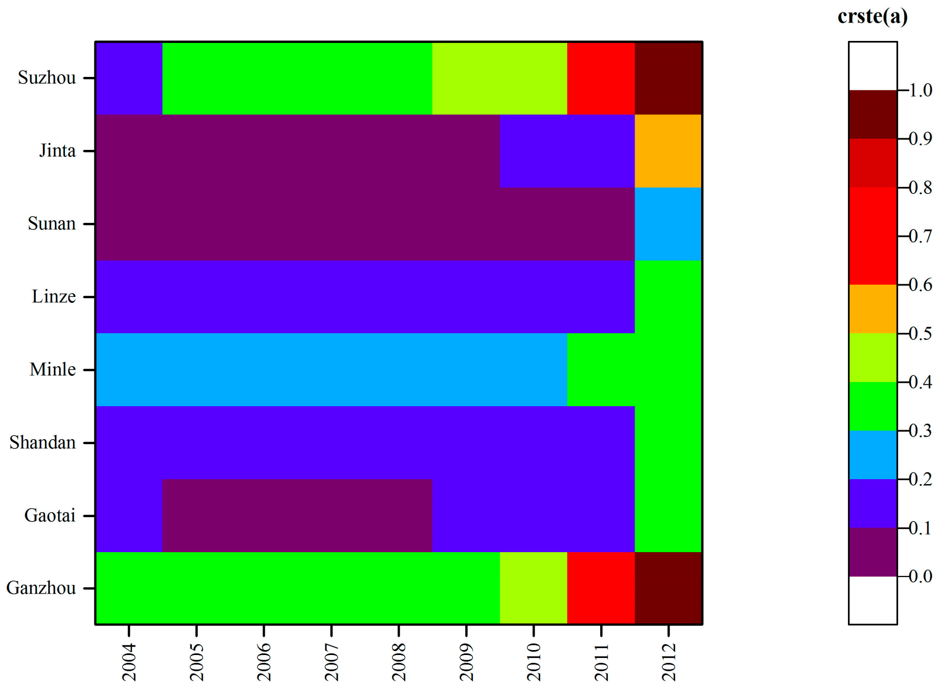
The regression coefficient of water resources endowment for the relaxation variable of fixed assets investment was negative throughout the significance testing. Water resources endowment had a positive effect on the other variables. This means that the increase of water resources endowment had a positive effect on the input to agricultural water resources, consistent with related research. In particular, the "resource curse" of certain scholars was strongly reflected.

The regression coefficient of the proportion of primary industry for the four relaxation variables was negative, meaning that the larger the proportion of primary industry, the stronger the scale effect. The increase in the proportion of primary industry generates more social capital to invest in primary industry, thereby improving water resource infrastructure and water resource efficiency.

3.3. Agricultural Water Use Efficiency in the Third Stage

After the adjustments, we used the same input–output variables as in the first stage, and the results show some differences. After adjustment (Figure 4), on average over the period 2004–2012, there were obvious differences in comprehensive efficiency across the areas. The technical efficiency (Figure 4a) of Ganzhou was maximal, with the mean equal to 0.45. The adjusted pure technical efficiencies of five counties were all above 0.91 (Figure 4b). The maximum scale efficiency was that of Ganzhou (Figure 4c).

Specifically, in 2012, the technical efficiency of Suzhou was the highest, reaching the frontier; i.e., an efficiency value = 1. The smallest technical efficiency value was that of Sunan. Compared with 2004, values for Sunan had not changed much overall, but its technical efficiency had clearly increased by a small amount. The pure technical efficiency of Sunan was >0.9 prior to 2012, and the scale efficiency difference was obvious, with an increase to 0.296 in 2012.



