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RESEARCH ARTICLE

A data envelopment analysis of agricultural technical efficiency of Northwest Arid Areas in China

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Abstract Severe resource shortage and waste of resource in agricultural production make it necessary to assess efficiency to increase productivity with high efficiency and ensure sustainable agricultural development. This paper adopted an input-oriented data envelopment analysis (DEA) method with the assumption of variable returns to scale to evaluate agricultural production efficiency of 100 major irrigation districts in Northwest China in 2010. Major findings of this paper were as follows: firstly, the average value of total technical efficiency, pure technical efficiency and scale efficiency of those irrigation districts in Northwest China were 0.770, 0.825 and 0.931, respectively; secondly, 30% of irrigation districts were technically efficient, while 42% and 32% of them showed pure technical and scale efficiency respectively. Among inefficient decision-making units, total technical efficiency score varied from 0.313 to 0.966, showing significant geographical differences, but geographical differences of pure technical efficiency was more consistent with that of total technical efficiency; thirdly, input redundancy was evident. Inputs of agricultural population, irrigation area, green water, blue water, consumption of fertilizer and agricultural machinery could be reduced by 34.88%, 40.19%, 43.85%, 47.10%, 41.53% and 42.21% respectively without reducing agricultural outputs. Furthermore, irrigation area, green water and blue water had relatively high slack movement though Northwest China which is short of water resources. Based on these results, this paper drew the following conclusions: First, there is huge potential for Northwest China to improve its agricultural production efficiency, and agro-technology not input scale had greater influence on improvement. Second, farmers needed proper guidance in order to reduce agricultural inputs and it is time to centralize agricultural management for overall agricultural inputs regulation and control.

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1 Introduction

With only 7% of global arable land and 6% of global water resources to feed 22% of the global population, food security has always been being a real challenge for China[1,2]. Dating back to the 1990s, Brown questioned the capacity of China to feed itself[3]; expressing the same concern, the International Institute for Applied Systems Analysis (IIASA) also voiced the question, 'Can China feed itself?'[4]. Nowadays, due to urban expansion[5], climate change[6,7] and environmental pollution[8], increasingly resources are becoming unavailable for agricultural production[9]. Yan et al. suggested that one percent urban population rise will lead to nearly 0.5% agricultural water use decrease[10]. Secondly, although food production capacity has generally improved over the past few decades, the growth rate in food demand out-weights that in food supply[11]. It is claimed that the rate of food demand is 1.3 times higher than growth in supply. It is estimated that food supply needs to increase by 30% by 2030 to meet the demand from the growing population in China[12,13]. Therefore, agricultural production faces many pressures: intrinsically finite natural resources[14], shrinking provision of natural resource[15] and increasing demand[16].

Under these circumstances, the question of how to increase food production with current resources levels becomes the key challenge to ensure food security[17,18]. Since food security is closely related to resource security, it has been universally agreed among researchers that resource productivity and efficiency should be improved so as to guarantee food production[19,20], which means to produce considerably more grain with unit input of resource. In terms of agricultural production, land and water resource are the factors that can most directly influence agricultural development[21,22]. Unsurprisingly, land use efficiency[23,24], water productivity[25–27] and the effect they have on grain yield[28] have been investigated extensively.

However, water and land are not the only factors that influence agricultural productivity[29]. In addition to these, fertilizers, pesticides, agricultural technology and agronomic management are increasingly important in raising grain yield and facilitating the improvement of agricultural productivity[30]. However, researchers claimed that overuse of fertilizers and pesticides is much too common, leading to serious environmental pollution and high risks in food security[31]. Shen et al. reported that from 1980 to 2010, cereal grain yields only increased by 65% whereas chemical fertilizer consumption increased by 512%[32]. Thus, environment and food quality have been threatened because of overuse of fertilizers[8]. Le et al. argued that eutrophication has been triggered by excessive and unbalanced use of nutrient resources and soil erosion has become increasingly serious because of overuse of irrigation water[33]. There is no doubt that at present growth of agricultural output is mainly driven by increased inputs. However, it is obvious that input-driven agriculture is inappropriate and unsustainable in the long-term. Excessive inputs in agricultural production not only hold back improvement of agricultural productivity but also result in environmental pollution. Being aware of this issue, researchers have begun to pay more attention to improving total factor efficiency in agricultural production, hoping to change the agricultural production model from input-driven to precision agriculture, which means developing a model for agriculture with both high productivity and high efficiency[32].

Methods and publications about agricultural efficiency assessment can be divided into two categories: partial measures of productivity and analysis of total factor productivity. In the former, the efficiency of water[7,27,28], land[34,35], fertilizer[36], machinery and labor[37] has been studied. Although partial measure of productivity works well in evaluating efficiency of a single factor, results can be misleading for overall productivity[38]. In the latter, stochastic productivity frontier (SPF) and data envelopment analysis (DEA) are the most common methods used to measure efficiency in agriculture. For example, Hu and McAleer estimated Chinese agriculture production efficiency with panel data from 1991 to 1997[39]. However, it was realized that provincial level estimates were too unreliable and did not adequately reflect geographical heterogeneity. So researchers such as Chen et al. started to analyze agricultural production efficiency and technology gap in China based on county-level data[40] with the method of meta-frontier. Recently, scientists have begun to measure both spatial and temporal differences in agricultural production efficiency in China. Li and Zhang analyzed factors influencing agricultural productivity, agricultural total factor productivity (TFP) growth and the gap between regions with provincial data from 1985 to 2010[41]. Li et al. used DEA to measure agricultural production efficiency in Hebei Province based on a survey of 99 household farms in Hebei Province in 2010[42]. Liu et al. measured agricultural efficiency in Hetao irrigation district from 2000 to 2008 at county-level using the DEA method[43].

