Ecological Indicators 96 (2019) 329–335

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Assessing China's agricultural water use efficiency in a green-blue water perspective: A study based on data envelopment analysis

Qingling Geng[a], Qingfu Ren[a], Rachael H. Nolan[b], Pute Wu[c], Qiang Yu[a,b,d,*]

[a] State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Northwest A&F University, Yangling, Shaanxi 712100, China

[b] School of Life Sciences, University of Technology Sydney, Sydney 2000, NSW, Australia

[c] Institute of Water Saving Agriculture in Arid Regions of China, Northwest A & F University, Yangling 712100, Shaanxi, China

[d] College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China

ARTICLE INFO

Keywords:
Blue water
Green water
Water use efficiency
Data envelopment analysis
China

ABSTRACT

Uneven water resources and growing food demand due to an increasing population bring challenges to China. One important mechanism to address these challenges is to enhance water use efficiency (WUE). This requires information on current efficiencies in water use for agricultural production. In this study, we provide a benchmarking tool to assess relative agricultural WUE in 31 provinces in China during 2003-2013. Data Envelopment Analysis (DEA) was used with both green-blue water and blue-only scenarios. Results show that China's agricultural WUE has improved evidently after 2008. Overall technical efficiency (TE) and the pure technical efficiency (PTE) in China based on the green-blue scenario are relatively high, with the average potential increase less than 10% (8% and 4%, respectively). However, there is a larger potential for blue water use efficiency (14% and 7% respectively). The PTE in Northern China (NC) is higher than that in Southern China (SC) while the TE in NC is lower under green-blue scenario. Moreover, the TE and PTE in NC are lower than that in SC under blue-only scenario. These results indicate that green water management techniques in NC are superior to SC but the scale efficiency (SE) in NC is lower. There are four provinces where the efficiency values are on the frontier in four cases, i.e. two scenarios (green-blue and blue-only) and two assumptions in DEA, but fourteen provinces where the efficiency values are not on the frontier in any case and most of them were located in SC. Our results also suggest that improving SE can substantially contribute to national WUE, but exploring the solutions to enhance blue water use efficiency in China is also a key task in the future works. The research results have important implications for China and different provinces to improve agricultural WUE by water policies and management.

1. Introduction

Global water consumption has increased over the past few decades, and is expected to continue to increase in the future (FAO, 2011). Water scarcity has been perceived as a global systemic risk (Liu et al., 2017; Sun et al., 2016). The largest consumer of freshwater resources is agriculture, which accounts for 90% of total freshwater use, and irrigation is responsible for approximately 70% of total blue water use (Gleick, 2014; Hoekstra and Mekonnen, 2012). Insufficient water resources can thus pose a substantial threat to agricultural production (Kang et al., 2017; Porkka et al., 2016). This highlights the need to reduce agricultural water use, while maintaining or increasing food production, which can only be achieved through gains in water use efficiency (WUE).

WUE is a broad concept that can be defined in many ways, including engineering concept and production concept (Cai et al., 2011; Singh et al., 2011). From the perspective of engineering, improving WUE can be achieved by reducing water losses, e.g. by canal seepage control and using drip irrigation (Schaldach et al., 2012). In agricultural production, WUE is often defined as physical and economic outputs per unit of water use, i.e. "crop per drop", standing for the benefits produced per cubic meter of water resources (Fishman et al., 2015; Ren et al., 2016).

Abbreviations: WUE, water use efficiency; TE, overall technical efficiency; PTE, pure technical efficiency; SE, scale efficiency; NC, Northern China; SC, Southern China; DMU, decision-making unit; CRS, constant returns to scale; VRS, variable returns to scale

* Corresponding author at: State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, Institute of Soil and Water Conservation, Northwest A&F University, Yangling, Shaanxi 712100, China

E-mail address: yuq@nwafu.edu.cn (Q. Yu).

https://doi.org/10.1016/j.ecolind.2018.09.011
Received 30 November 2017; Received in revised form 2 July 2018; Accepted 6 September 2018
1470-160X/