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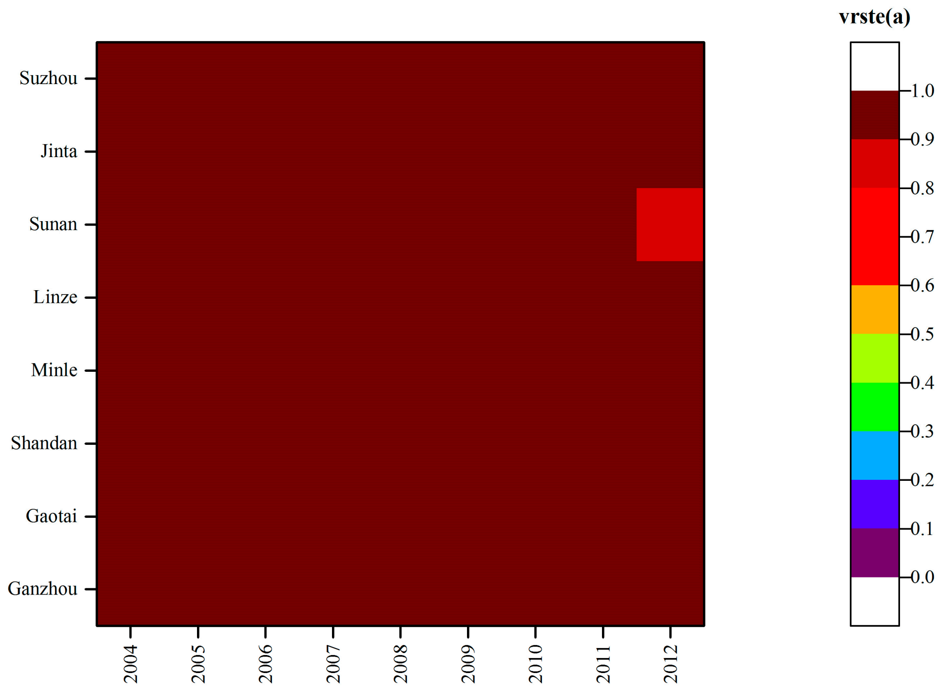

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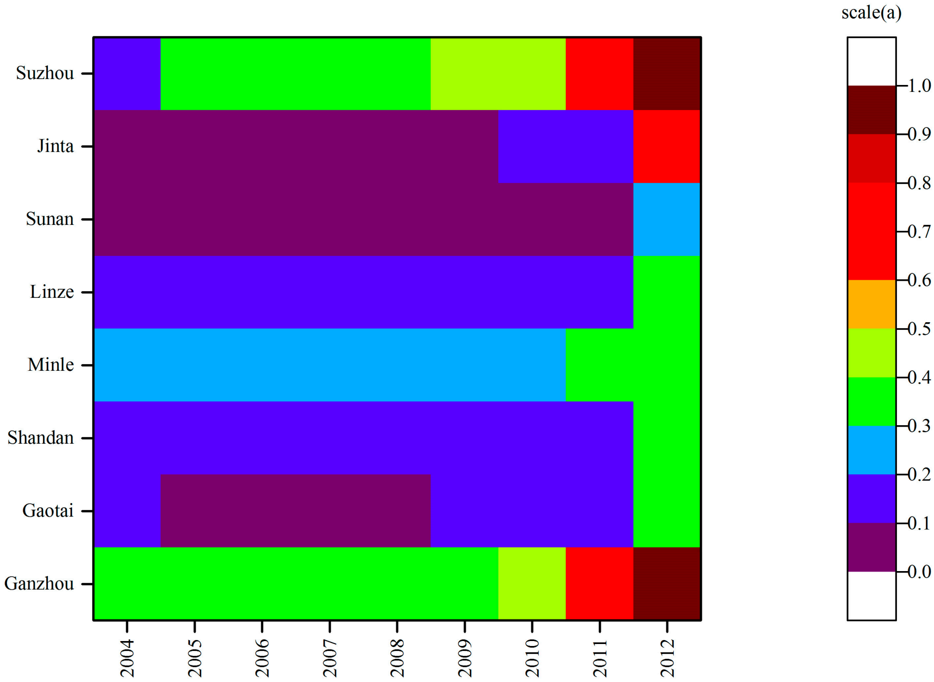


(**c**)

Figure 4. Adjusted technical, pure technical and scale efficiency in the Heihe agricultural area. (**a**) technical efficiency; (**b**) pure technical efficiency; (**c**) scale efficiency.