In summary, assessment of agricultural productivity has mainly focused on China as a whole or a single province, but analysis of representative areas is still lacking. Kang et al. reported that irrigated land produced 40% of the total grain output with only 20% of total land acreage[13], which showed the importance of irrigated districts in ensuring China's food security. Therefore, this study focused on major irrigation districts of arid areas in Northwest China, the most arid areas in China. Initially, we used the DEA method to measure total technical efficiency, pure technical efficiency and scale efficiency in every irrigation district. Then we analyzed input redundancy of inefficient irrigation districts, including radial movement and slack movement. Our purpose was to address the following issues: First, the significance of geographical differences of agricultural production efficiency in the arid region. Second, the potential opportunity for the reduction in inputs. Our ultimate aim is to provide suggestions for policy makers and farmers, and advice on agricultural activities in this region so that agricultural production can continue to be improved.

2 Materials and methods

2.1 Study area and data

The most arid areas of China are in Northwest from 31°33′ to 49°11′ N, 73°28′ to 119°54′ E, including Gansu, Ningxia, Qinghai, Xinjiang, the Guanzhong Plain, Northern Shaanxi and the Inner Mongolian Plateau, and cover a total area of 3.74×10^6 km^2, accounting for 39% of the country[44]. Also, the area is an important grain reservoir. In 2010, it yielded about 10% of the national grain production from 13% of the grain acreage using 10% of the nation's irrigation water.

However, usage of agriculture inputs in this region is less efficient than the average level for China. For example, water productivity in this area is less than 1 kg·m^{-3}, which is much lower than the national average of about 1.6 kg·m^{-3}, indicating that there is considerable opportunity to increase agricultural production efficiency in this region. Furthermore, we believe that improvement in agricultural production efficiency will benefit not only agricultural production but also the ecological environment in this region. In this paper, a hundred irrigation districts were selected among all those arid areas. Their distributions in each area are shown in Fig. 1. The number of irrigation districts in Inner Mongolia, Gansu, Ningxia, Qinghai, Shaanxi and Xinjiang was 6, 19, 2, 13, 11 and 49, respectively.

Six input and two output factors were chosen from available published data. The inputs used were agricultural population (AP, 10^4 persons), irrigated area (IA, 10^3 hm^2), green water (GW, 10^8 m^3), blue water, i.e., irrigation water, (BW, 10^8 m^3), chemical fertilizer (CF, t) and agricultural machinery (AM, 10^4 kw). The outputs used were: agricultural value (AV, 10^8 CNY) and grain output (GO, 10^4 t). AP, IA, BW, AV, GO were provided by China Irrigation and Drainage Development Center. CF and AM were taken from the Statistical Year Book 2011. GW was calculated as effective precipitation multiplied by the growing area. For each irrigation district, effective precipitation was calculated with the formula recommended by USDA soil conservation service (Eq. (1)).

$$P_e = \begin{cases} \dfrac{P(4.17-0.02P)}{4.17} & P < 83 \\ 41.7 + 0.1P & P \geqslant 83 \end{cases} \tag{1}$$

where P_e and P are the 10-day effective precipitation and precipitation, respectively, in mililiter. Table 1 lists the statistical characteristic of inputs and outputs.

2.2 Technical efficiency assessment

Production departments always want to produce as many outputs as possible with given inputs or reduce inputs under current outputs level. When actual inputs are beyond minimum inputs or actual outputs do not equal "target" outputs, a firm will be affirmed as technically inefficient. Corresponding to the above two measures, technical efficiency assessment can be input-oriented or output-oriented. When it is input-oriented, technical efficiency can be measured as the ratio of the minimum inputs with actual inputs under current level of outputs. When it is output-oriented, technical efficiency can be measured as the ratio of actual outputs with "target" outputs without increasing inputs.

When there is only a single input x and single output y, as shown in Fig. 2, the curve OF′ is the production frontier, which reflects the relationship between inputs and outputs. Firms B and C locate at the production frontier. They reflect the current technological level of firms B and C and represent the maximum output under current inputs. These firms are technically efficient. In contrast, firm A is off the production frontier. Without increasing any input, its output could be increased to B. Thus we know firm A is technically inefficient. Based on the aforementioned definition, with input-oriented perspective, for firm A, its technical efficiency equals CC′/AC′; with output-oriented perspective, its technical efficiency equals AA′/BA′.

Besides lack of advanced technology, due to scale inefficiency, firms may also not be at the optimal production scale, which leads to relatively low total technical efficiency (TTE). There are three kinds of production scales: Increase Return to Scale (IRS), Decrease Return to Scale (DRS) and Constant Return to Scale (CRS). When firms operate at IRS, it means that when inputs increase by k times, outputs would increase by more than k times. Then firms can enlarge their production

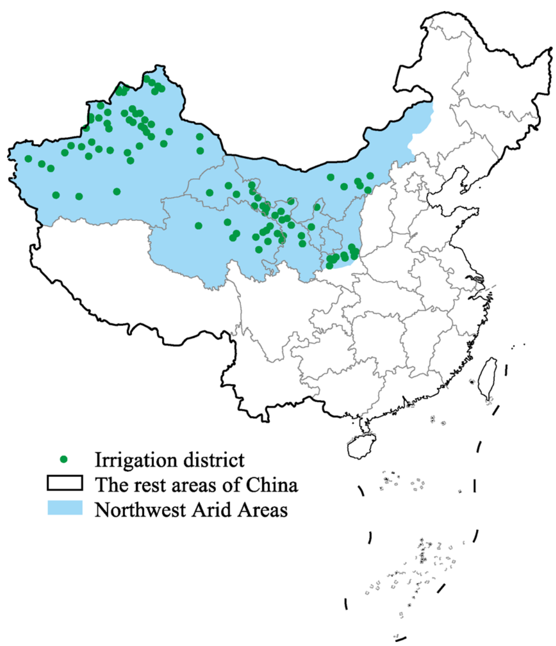

Fig. 1 Provisional distribution of irrigation districts in Northwest Arid Areas in China

Table 1 Statistical characteristic of inputs and outputs

Item	AP	IA	GW	BW	CF	AM	AV	GO
Min	0.59	0.15	0.01	0.03	670.44	1.09	0.06	0.01
Max	262.75	57.33	10.47	51.43	586425.04	362.24	93.25	240.45
Mean	22.78	5.41	1.01	4.42	51549.67	27.93	12.43	19.71
SD	39.24	8.08	1.60	8.00	91880.34	46.61	18.41	37.73
C.V.	1.72	1.49	1.58	1.81	1.78	1.67	1.48	1.91

Note: "AP" represents agricultural population, 10^4; "IA" represents irrigated area, 10^3 hm^2; "GW" represents green water, 10^8 m^3; "BW" represents blue water, 10^8 m^3; "CF" represents chemical fertilizer, t; "AM" represents agricultural machinery, 10^4 kw; "AV" represents agricultural value, 10^8 CNY; "GO" represents grain output, 10^4 t.