There have been many studies focused on assessing agricultural WUE. For the most part, these studies have examined water use efficiency at a local (or field) scale, i.e. they are strongly place-based and crop-based (Grassinia et al., 2015; Cao et al., 2018b). These studies have provided important information about specific interventions which can maintain both high and stable agricultural production and reduce on-farm water use, e.g. mulching, water-saving technology, and intercropping (Brauman et al., 2013; Gong et al., 2017; Li and Sun, 2016; Xue and Ren, 2016). However, these interventions did not always result in real water savings. There can be a rebound effect whereby the total area under irrigation is expanded following the implementation of water saving measures, so that water saving investments actually increase rather than decrease rates of water consumption (Berbel et al., 2015; Berbel and Mateos, 2014; Song et al., 2017; Ward, 2014). This has been documented in US and Pakistan (Ahmad et al., 2007; Ward and Pulido-Velazquez, 2008). For example, Ward and Pulido-Velazquez (2008) indicated that overall water use increased with a progressively increasing public subsidy of drip irrigation, which can increase 36,700 acre-feet per year under the highest subsidy compared with the scenario with no subsidy. Meanwhile, expansion of sprinklers and microirrigation could cause a 70-fold increase in GHG emissions affected by rebound effects in China (Cremades et al., 2016). Additionally, local improvements in irrigation efficiency may not translate into basin-wide efficiency gains, if water used for irrigation is subsequently utilized across a larger area due to the return of flows through the aquifer to the river (Scheierling et al., 2014; Soltani, 2013; Cao et al., 2018a). As a result, an understanding of local WUE may not assist in decision-making and policy design at a regional/basin scale. Further, these local studies tended to apply a single-factor measure of productivity (i.e. all variations in output are attributed to the water input) and did not take into account other factors that may explain variation in productivity, such as other environmental or economic influences (Scheierling et al., 2014; Speelman et al., 2008). Thus these smaller-scale studies can give an incomplete understanding of productivity changes, and it can be problematic if they form the basis of policy recommendations for improving WUE at regional or national scales (Scheierling et al., 2014).

Data envelopment analysis (DEA) is a method for measuring relative efficiency at different spatial scales (local, regional/basin, global) (Deng et al., 2016; Toma et al., 2017). It has the advantage of being able to deal with multi-input and multi-output problems. Currently, this approach has been applied to WUE calculations worldwide, including in Africa (Frija et al., 2009; Speelman et al., 2008), India (Manjunatha et al., 2011), the United States (Lilienfeld and Asmild, 2007; Ward, 2014), England (Gadanakis et al., 2015), Canada (Ali and Klein, 2014), and Australia (Azad et al., 2015). In EU, the application potentials of DEA have also been confirmed to help policy-makers to obtain significant results in agricultural productive patterns and sustainable development planning (Toma et al., 2017). In China, a serious conflict exists between water availability and sustainable food production, due to the large population and uneven distribution of water resources. 21% of the world's population needs to be fed with only 6% of global freshwater resources. Further, 61% of cultivated land area, 56% of food production and 42% of the population are in the northern part of China, where there is only 20% of China's total water resources (as shown in Fig. 1). Moreover, China's population is still increasing, until 2030 when it will be peak (Cao et al., 2017b). Thus, there have been many attempts to apply various approaches to enhance WUE in China, including the DEA approach (Deng et al., 2016; Tang et al., 2015; Wang et al., 2015a). However, to date, previous studies applying the DEA method have only focused on blue water, which is the renewable surface and groundwater resources related to irrigation. Little attention has been paid to green water, which is the effective precipitation (Cao et al., 2017a; Rost et al., 2008). This is an important omission, since 80% of global cropland is rain-fed, and over 60% of global food supply is produced on rain-fed land, i.e. solely with green water (Kang et al., 2017; Rockström and Barron, 2007). Additionally, green water is also important on irrigated land, as blue water is supplied on the premise that precipitation is not sufficient for maintaining crop growth. The annual green water consumption on rain-fed and irrigated cropland is more than three times the blue water consumption globally (Rost et al., 2008). In China, green water footprint accounts for 65.6% of total agricultural water footprint while blue water footprint only 12.7%, and the remained 21.7% is grey water footprint (Cao et al., 2017a). Even if not considering green water consumption from irrigated fields, 38% of food production was dependent on green water. Hence, green water should not be over-looked in investigations of agricultural WUE.

In this work, we employed the DEA approach to quantify agricultural WUE under two scenarios: first, we consider blue water only; the second scenario integrates green water and blue water. We then compare the results between the blue-only and the green-blue water scenarios, and the implications of this for assessing China's agricultural WUE. The results of this study can provide important references for allocation of water resources and the evaluation of decision-making by identifying major research areas for improving agricultural water productivity in the future.

2. Methods

In the present study, WUE is a dimensionless ratio of outputs/inputs, reflecting a production unit's (firm, farm, or region) ability to produce a given set output with minimum inputs (Frija et al., 2009; Ali and Klein, 2014; Pereira and Marques, 2017). This definition allows us to employ a method based on mathematical programming techniques to assess WUE among different production units, e.g. data envelopment analysis (DEA) model. Here, we investigated agricultural WUE of 31 provinces of China (not including Hongkong, Macao and Taiwan) over 2003–2013. We evaluated relative WUE by integrating both green water and blue water.