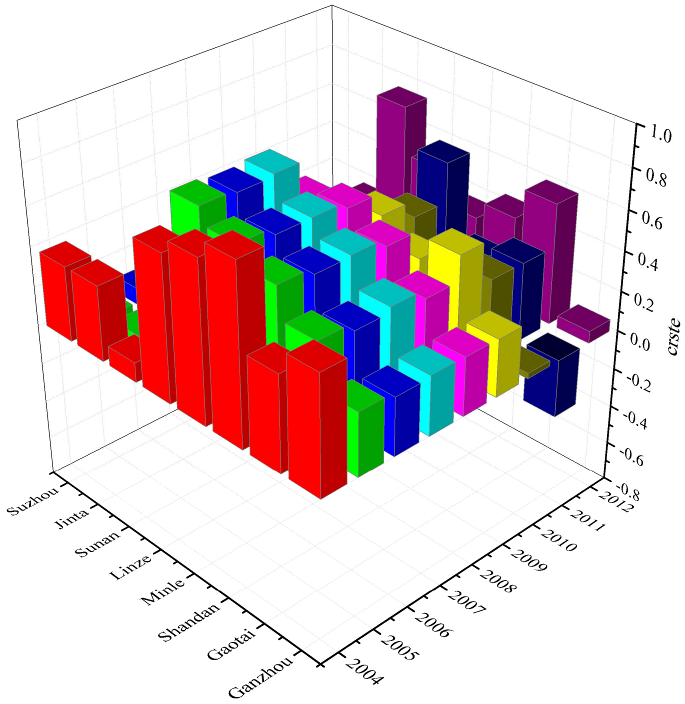
3.4. Agricultural Water Use Efficiency Change during 2004–2012

From a comprehensive viewpoint (Figure 5), technical efficiency of the counties declined significantly after eliminating the effects of environmental and stochastic factors. Regarding technical efficiency, the major change in performance was a declining trend (Figure 5a), in which Minle's efficiency decreased the most. According to the estimated result, in 2007, Minle's original and adjusted technical efficiency values had an obvious difference. As for Ganzhou in 2011, and Suzhou from 2007 to 2012, technical efficiency had an upward trend. In particular, for Suzhou, after elimination of the relevant effects of technical efficiency (Figure 5b), there was an upward trend over many years. For scale efficiency, in addition to Suzhou in 2011, the other counties had a downward trend (Figure 5c).

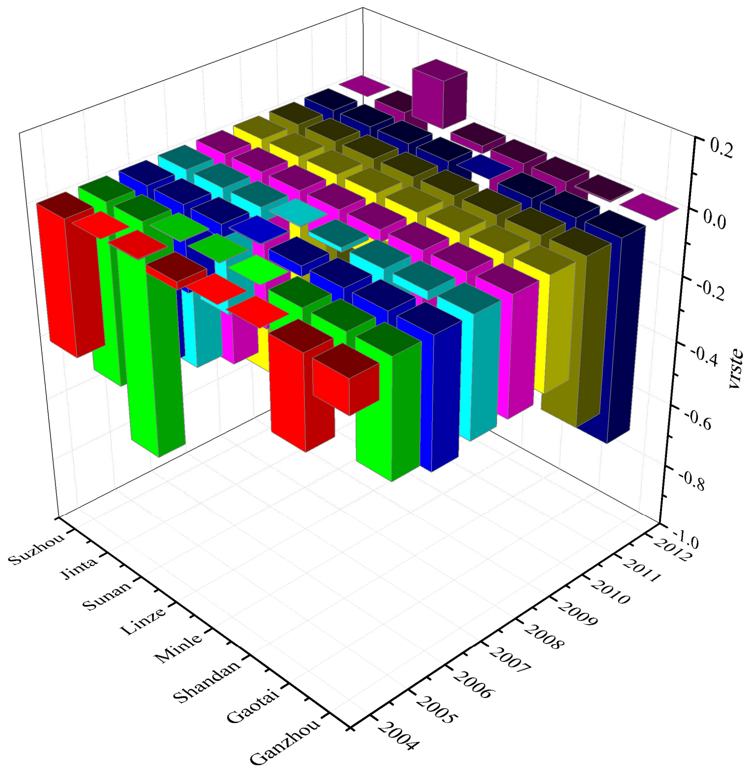
Thus, according to the study, the technical efficiency in the study is overestimated (except for the year of 2011). It is also evident that the pure technical efficiency is underestimated, as the PTE values in the study area are almost all above 0.85 (Figure 4b), thus meaning that the possibility for agricultural water conservation on the technical level is almost nil. The overestimation mainly comes from the scale efficiency, thus meaning that enlarging the scale could improve the technical efficiency; however, considering the water restriction, the area could not be too large.