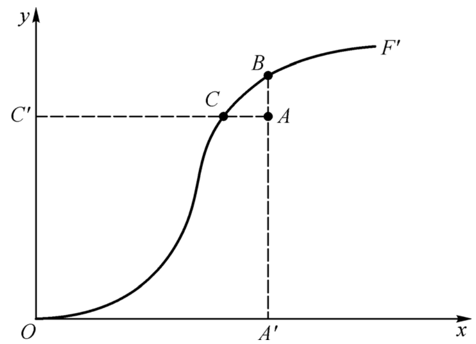

Fig. 2 Production frontier and technical efficiency

scale to improve scale efficiency (SE), thus improving TTE; when firms locate at DRS, it means that when inputs increase by k times, outputs would increase by less than k times. Then firms should shrink their production scale to improve SE, thus improving TTE; when firms locate at CRS, it means that when inputs increase by k times, outputs would also increase by k times. Then firms can just remain at the current production scale. If k is larger than 1, the equations can be expressed as Eq. (2).

$$\begin{aligned} f(k\boldsymbol{x}) &< kf(\boldsymbol{x}) \Leftrightarrow \text{IRS} \\ f(k\boldsymbol{x}) &> kf(\boldsymbol{x}) \Leftrightarrow \text{DRS} \\ f(k\boldsymbol{x}) &= kf(\boldsymbol{x}) \Leftrightarrow \text{CRS} \end{aligned} \tag{2}$$

2.3 Input-oriented DEA models

DEA is very widely used in technical efficiency assessment. It is a non-parameter method, using linear programming to construct a piece-wise frontier that envelops observations of all firms, that is, all decision making units (DMUs)[41,45,46], then calculating technical efficiency of every DMU according to the frontier. As mentioned in 2.2, efficiency assessment could be input-oriented or output-oriented. Given that it is difficult for farmers to control outputs in contrast, they can easily control the amount and combination of inputs. Therefore, this paper adopted input-oriented DEA method to measure technical efficiency of 100 major irrigation districts in Northwest China. As mentioned in 2.2, production scale of a firm can be at IRS, DRS or CRS. However, without scale efficiency assessment, it is difficult to figure out which scale status a firm is locating at. For DEA method, at first it assumes that all firms are at the optimal production scale, which means they are at CRS. With CRS DEA method, total technical efficiency (TTE) can be measured. Obviously, CRS DEA method could not tell whether it is technology or production scale that has negative influence on TTE. Then VRS DEA method was introduced, which takes production scale variability into account. With VRS DEA method, pure technical efficiency (PTE) could be measured. Only when a firm is really scale efficient, TTE equals to PTE. Otherwise, TTE < PTE, and scale efficiency (SE) equals to TTE/PTE. This paper wants to know exactly what the factor is, technology or production scale, that leads to relative low total technical efficiency of irrigation districts in Northwest China. Therefore, the paper used both CRS DEA and VRS DEA methods to assess technical efficiency. The linear programming equations and computer software used to solve those equations are described in the following section.

To explain the DEA method with equations, this paper first defined some parameters. The number of decision making units (DMUs) was defined as I (here, $I = 100$). For every DMU, there are N inputs (here, $N = 6$) and M outputs (here, $M = 2$), as listed in Table 1. For *i-th* DMU, the column vectors $\boldsymbol{x}_i$ and $\boldsymbol{q}_i$ represent its inputs and outputs, respectively. Then, for the total I DMUs, there is an $N \times I$ input matrix, $\boldsymbol{X}$, and $M \times I$ output matrix, $\boldsymbol{Q}$. Then the technical efficiency with CRS DEA model could be measured as in the following linear programming:

$$\begin{aligned} &\max_{v',v}(\boldsymbol{u}'\boldsymbol{q}_i/\boldsymbol{v}'\mathbf{x}_i) \\ &st \quad \boldsymbol{u}'\boldsymbol{q}_i/\boldsymbol{v}'\boldsymbol{x}_i \leqslant 1, \quad i = 1, 2, ..., I \\ &\quad \boldsymbol{u},\ \boldsymbol{v} \geqslant \boldsymbol{0} \end{aligned} \tag{3}$$

where $\boldsymbol{u}$ represents output weight vector $M \times 1$; $\boldsymbol{v}$ represents input weight vector $N \times 1$. For Eq. (3), there are infinite results. To solve this problem, constraint $\boldsymbol{v}'\boldsymbol{x}_i = 1$ was added to Eq. (3). Then the linear programming could be expressed as Eq. (4),

$$\begin{aligned} & \max_{\boldsymbol{u},\boldsymbol{v}}(\boldsymbol{\mu}'\boldsymbol{q}_i) \\ & st \quad \boldsymbol{v}'\boldsymbol{x}_i = 1 \\ & \quad \boldsymbol{\mu}'\boldsymbol{q}_i - \boldsymbol{v}'\boldsymbol{x}_i \leqslant 0, \quad i = 1, 2, ..., I \\ & \quad \boldsymbol{\mu}\ , \boldsymbol{v} \geqslant \boldsymbol{0} \end{aligned} \tag{4}$$