2.1. Data envelopment analysis model

Data envelopment analysis is a nonparametric, linear programming approach introduced by Charnes et al. (1978). In DEA, the basic unit of analysis is defined as the decision making unit (DMU). All DMUs constitute an evaluation group. The efficiency of each DMU can be evaluated by comparing it to the other DMUs (Frija et al., 2009; Susaeta et al., 2016). In the evaluation group, a non-parametric production frontier (i.e. the best practice frontier of a sample of DMUs) is constructed through solving a sequence of linear programming problems (Frija et al., 2011; Ali and Klein, 2014; Bonfiglio et al., 2017). Every DMU has a value of efficiency, and the level of inefficiency is the distance to the frontier surface. That is, when the technical value equals 1, the DMU is on the production frontier, and the actual production value has no difference with the possible maximum value, i.e. water use efficiency is maximized. When the efficiency is lower than 1, this implies that there is still potential improvements in efficiency for that DMU. Thus, DEA provides a straightforward approach to measure the gap between a given DMU and the best production practice within the evaluation group (Speelman et al., 2008; Manjunatha et al., 2011). This method is designed to measure the relative efficiency of a DMU.

In DEA, two models with different assumptions can be used; these are the CCR model and BCC model (Speelman et al., 2008; Frija et al., 2009; Chen et al., 2015). The CCR model considers constant returns to scale (CRS) assuming that the variation in inputs will produce the same proportional variation in outputs. That is, the DMUs are assumed to be operating at an optimal scale. However, this is not the case in agricultural production where increased inputs, i.e. water, do not proportionally increase outputs, i.e. crop production. In contrast, the BCC model considers variable returns to scale (VRS) assuming that the scale of benefit of production technology is changeable. The DMUs are not operating under an optimal scale. Thus, the VRS assumption is considered to be more appropriate in the case of agricultural production (Asmild and Hougaard, 2006; Lilienfeld and Asmild, 2007). By

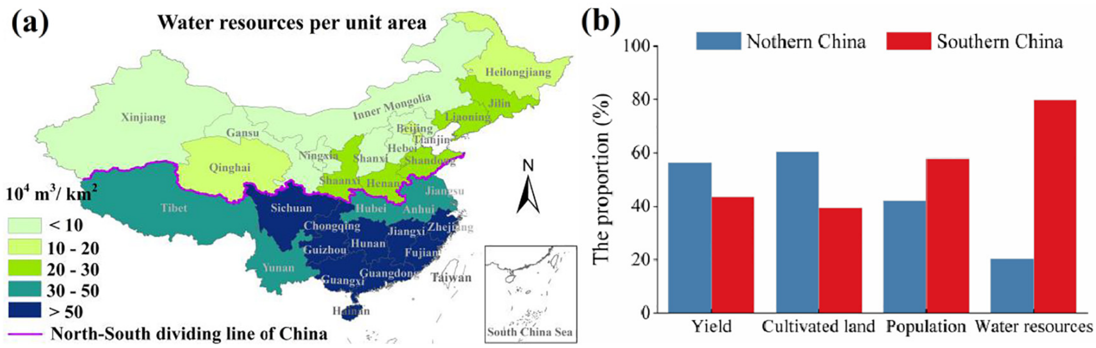

Fig. 1. Spatial distribution of water resources per unit area in China by province and subarea of southern and northern China (a) and differences between Northern China and Southern China in grain crop yield, cultivated land area, population and total water resources (b).

changing the returns to scale assumption from constant to variable, the BCC model distinguishes pure technical efficiency (PTE) from scale efficiency (SE), and thus can measure whether a DMU is on the optimal production scale (Ren et al., 2016). In addition, depending on the purposes of the analysis, DEA models can be either input or output orientated. An input-oriented model aims to continue producing the same outputs while minimizing the inputs, whereas the output-oriented model aims to maximize outputs using the same level of inputs. In this study an input-oriented DEA model was used to identify inefficient DMUs that can be targeted for reducing inputs, i.e. increasing water savings, because, in the context of increasing water scarcity in China, it is more relevant to consider potential decreases in water use than increases in output.

To formalize the above, suppose that there are n DMUs, each DMU j= (1, 2, ..., n) has m inputs and s outputs. *istheis* the i^{th} input of the *j* DMU; *istheis* the r^{th} output of the *j* DMU. $x_j = (x_{1j}, x_{2j}, ..., x_{mj})^T$, *denoteinput* denote input and output vector, respectively; For an ordinary linear programming model, it has a linear programming dual form. In applied analysis the dual version of this model is actually preferred since the dual problem has fewer constraints to solve than the primal model (Frija et al., 2009; Ali and Klein, 2014). The dual form of an equivalent primal model specification that maximizes the outputs for given inputs can be written as Eq. (1). For a general exposition of primal and dual DEA models see, e.g. Charnes et al. (1978) and Coelli et al. (1998):

$$\begin{cases} \min\theta \\ \text{s.}t.\ \sum_{j=1}^{n}\lambda_j x_j \le \theta x_0 \\ \sum_{j=1}^{n}\lambda_j y_j \ge y_0 \\ \sum_{j=1}^{n}\lambda_j = 1 \\ \lambda_j \ge 0 \end{cases} \tag{1}$$

where (0<(0 < <1) < 1) represents the technical efficiency between 0 and 1 and hence the percentage of radial reduction to which each of the inputs is subjected. λ_j is the weighting variable. *and* and *are* are the input and the output vectors of the DMU$_{j0}$, respectively. By introducing the slack variable S- and the surplus variable S^+, inequality constraints in Eq. (1) can be transformed into equality constraints. That is,

$$\begin{cases} \min\theta \\ \text{s.}t.\ \sum_{j=1}^{n}\lambda_j x_j + S^- = \theta x_0 \\ \sum_{j=1}^{n}\lambda_j y_j - S^+ = y_0 \\ \lambda_j \ge 0,\ \sum_{j=1}^{n}\lambda_j = 1 \\ S^- \ge 0,\ S^+ \ge 0 \end{cases} \tag{2}$$