To elucidate changes of different counties in detail, we took Ganzhou District as an example (Figure 6). Here, we could precisely see the difference before and after adjustment. It is seen that after adjustment of the technical and scale efficiencies of agricultural production, those efficiencies showed a declining trend, while the pure technical efficiency had an upward trend. In 2012, changes of scale efficiency led to all technical efficiency changes, i.e., in the first stage of the estimation, scale efficiency was overestimated. This means that the region's agricultural scale efficiency did not seriously affect agricultural water resources efficiency.

The changes in Ganzhou County vividly depict the changes overall. The technical efficiency is overestimated from 2004 to 2012, except in 2011; the difference in 2011 may be due to that year's drought. It is evident that the scale efficiency is overestimated in Ganzhou County.

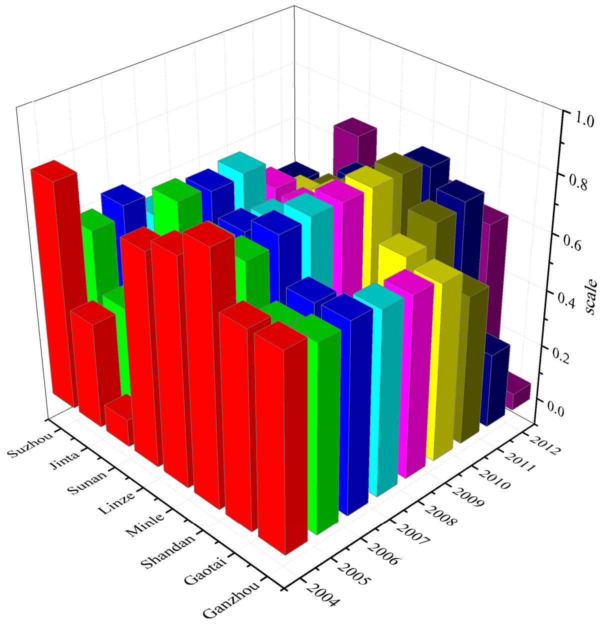


(**a**)



(**b**)

Figure 5. *Cont*.



(**c**)

Figure 5. Differences in technical efficiency in the Heihe agricultural area before and after adjustment. (**a**) technical efficiency; (**b**) pure technical efficiency; (**c**) scale efficiency.