In Eq. (4), we use $\boldsymbol{\mu}$ instead of $\boldsymbol{u}$ to indicate that the linear programming is different. According to duality of linear programming, Eq. (4) could be expressed as Eq. (5):

$$\begin{aligned} & \min_{\theta,\lambda}\ \theta_i \\ & st \quad -\boldsymbol{q}_i + \boldsymbol{Q\lambda} \geqslant \boldsymbol{0} \quad i = 1, 2, ..., I \\ & \quad \theta\boldsymbol{x}_i - \boldsymbol{X\lambda} \geqslant 0 \\ & \quad \boldsymbol{\lambda} \geqslant 0 \end{aligned} \tag{5}$$

where θ is a scalar and $\boldsymbol{\lambda}$ is an $I \times 1$ vector of constants. By solving Eq. (5) I times, the efficiency value, θ, of each firm can be obtained and it satisfies $\theta \leqslant 1$. If θ equals one, it indicates that the DMU is a technically efficient irrigation district. Otherwise, it means the DMU is technically inefficient. If the efficiency value θ in a certain irrigation district equals 1, this means that the DMU is a best practice area and can serve as a benchmark for irrigation districts whose θ is lower than 1.

Via Eq. (5) total technical efficiency (TTE) can be measured. To calculate pure technical efficiency (PTE), the convexity constraint $I1'\boldsymbol{\lambda} = 1$ is added to Eq. (5), as shown in Eq. (6), that is, VRS DEA method.

$$\begin{aligned} & \min_{\theta,\lambda}\ \theta_i \\ & st \quad -\boldsymbol{q}_i + \boldsymbol{Q\lambda} \geqslant \boldsymbol{0} \\ & \quad \theta\boldsymbol{x}_i - \boldsymbol{X\lambda} \geqslant \boldsymbol{0} \quad i = 1, 2, ..., I \\ & \quad \boldsymbol{I}'\boldsymbol{\lambda} = 1 \\ & \quad \boldsymbol{\lambda} \geqslant \boldsymbol{0} \end{aligned} \tag{6}$$

where $\boldsymbol{I1}'$ is a vector whose elements all equal to 1, thus the TTE score obtained by the CRS DEA method is decomposed into two components, PTE score obtained by VRS DEA method and SE. The relationship between them is that TTE = PTE × SE.

2.4 Radial redundancy and slack redundancy

Technically inefficient DMUs have input redundancy or they do not achieve their "target" outputs. With the input-oriented DEA method, input redundancy is measured. Corresponding to pure technical inefficiency and scale inefficiency, input redundancy could be decomposed into radial redundancy and slack redundancy. Radial redundancy means the quantities of inputs which a certain DMU could reduce in accordance with the same proportion[47]. For pure technically inefficient DMUs, all inputs have radial redundancy. Slack redundancy is different from radial redundancy and indicates decrements for individual inputs of a certain DMU.

In this research, each irrigation district is a DMU and there are 100 DMUs in total. For each DMU, based on the chosen inputs and outputs, linear programming can be done according to Eqs. (3)–(6). By solving linear programming, TTE, PTE and SE for each DMU could be measured. Meanwhile, the input redundancy of the technically inefficient DMUs can be obtained by solving the linear programming.

A great deal of computing software has been generated to aid the application of the DEA method. DEAP 2.1 is one of them that has been widely used. To operate DEAP 2.1, input factors and output factors need to be edited correctly in an EXCEL file then saved as a TXT file. Secondly, the scale assumption, VRS or CRS, and the pattern, input-oriented or output-oriented need to be set. Also parameters such as the number of DMUs, input factors and output factors need to be offered. When DEAP 2.1 is operated, the embedded programs can be called and equations can be calculated. TTE, PTE, SE score and input redundancy are revealed in the outputs of DEAP 2.1. For this paper, as in 2.3, the number of DMUs is 100 and there are two kinds (AV and GO) of output factors and six kinds (AP, IA, GW, BW, CF and AM) of input factors for each DMU. In summary, 200 output data and 600 input data, were filed appropriately in a TXT file before operating DEAP 2.1. Then with given parameters, DEAP 2.1 could be operated and results analyzed based on the outputs of DEAP 2.1, which is showed in results.

3 Results

3.1 Total technical efficiency

Results showed that of the 100 DMUs, 30 (30% of the total) were overall technically efficient with TTE score equal to one. The agricultural production of these units was relatively efficient and they were benchmarks for the technically inefficient DMUs. Figure 3 shows the TTE score of every irrigation district. The average TTE score in Northwest China was 0.770, suggesting that this area could produce the same output with a 23% reduction in inputs. In general, the TTE score in Ningxia (0.981) was the highest, while that of Xinjiang (0.725) was the lowest. Partially, these results might be influenced by the number of irrigation districts because their provincial distributions were not even. But most likely, it is because the irrigation districts in Ningxia were along the Yellow River and the government's investment in improving its infrastructure and training professional farmers has been greater. Consequently, high-level agricultural management in this area contributed to its high agricultural technical efficiency. These objective and subjective factors do not compromise the pragmatic value of this study. TTE scores for Shaanxi and Inner Mongolia were 0.868 and 0.802, respectively. These results were not unexpected because irrigated districts in Shaanxi Province were mainly located on the Guanzhong Plain where agricultural management and technology were relatively advanced. The TTE scores of Gansu and Qinghai Provinces were 0.786 and 0.783, respectively.

As shown in Table 2, the proportion of inefficient DMUs over total DMUs in Qinghai, Ningxia and Shaanxi was around 50%, and the proportion of inefficient DMUs in the other three areas was over 66%. For those inefficient DMUs, TTE scores varied from 0.313 to 0.966, showing great geographical difference.