The above equation is a DEA model based on a VRS assumption. The equation *isaconvexity* is a convexity constraint, which describes a DEA model based on a VRS assumption. Without this convexity constraint, the DEA model will be a CCR model describing a CRS framework (Frija et al., 2009).

By estimating TE and PTE scores, we can obtain the SE according to the following equation.

$$SE = TE/PTE \tag{3}$$

The value of SE is also between 0 and 1, and is a measure of the impact of scale size on the productivity of the DMU. When SE = 1, the DMU is operating at an optimal scale size and otherwise if SE < 1. According to the value of SE, we can estimate potential benefits from adjusting production scale (Gadanakis et al., 2015). In this study both the CRS and the VRS DEA models for estimating technical efficiencies were conducted using the program DEAP (Coelli, 1996).

2.2. Data sources and indicator selection

In a DEA model, the input parameters required includes input and output variables in agricultural production. Here, we define input variables of agricultural WUE as water resources (blue water and green water), land resources (cultivated area), fertilizers and labor. Output variables include grain yield and agricultural economic output. Specifically, blue water refers to surface and groundwater, i.e. the water in rivers, lakes, reservoirs, ponds and aquifers (Rockström, 1999; Liu et al., 2009; Hoff, 2010; Veettil and Mishra, 2016). Blue water is obtained based on the annual scale in the present study. Considering the time scale and the conversion between surface water and groundwater, blue water is calculated by subtracting the repetition between them from the sum of surface and groundwater. In the agricultural sector, blue water is agricultural water use which can be obtained from the China Water Resources Bulletin. Green water is the water that comes from precipitation, stored in the unsaturated soil zone and is available to plants. Green water can also be considered as effective precipitation (Liu et al., 2009; Vanham and Bidoglio, 2013). Daily precipitation data during 2003–2013 was obtained from the China Meteorological Administration and was used to calculate green water according to the method from the USDA Soil Conservation Service (Eq. (4). This method has been widely used in different regions (Cao et al., 2018a; Chakraborty et al., 2015; Döll and Siebert, 2002; Sun et al., 2013), and recommended in the FAO CROPWAT model (FAO, 2010; Smith, 1992). Other data were derived from the China Statistical Yearbook. Descriptive statistics of input and output variables used in estimations of water use efficiency are listed in Table 1.

$$P_e = \begin{cases} P \times (4.17 - 0.02 \times P)/4.17 & P \le 83 \\ 41.7 + 0.1 \times P & P > 83 \end{cases} \tag{4}$$

where the calculation step length in Eq. (3) is ten days, i.e. P is the 10 days precipitation (mm).

Table 1
Descriptive statistics of the input parameters used in the DEA model.

Variable	Parameter types	Unit	Min	Max	Mean	SD
Blue water	Input	10^8 m^3	9.10	561.70	118.71	99.02
Green water	Input	mm	112.01	1967.44	560.74	245.35
labour	Input	10^4 persons	37.09	3332.00	988.89	740.83
Fertilizers	Input	10^4 ton	3.20	857.27	174.20	142.60
Cultivated area	Input	10^4 ha	18.80	1586.41	358.74	273.71
AgroGDP	output	10^8 RMB	25.30	4509.88	993.21	872.34
Yield	output	10^4 ton	58.00	6004.07	1695.86	1374.41

Note: AgroGDP represents the total output value of the agricultural sector.

3. Results

3.1. Agricultural WUE from the green-blue water approach

Agricultural WUE of 31 provinces of China during 2003–2013 was calculated under a scenario integrating green water and blue water. On average, the TE and PTE were 0.916 and 0.962, respectively. The differences between them indicate that many provinces did not operate at an efficient scale and that adjusting the scale of production could improve WUE, according to the computing method in Eq. (2). An increasing trend for TE and PTE was found over time, but the rate of increase in TE was larger than that for PTE. Considerable increasing for TE mainly occurred around 2008 (Fig. 2), showing that agriculture water management has made clear improvement since 2008. The result is more related to the change of SE because the increasing of PTE is relatively stable.