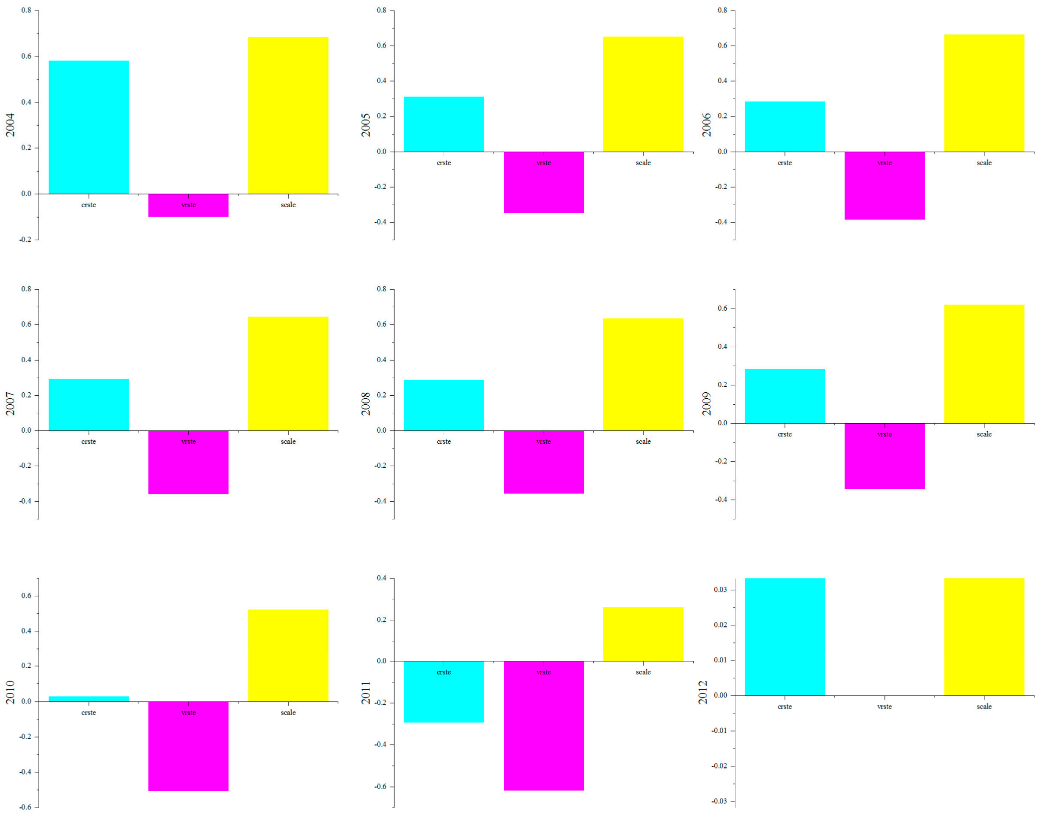


Figure 6. Difference in technical and scale efficiencies before and after adjustment in Ganzhou County.

4. Discussions and Conclusions

In this work, a three-stage DEA was used to analyze the efficiency of agricultural water resource utilization in the Heihe agricultural production area over the period 2004–2012. As a result of regional analysis, after exclusion of external environmental and random factors, regional agricultural water efficiency underwent great changes. Comprehensive technical efficiency and scale efficiency mainly manifested as overestimated trends, and pure technical efficiency had an underestimated trend. Therefore, the three-stage DEA could produce a better description of WUE in the Heihe agricultural production area. Based on the above conclusions, technology is not the main factor restricting the improvement of agricultural water resource efficiency in the region; the main restriction on the efficiency of agricultural water resources is the scale factor.

A favorable scale of agriculture has always been a focus of research, especially the resource-saving effect of operation at scale. There is serious water wastage in irrigation areas of China, and the ecological environment of general irrigation areas is relatively fragile. A reasonable irrigation scale will greatly improve the efficiency of agricultural water resources. Improvement in water efficiency of traditional agriculture is more focused on technical improvements, and studies have shown that the possibility for agricultural water conservation on the technical level is almost nil.

Comparing the water-related efficiency with findings from other studies, this paper solved the water-related questions in study areas, as this method has the advantage of being able to precisely calculate local water issues by using data from surveys or government collection. In this way, it will play a vital role in addressing these problems. Furthermore, this method could be used to calculate the national WUE in the near future. This method could calculate the economic performance of agricultural water use in a limited data situation, especially at the county level. The water use efficiency calculation is of vital importance to China, especially at the county level. In China, there are more than 1000 counties, encompassing 459 irrigated areas with different levels of irrigation technique. Improving water use efficiency is a very complex system task; the government aims to improve irrigation techniques, which may be important in some areas. However, using only this method could not truly save on water usage; we should convert our water saving method to water control rather that water resource control.

In the present work, owing to limitations of data acquisition, the change in regional agricultural water resource efficiency was studied for the period 2004–2012 only. In the future, input–output indicators will be an important component of the DEA model. Moreover, this paper focused on determining water use-related efficiency in this area at the county level only. At farmer-level production, the problem of not being able to manage water use efficiency—possibly due to illness—may also be encountered. If agricultural water use efficiency is calculated using only the economic model, it could not reflect this small-scale situation.

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