With this method of input-oriented DEA, the inefficient DMUs indicate that it would be possible to reduce inputs while maintaining the current output level. However, how much effort would be required to improve the TTE score depends on the current efficiency level, local resource endowment and resource allocation. It may be somewhat challenging for DMUs with relatively high TTE scores to step to another level. Therefore, for this paper, inefficient DMUs were grouped by TTE score and shown as percentages in Table 3, so that suggestions could be made according to the common characteristics of DMUs in each group. Generally speaking, the results were consistent with the data showed in Table 2, in that the distribution of TTE score between the groups was uneven. It was obvious that, except for Ningxia, the proportion of inefficient DMUs, whose TTE score was below 0.600, was high among local inefficient DMUs, especially in Qinghai (100%) and Xinjiang (50%). For Northwest China as a whole, the proportion was 46%. For DMUs with relative high TTE scores, it could be challenging to improve efficiency. However, for DMUs below 0.600, increasing the TTE score to 0.600 maintaining the current level of agricultural production would provide a great saving of resources, indicating that in Northwest China there is still considerable opportunity to improve agricultural production.

3.2 Pure technical efficiency and scale efficiency

Pure technical efficiency (PTE) reflects whether the potential technology for production was fully developed or not. Scale efficiency measures whether production scale and input allocations were reasonable. Apart from the 30 efficient DMUs, there were another 12 DMUs (42 DMUs in total) with PTE score equal to one and two additional DMUs (32 DMUs in total) with SE scores equal to one. Average PTE score and SE scores in Northwest China were 0.825 and 0.931, respectively.

Figure 4 shows PTE and SE scores for each DMU. PTE scores varied from 0.369 to 0.998 and among the 58 pure technically inefficient DMUs the proportion of DMUs with PTE score higher than 0.600 was 67%. The difference in PTE score among DMUs was also significant. For the 68 scale inefficient DMUs, SE score varied from 0.395 to 0.999, with the lowest SE score in Qinghai, 97% of DMUs with SE scores were above 0.6. Also, the percentage of DMUs with an inefficient scale but with an SE score higher than 0.8 was 81% of total scale inefficiency DMUs, meaning that though 68 of 100 DMUs were inefficient in scale, their SE scores were still relatively high and most SE scores were clustered in high value groups. This means in

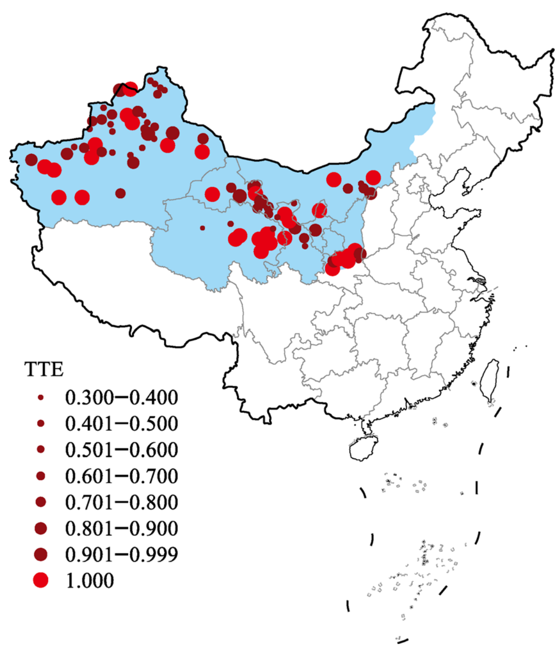

Fig. 3 Total technical efficiency for agricultural production of 100 irrigation districts in Northwest Arid Areas in China, 2010

Table 2 Statistical characteristic of total technical efficiency score for inefficient DMUs of Northwest Arid Areas in China in 2010

Area	%	Min	Max	Mean	Std. v
Inner Mongolia	66.66	0.478	0.830	0.703	0.157
Gansu	78.95	0.436	0.966	0.729	0.180
Ningxia	50.00	0.961	0.961	0.961	0.000
Qinghai	46.15	0.394	0.595	0.530	0.078
Shaanxi	54.55	0.424	0.951	0.757	0.211
Xinjiang	77.55	0.313	0.958	0.646	0.175
Northwest China	70.00	0.313	0.966	0.671	0.058

Table 3 Inefficient DMUs (%) grouped by total technical efficiency in Northwest Arid Areas in China in 2010

Area	Number	Proportion of DMUs in each group/%						
		0.9–1.0	0.8–0.9	0.7–0.8	0.6–0.7	0.5–0.6	0.4–0.5	0.3–0.4
Inner Mongolia	4	–	25	50	–	–	25	–
Gansu	15	33	–	20	20	13	13	–
Ningxia	1	100	–	–	–	–	–	–
Qinghai	6	–	–	–	–	66	17	17
Shaanxi	6	33	33	–	–	17	17	–
Xinjiang	38	8	13	18	11	34	8	8
Northwest China	70	16	11	17	10	29	11	6

Note: – indicates no inefficient DMUs in the group.