On a sub-national scale, the average TE in NC (0.901) was lower than that in SC (0.931), but there was a noticeable upward trend before 2010 for TE in NC. The PTE with the average value of 0.984 in NC was higher than that in SC during the entire period of 2003–2013 (Fig. 3). This may be explained by the availability of water resources, with more abundant water resources typically accompanied by weaker awareness of lower investment in water conservation practices. In NC, water resources are relatively scarce (Fig. 1), and this has resulted in greater water-saving measures including regulated deficit irrigation, low-pressure pipe irrigation, and canal lining (Wang et al., 2015b; Xu et al., 2016). The lower TE but higher PTE in NC also implies the lower scale efficiency.

At a provincial scale, there were nine provinces where the TE was on the production frontier (Fig. 4). The lowest TE was found in Ningxia with an average value of 0.607 over 2003–2013, following by Guangxi (0.679). In contrast, more provinces occurred where the PTE reached the frontier. These provinces were mainly located in NC. There were only two provincial regions (Tibet and Zhejiang) with the effective PTE in SC, except four provinces (Sichuan, Chongqing, Jiangxi and Shanghai) with the effective TE. The province with the lowest PTE was

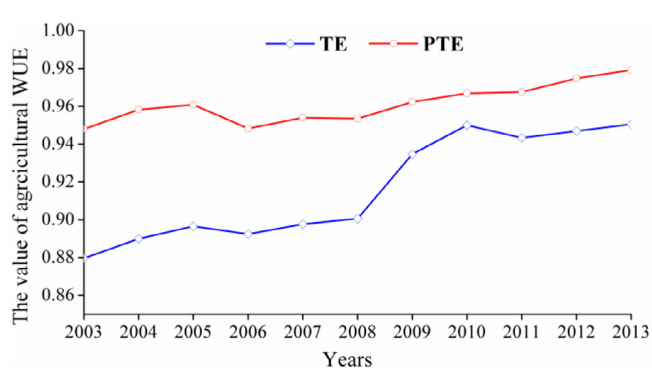

Fig. 2. The changes of agricultural WUE (TE and PTE) under CRS and VRS assumptions based on the green-blue water approach in China during 2003 – 2013.

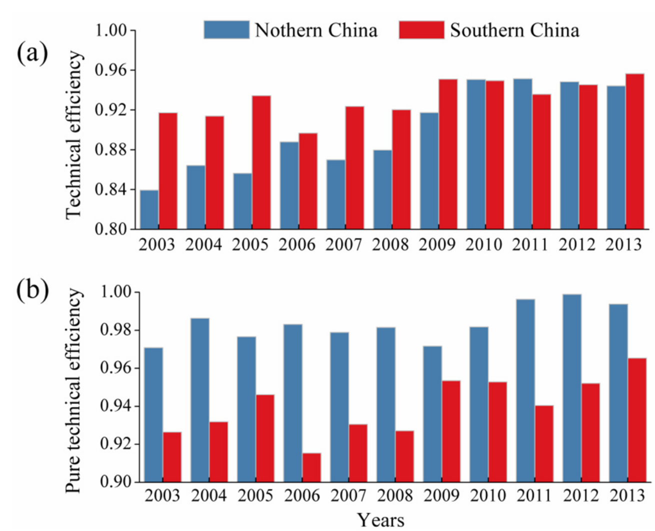

Fig. 3. The changes of agricultural WUE based on the green-blue water approach in Northern China and Southern China. (a) Technical efficiency, (b) Pure technical efficiency

Guangxi (0.686). That is, the TE and PTE were low in Guangxi. Thus, Guangxi should be paid more attention on enhancing overall agricultural WUE. Different from Guangxi, the PTE in Ningxia equals to 1.0 while the TE is the lowest among 31 provinces. The lower TE is thus related to the scale efficiency in Ningxia. Among the provinces where the PTE did not reach the frontier, most of them distributed in SC. Only four provinces (i.e. Tianjin, Hebei, Shanxi and Shaanxi) were located in NC.

3.2. Agricultural water use efficiency considering blue water only

Under a scenario considering blue water only, the average TE and PTE in China during 2003–2013 were 0.858 and 0.925 respectively, both of which were lower than that under the scenario of green-blue water. It indicates that green water can contribute to the improvement of overall agricultural WUE, and also confirms that it is necessary to improve green water management in agricultural production. In similar to the scenario of green-blue water, however, the increasing trend for TE can be identified as two stages (Fig. 5). The increase was slow in the period of 2003-2008, but there was an evident increase after 2008. The result shows that other inputs (i.e. blue water, cultivated area, labor and fertilizer) rather than green water has more effects on the tendency.

On a sub-national scale, the TE and PTE in SC (0.884 and 0.936, respectively) were higher than that in NC (0.832 and 0.915, respectively) (Fig. 6), which is different from the result based on the green-blue scenario. The higher PTE under the blue-only scenario in SC illustrates that there is more abundant green water supply, and hence less usage of blue water for agricultural production. These results may also be a function of more effectively managed green water in NC enhancing the PTE. However, the TE was still lower in NC due to the lower scale

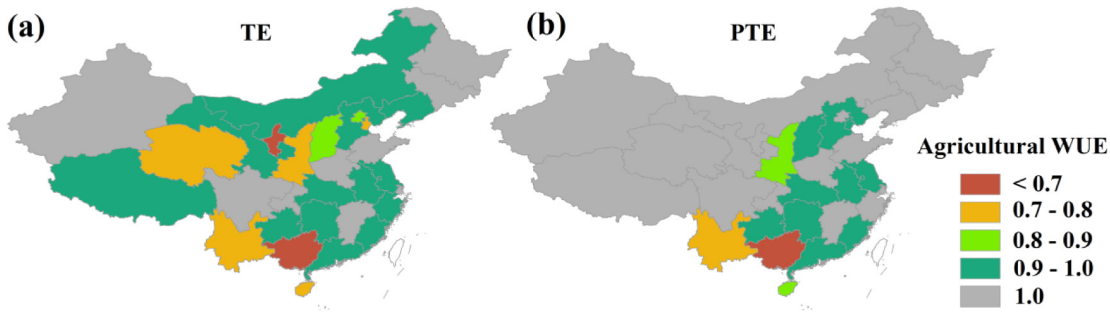

Fig. 4. The average agricultural WUE based on the green-blue water approach in 31 provinces in China during 2003–2013. (a) Technical efficiency, (b) Pure technical efficiency

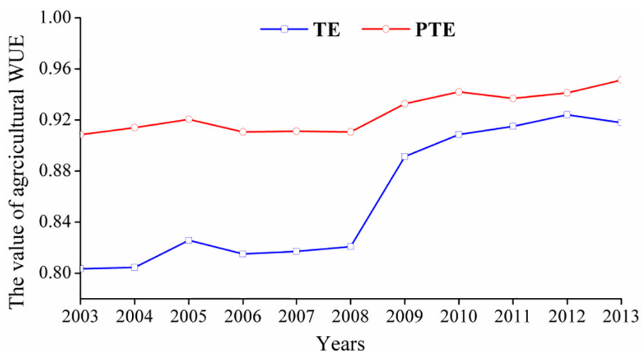

Fig. 5. The changes of agricultural WUE (TE and PTE) under CRS and VRS assumptions based on the blue-only approach in China during 2003–2013.

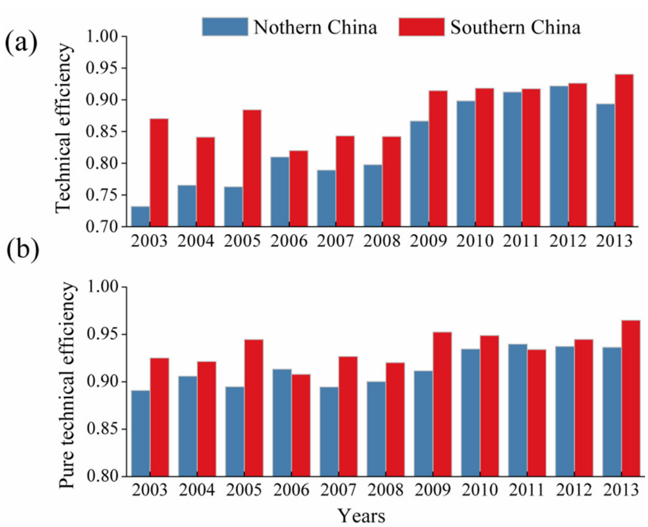

Fig. 6. The changes of agricultural WUE under the blue-only scenario in Northern China and Southern China. (a) Technical efficiency, (b) Pure technical efficiency.

efficiency. Similar to the result based on the green-blue scenario, an increasing trend was found for TE in NC, which further confirmed that the scale efficiency in NC increased during 2003–2013.

At a provincial scale, there was varying TE among different provinces. Two provinces, i.e. Jilin and Heilongjiang, were identified as having a technical efficiency of 1.0 in the CRS model (Fig. 7). Also, these two provinces were regions where the efficiency values were on the frontier in four cases, i.e. two scenarios (green-blue and blue-only) and two assumptions (VRS and CRS). The TE in Guangxi and Ningxia was the lowest, with average values of 0.592 and 0.582 respectively. Under the VRS assumption, there were eleven provinces where the PTE was the benchmark for other regions. The two provinces with the lowest PTE were also Guangxi and Ningxia with average values of 0.659 and 0.675 respectively. Thus, the water use efficiency values in Guangxi and Ningxia were the lowest under three different modeling cases (i.e. the assumptions of VRS and CRS not considering green water, and the CRS assumption considering green water). Only the scenario considering green water for the VRS model was an exception where the PTE equaled 1.0 in Ningxia, indicating that green water use in Ningxia improved agricultural WUE effectively. This suggests that provinces with lower PTE, particularly in NC region, could draw on the knowledge and experiences of green water use in Ningxia.