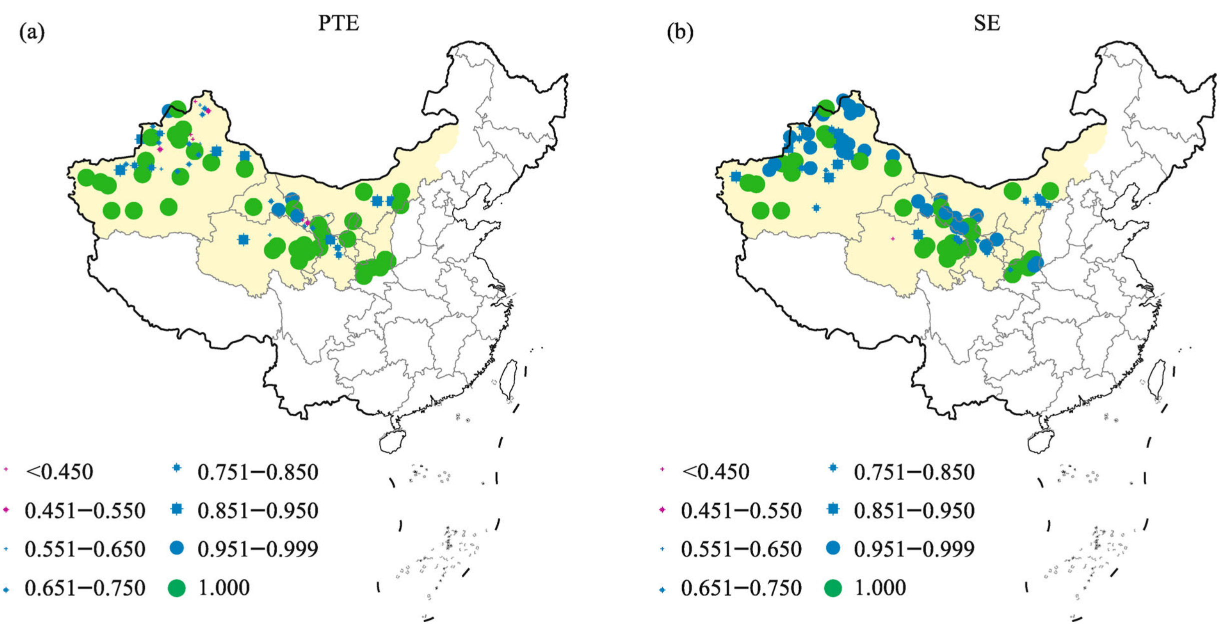

Fig. 4 Pure technical efficiency (PTE) and scale efficiency (SE) of 100 irrigation districts of Northwest Arid Areas in China in 2010

most arid areas in Northwest China, scale efficiency was not as acute a problem as total technical efficiency or pure technical efficiency was. Therefore, it was agricultural technology not production scale that was likely to be responsible for the low value of TTE for most irrigation districts. This paper drew a conclusion that agro-technique must be made full use of in order to improve efficiency, especially for those areas with high scale efficiency and low total technical efficiency. Certainly, for DMUs whose PTE score equal to one, the only way to improve their agricultural technical efficiency would be to adjust their production scale.

Generally, it is considered that intensive production would be more efficient than decentralized production. For example, Wan and Cheng found that simply by eliminating land fragmentation, the grain production of China would rise by 71.4 Mt[48]. Thus, this paper calculated both area-weighted average value and arithmetic average value for TTE, PTE and SE to assess if larger irrigation districts would have a relatively higher efficiency value. The formulas were shown as Eq. (7) and Eq. (8), respectively.

$$\mathrm{TTE}_j^{\prime}=\frac{\sum \mathrm{TTE}_i \times \mathrm{IA}_i}{\sum \mathrm{IA}_i} \tag{7}$$

where $\mathrm{TTE}_j{}'$ is the area-weighted average value of TTE for *j-th* province; TTE_i is the original TTE calculated by DEAP 2.1 for *i-th* DMU in *j-th* province, IA_i is the irrigated areas of *i-th* DMU in *j-th* province. Similarly, PTE′and SE′ can also be calculated.

$$\mathrm{ATTE}_j=\frac{\sum \mathrm{TTE}_i}{n} \tag{8}$$

where ATTE_j is the arithmetic value of TTE for *j-th* province; TTE_i has the same meaning as in Eq. (7), n is the number of DMUs in *j-th* province. Similarly, APTE_j and ASE_j can also be calculated.

For Inner Mongolia, Ningxia and Xinjiang areas, irrigation areas varied from less than 15 to nearly 600 thousand hectares, and the TTE score showed the rough trend that the larger the irrigation areas were, the higher the TTE score was. For the 43 irrigation districts in Shaanxi, Qinghai and Gansu Provinces, the irrigation areas were all less than 5 thousand hectares in Qinghai Province, around 22 thousand hectares in Gansu Province, and around 47 thousand hectares in Shaanxi Province. Thus, irrigation areas in these three provinces were relatively small and the proportion of small irrigation districts was relatively higher than that in Inner Mongolia, Ningxia and Xinjiang areas. Table 4 showed the area-weighted average values for Inner Mongolia, Ningxia, Xinjiang and Northwest China were higher than their arithmetic average values, while area-weighted average values for Gansu, Qinghai and Shaanxi Province were smaller or close to their arithmetic average values. This confirmed our conjecture that larger irrigation districts had more access to advanced technologies and can allocate resources more effectively and thus be more technically efficient.

In terms of status of production scale, 58% DMUs with SE score less than 1 were at DRS. For these irrigation districts, it would be unreasonable to enlarge their production scale. At the provincial level, all scale inefficient DMUs in Inner Mongolia were at DRS. In Gansu, Shaanxi and Xinjiang areas, the proportion of DMUs at DRS were 62%, 83% and 57%, respectively. In Xinjiang, the DMUs at IRS were mostly under centralized management and owned by government. There were two possible explanations for this. Firstly, compared with farmland owned by household farmers, these irrigation districts had much greater access to advanced agricultural technology; secondly, the farmland was operated as a whole, therefore resource allocation was more appropriate and management was more precise. Therefore, if possible, these DMUs could increase their production scale to improve SE scores. Scale inefficient DMUs in Qinghai Province were all at IRS and could increase their production scale to achieve higher efficiency.

Based on these results, this paper concluded that resource allocation has been inefficient in traditional agricultural areas of Northwest China. Excessive inputs have been common and production scale for agriculture should decrease as a whole, while centralized management of agricultural areas and areas thought to have no advantage for development of agriculture could increase their production scale.