4. Discussion and conclusions

Evaluating agricultural WUE in different regions can identify major research areas that need further study for improving agricultural water use and productivity in the future. The substantial importance of green water and the need for including green water flows in assessments of water resources has been demonstrated and emphasized in previous studies (Rockström et al., 2009; Rost et al., 2008). Without considering green water, water use assessments are incomplete and may even be misleading in many cases (Liu et al., 2009). In this study, we considerably extend the current knowledge of assessing agricultural WUE based on DEA models by including green water into analyses. The results were compared with a DEA model not including green water.

Our calculations indicated that agricultural WUE was higher when incorporating green water into analyses; there was an average potential of less than 10% to improve in China. Moreover, the PTE in NC was higher than that in SC under the green-blue scenario. Theoretically, this finding may be related to the degree of water abundance. According to Deng et al. (2016), abundance of water resource can affect WUE by affect individual awareness of water conservation. Nevertheless, this reason can't be considered a valid conclusion. For example, in the North China Plain, flood irrigation is still the prevalent form of irrigation. Blue water was not protected reasonably. Overexploitation of underground water has led to rapid depletion of groundwater reserves and then caused many groundwater funnels (Fu et al., 2004; Lei and Yang, 2010). As shown in the present study, the efficiency values were not on the frontier in Hebei, Tianjin and Shanxi in four cases (i.e. two scenarios and two assumptions). Our result also showed that the PTE in NC was lower than that in SC when only blue water was considered. Therefore, further investigation is needed to clarify the specific reasons.

It has been assumed that there is a linear relationship between biomass growth and water supply, if the yield is more than 3 t ha^{-1}. That is, every new unit of food produced requires an equivalent increase in units of water (Rockström and Barron, 2007; Rockström et al., 2007). Thus, it is critical to reduce blue water and improve green water use as much as possible due to the low-opportunity cost of green water as opposed to blue water (Liu et al., 2009). In NC, green water use efficiency was high that the PTE was on the production frontier in most regions, except four provinces (Shaanxi, Shanxi, Hebei and Tianjin).

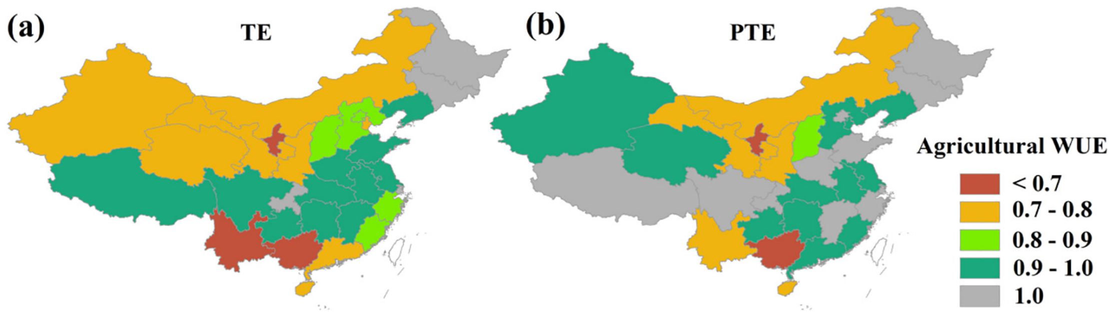

Fig. 7. The average agricultural WUE under the blue-only scenario in 31 provinces in China during 2003–2013. (a) Technical efficiency, (b) Pure technical efficiency.

Thus, it is urgent to improve green water use efficiency in these four provinces in the future agricultural water management. According to Rockström et al. (2009), there can be a large potential for increasing food production through minimizing evaporative losses of green water and thereby enhancing water available for transpiration. Thus, food production can be enhanced without requiring the addition of blue water resources. Such measures may partly explain the higher PTE in NC even if water is scarce. However, there is a limit to relying on green water for agricultural production, particularly under climate change which is projected to increase variability in rainfall (Cai et al., 2016; Li et al., 2015). More extreme events, e.g. droughts and floods, bring more challenges in green water management. Thus, agriculture is likely to be more vulnerable to water shortages in NC, while blue water is prone to be over exploited.

In the present study, a provincial unit was considered as a DMU, which is a relatively large sample unit. The large-scale DMU could indirectly affect the level of WUE, but the smaller DMU means the more detailed data, which improved the difficulty of data acquisition. Moreover, in DEA, efficiency measures are not significantly affected by a small sample size as long as the number of inputs is not too high in comparison to the sample size (i.e. the number of all DMUs) (Speelman et al., 2008). Exactly, the number of DMUs is more than double the sum of inputs and outputs (Liu et al., 2014). Therefore, the results are reliable based on the provincial scale in this study. The previous research also has indicated that DEA is feasible for calculating WUE of different provinces of China (Deng et al., 2016).