3.3 Analysis of radial and slack movement

Only pure technically inefficient DMUs have input redundancy, i.e., about 58 of the 100 DMUs in this study. Table 5 shows the percentage of redundancy over original inputs. First, it was not unexpected that lower TTE score was associated with higher input redundancy. Also, input redundancy was mainly caused by pure technical

Table 4 Area-weighted and arithmetic average value of total technical efficiency (TTE), pure technical efficiency (PTE) and scale efficiency (SE)

Area	Area-weighted average value			Arithmetic average value		
	TTE′	PTE′	SE′	ATTE	APTE	ASE
Inner Mongolia	0.926	0.965	0.955	0.802	0.899	0.886
Gansu	0.775	0.802	0.964	0.786	0.815	0.962
Ningxia	0.994	1.000	0.994	0.981	1.000	0.981
Qinghai	0.769	0.851	0.899	0.783	0.884	0.883
Shaanxi	0.856	0.901	0.953	0.868	0.895	0.970
Xinjiang	0.755	0.822	0.913	0.725	0.781	0.927
Northwest China	0.813	0.865	0.934	0.770	0.825	0.931

Table 5 Redundancy percentage over original inputs

Range	Number of DMUs	TTE	PTE	SE	AP	IA	GW	BW	CF	AM	Proportion of IRS DMUs
0.9–1.0	6	0.93	0.95	0.97	5.47	22.14	14.49	5.78	31.35	31.64	17
0.8–0.9	3	0.85	0.87	0.97	17.25	18.33	18.77	28.22	17.78	21.31	33
0.7–0.8	10	0.76	0.84	0.92	18.67	29.10	27.22	37.72	25.80	26.94	50
0.6–0.7	7	0.64	0.67	0.96	38.58	47.89	38.57	48.69	37.36	49.06	57
0.5–0.6	20	0.56	0.62	0.91	45.22	46.33	50.94	54.09	47.69	50.34	35
0.4–0.5	8	0.45	0.53	0.88	55.19	55.92	56.82	64.17	63.57	59.48	63
0.3–0.4	4	0.35	0.59	0.68	47.13	47.08	61.63	51.48	67.36	45.29	75

Note: TTE, total technical efficiency; PTE, pure technical efficiency; SE, scale; AP, agricultural population, 10^4; IA, irrigated area, 10^3 hm^2; GW, represents green water, 10^8 m^3; BW, blue water, 10^8 m^3; CF, chemical fertilizer, t; AM, agricultural machinery, 10^4 kw.

inefficiency. Therefore, for DMUs locating in the range 0.3 to 0.4, the redundancy percentage was lower or close to that of DMUs in the range 0.4 to 0.5. In addition, with a critical efficiency value (TTE score) of 0.7 and above, the average redundancy percentage of all input factors was around 20%; while for a value of 0.7 or below, the average redundancy percentage of all input factors was more than 35%. Therefore, this paper drew the conclusion that it is very urgent for these DMUs to make full use of agricultural technical advantages in order to achieve high use efficiency of resource and sustainable development of agriculture. Even small enhancements in efficiency value could make a big difference in reducing input redundancy.

For DMUs with input redundancy, the proportion of DMUs at IRS was 45%. From the last column in Table 5, we observed that the lower the TTE score, the higher the percentage of DMUs at IRS. Therefore, if it would be difficult for these DMUs to make full use of its potential technology, then at least production scale could be increased without changing the input level.

Input redundancy for all areas is given in Table 6. DMUs in Ningxia had pure technical efficiency and therefore were without input redundancy. In Northwest China, the percentages of redundant input for AP, IA, GW, BW, CF and AM were 34.88%, 40.19%, 43.85%, 47.10%, 41.53% and 42.21%, respectively. In particular, radial movement of inputs was around 30.00% of current input and GW and BW had relatively high slack movement. There were two possible explanations for this. The first could be that green water (rainfall) was insufficient in this area, however, the farmers lacked both the awareness and technology to use this limited green water efficiently. Alternatively, it could be that administrators of irrigation districts often adopted a rotation flow system, so farmers overuse blue water (irrigation water) when it was their turn for fear that there might be insufficient water available at the next irrigation. These two possibilities could also explain why slack movements of GW and BW were larger than other input factors in Inner Mongolia, Qinghai and Xinjiang. This has to be changed; otherwise, it could result in deterioration of agricultural production; reducing water misuse may be the important factor that could lead to agricultural sustainable development in these areas.

Percentage of input redundancy varied between areas. For instance, redundant percentage of AP in Qinghai Province was more than 60%, which was three times that of Inner Mongolia. This could be explained by the fact that agricultural population per DMU in Qinghai was 3.7 times greater than that in Inner Mongolia. Apart from radial movement, all input factors had slack movement for those DMUs in Qinghai. This was consistent with the conclusion that they could increase their production scale. Second only to Ningxia, the PTE score for Inner Mongolia was 0.899. This explains why its radial movement was smaller than that for the other four areas, which had radial movements for input close to 30% or more. Therefore, it was still urgent to guide farmers to make good use of agricultural technology and invest properly for agricultural production in these regions. All these findings indicate that each district has its unique characteristics, thus methods for improvement differ accordingly. Agriculture is not a monolithic operation, instead, it should be practiced with attention to local factors and intensive care.

4 Discussion

Data envelopment analysis is an efficient and widely used method for assessment of technical efficiency. This research evaluated the TTE, PTE and SE of 100 irrigation districts in Northwest China via both CRS and VRS input-oriented DEA method. The purpose was to guide policy makers and farmers to allocate agricultural inputs appropriately according to its production scale so that "double high" agriculture could be achieved, which means high yield with high technical efficiency. Meanwhile, Northwest China is an ecologically vulnerable area because of the limited access to water and much agricultural pollution. Therefore, proper guidance for agriculture to reduce water and fertilizer inputs will also benefit this area's ecology.

Firstly, the average value of TTE, PTE and SE of irrigation districts in Northwest China were 0.770, 0.825

Table 6 Percentage of slack movement and radial movement over original input

Area	Percentage of slack movement/%						Percentage of radial movement/%					
	AP	IA	GW	BW	CF	AM	AP	IA	GW	BW	CF	AM
Inner Mongolia	0.00	3.38	22.98	8.79	0.00	3.42	19.38	17.89	18.69	17.19	17.91	17.91
Gansu	2.21	13.13	3.24	0.89	14.60	25.86	26.90	26.41	29.62	27.06	27.56	26.86
Qinghai	37.25	0.19	11.83	19.62	12.54	25.41	22.96	28.60	28.73	28.52	30.08	30.04
Shaanxi	0.00	0.49	3.38	1.06	4.98	5.02	33.98	36.29	35.30	38.80	36.30	36.30
Xinjiang	5.45	9.01	12.31	17.35	9.39	4.93	33.49	33.79	35.28	33.68	32.96	33.30
Northwest China	4.05	8.44	10.63	14.85	9.07	11.49	30.83	31.76	33.21	32.25	32.46	30.72

Note: AP, agricultural population, 10^4; IA, irrigated area, 10^3 hm^2; GW, represents green water, 10^8 m^3; BW, blue water, 10^8 m^3; CF, chemical fertilizer, t; AM, agricultural machinery, 10^4 kw.

and 0.931, respectively. This indicated that 23 percent of inputs could be reduced without decreasing agricultural outputs. The average value of SE was relatively high at 0.931. This indicated that agricultural production scale in Northwest China was not such an acute challenge as agricultural technology has been. This indicated that it was agricultural technology not production scale that should take more responsibility for low total technical efficiency. This conclusion was also confirmed by the finding that the geographical difference of PTE was more consistent with that of TTE, while the value of SE was clustered in high value range. Of all DMUs 97% had SE scores higher than 0.600.

Secondly, the percentage of total technically efficient DMU, pure technically efficient DMU and scale efficient DMU was 30%, 42% and 32%, respectively. For pure technical inefficient DMUs, their input redundancy was large. For Northwest China, the percentages of input redundancy over original input for AP, IA, GW, BW, CF and AM were 34.88%, 40.19%, 43.85%, 47.10%, 41.53% and 42.21%, respectively. The above two points should attract the attention of policy makers and farmers. Among agricultural inputs, AP and AM are both equivalence to agricultural labor and carry with them more than 30.0% input redundancy. On the one hand, due to its under-developed economy, farmers in Northwest China depended heavily on their farmland. Though labor transfer is happening with the process of urban expansion, traditional farmers still view agricultural operations as a guarantee for their income. Thus, there was no surprise in AP over input. For AM, farmers that own harvesting and seeding machinery may lend their equipment to farmers who are able to pay, but the private ownership of AM makes it difficult for some farmers for whom the rental is too high to pay. In addition, fragmentary land owned by separate farmers also limits the use of AM. Theoretically speaking, the inputs of agricultural labor and agricultural machinery should be regulated as a whole because they are complementary to each other. But the private ownership of AM and lacking of overall planning leads to inputs redundancy of AM and AP. The overall inputs of IA, GW, BW and CF did not only have influence on low total technical inefficiency and could also harm ecological environment in Northwest China. Irrigation authorities and farmers there have perceived that without irrigation there would be no agriculture. Consequently, with the practice of rotation irrigation farmers just let their farmland become saturated for they are fear of that there would be no more water for them to do the next irrigation. Obviously, this deep-rooted sense of potential crisis may drive them to overuse BW and IA. Though rainfall (GW) is scarce, farmers lack the knowledge and the technology to make full use of GW. Thus, redundancy of GW is also large. Both the low percentage of technically efficient DMUs and the high percentage of overuse inputs show that there is still huge room for Northwest China to improve its agricultural technical efficiency.

Lastly, nearly 60% of scale inefficient DMUs were at DRS. While for irrigation districts under management of Xinjiang Production & Construction Group and irrigation districts in Qinghai Province, places regarded as having no advantage to develop agriculture, were all surprisingly at IRS. This finding verified that compared with fragmentary farmland, centralized management was more successful in improving agricultural technical efficiency and could allocate agricultural inputs more precisely.

5 Conclusions

Northwest China, the most arid area in China, plays an important role in grain supply and thus contributes significantly to food security in China. However, Northwest China is also a relatively undeveloped area and its agricultural production is sluggish and conservative. Even so, as a typical arid area, its agricultural technical efficiency has not been investigated before. This paper adopted the DEA method to evaluate TTE, PTE and SE of 100 irrigation districts in this area. The unique contribution of our research is that this paper is the first to assess agricultural technical efficiency for irrigation districts in the most arid areas of China; secondly, it analyzes in details the extent to which inputs could be reduced. Thirdly, it reminds policy makers of the need to inspect the traditional agricultural areas from the perspective of efficiency. The main conclusions of this paper are as follows:

Firstly, there are still many irrigation districts with relatively low TTE and PTE. Also the percentage of input redundancy was high, around 40%, indicating that there was huge room for Northwest China to improve its agricultural technical efficiency. Based on our research, agricultural technology instead of production scale bore greater responsibility for low TTE. Therefore, some suggestions for policy makers to follow are: (1) they should improve local agricultural technology, such as transforming flood irrigation into water-saving irrigation; (2) it is time to carry out land transaction to centralize agricultural management, thus comprehensively regulating agricultural inputs as a whole. In this way, resources could be allocated more precisely, thus achieving the goal of "double high" agriculture.

Secondly, this paper found that the proportion of TTE with scores lower than 0.600 was around 46%. Therefore, if it is difficult for irrigation districts with high TTE score to move to another level, it should be a priority for the irrigation districts with low TTE score. After all, due to its high percentage, if TTE scores for these irrigation districts could be improved, lots of resources would be saved. In addition to that, this paper found that the traditional agricultural areas were often over explored and the production scale of these areas tended to locate at the decrease return to scale. In contrast, production scale for those areas that were thought to have no advantage to develop agriculture tended to locate at increase return to scale. Therefore, with food security becoming a more serious issue, policy makers should not ignore these areas any more. Meanwhile, agriculture is closely related with the geographical and meteorological features of an area, thus intensive care and analysis should be given before exploring these areas.

Of course, like many other researches, there were a few uncertainties in this paper due to the absence of data: (1) we assumed that these irrigation districts were sufficiently homogeneous in terms of environmental factors including geography, soil quality, weather and social-economic characteristics; (2) the differences of plant structures were ignored in this paper. This paper only aggregated agricultural output into grain production and agricultural value, though the symmetric disturbance term absorbs a certain amount of unobserved factors, which may lead to a discrimination of efficiency. After all, some crops do need more resources to produce the same amount of outputs than other crops in a given meteorological and geographical situation. If possible, these factors should be taken into account to make more precise assessments in future.

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