To conclude, a detailed assessment of agricultural WUE based on blue-only and green-blue water approaches in a DEA model were conducted, and results between two scenarios were compared. These results revealed that agricultural WUE when considering green water is relatively high, with the average potential increase less than 10% (8% and 4%, respectively for TE and PTE). If we did not consider green water in the DEA approach, there was a larger potential for improving agricultural WUE, which were respectively 14% and 7% under CRS and VRS assumptions. Meanwhile, there was a marked increase for PTE after 2008 under blue-only and green-blue water scenarios. At the subnational level, we conclude that green water use improved agricultural WUE in NC, but there was still the potential for higher WUE because SE needs to be more effective. In comparison with the green-blue water scenario, there were more provinces where the efficiency values were not on the frontier under the blue-only scenario, although the TE and PTE were higher in SC than that in NC. Thus, exploring the solutions to enhance blue water use efficiency in China is a key task in the future works, especially in NC. Meanwhile, both national and provincial governments should be focus on agricultural structural adjustment to improve the SE so as to reduce the gap between TE and PTE and promoting optimal allocation of resources. This paper complements the previous studies based on the blue-only approach, and can contribute to formulate more active water policies and management for improving agricultural WUE.

Acknowledgements

This work was supported by National Natural Science Foundation of China (grant number 41730645), China Postdoctoral Science Foundation Funded Project (grant number 2017M613219) and the International Partnership Program of the Chinese Academy of Sciences (161461KYSB20170013).

References

Ahmad, M., Giordano, M., Turral, H., Masih, I., Msood, Z., 2007. At what scale does water saving really save water? Lessons from the use of resource conservation technologies in Pakistan. J. Soil Water Conserv. 62 (2), 29A–35A.
Ali, M.K., Klein, K.K., 2014. Water use efficiency and productivity of the irrigation districts in Southern Alberta. Water Resour. Manage. 28, 2751–2766. https://doi.org/10.1007/s11269- 014-0634-y.
Asmild, M., Hougaard, J.L., 2006. Economic versus environmental improvement potentials of Danish pig farms. Agr. Eco. 35, 171–181. https://doi.org/10.1111/j.1574-0862.2006.00150.x.
Azad, M.A.S., Ancev, T., Hernandez-Sancho, F., 2015. Efficient water use for sustainable irrigation industry. Water Resour. Manage. 29, 1683–1696. https://doi.org/10.1007/s11269- 014- 0904-8.
Berbel, J., Gutierrez-Martin, C., Rodriguez-Diaz, J.A., Camacho, E., Montesinos, P., 2015. Literature review on rebound effect of water saving measures and analysis of a Spanish case study. Water Resour. Manage. 29, 663–678. https://doi.org/10.1007/s11269- 014-0839-0.
Berbel, J., Mateos, L., 2014. Does investment in irrigation technology necessarily generate rebound effects? A simulation analysis based on an agro-economic model. Agr. Sys. 128, 25–34. https://doi.org/10.1016/j.agsy.2014.04.002.
Bonfiglio, A., Arzeni, A., Bodini, A., 2017. Assessing eco-efficiency of arable farms in rural areas. Agr. Sys. 151, 114–125. https://doi.org/10.1016/j.agsy.2016.11.008.
Brauman, K.A., Siebert, S., Foley, J.A., 2013. Improvements in crop water productivity increase water sustainability and food security—a global analysis. 024030. Environ. Res. Lett. 8. https://doi.org/10.1088/1748-9326/8/2/024030.
Cai, X.M., Yang, Y.C.E., Ringler, C., Zhao, J.S., You, L.Z., 2011. Agricultural water productivity assessment for the Yellow River Basin. Agr. Water Manage. 98, 1297–1306. https://doi.org/10.1016/j.agwat.2011.03.010.
Cai, X., Yin, Z., Wang, X., Sun, Y., 2016. Spatiotemporal variations of precipitation extremes of China during the past 50 years (1960–2009). Theor. Appl. Climatol. 124, 555–564. https://doi.org/10.1007/s00704-015-1436-8.
Cao, X.C., Ren, J., Wu, M.Y., Guo, X.P., Wang, Z.C., Wang, W.G., 2018a. Effective use rate of generalized water resources assessment and to improve agricultural water use efficiency evaluation index system. Ecol. Indic. 86, 58–66. https://doi.org/10.1016/j.ecolind.2017.12.016.
Cao, X.C., Wu, M.Y., Guo, X.P., Zheng, Y.L., Gong, Y., Wu, N., Wang, W.G., 2017a. Assessing water scarcity in agricultural production system based on the generalized water resources and water footprint framework. Sci. Total Environ. 609, 587–597. https://doi.org/10.1016/j.scitotenv.2017.07.191.
Cao, X.C., Wu, M.Y., Zheng, Y.L., Guo, X.P., Chen, D., Wang, W.G., 2017b. Can China achieve food security through the development of irrigation? Reg. Environ. Change. https://doi.org/10.1007/s10113-017-1214-5.
Cao, X.C., Wu, M.Y., Shu, R., Zhuo, La., Chen, D., Shao, G.C., Guo, X.P., Wang, W.G., Tang, S., 2018b. Water footprint assessment for crop production based on field measurements: a case study of irrigated paddy rice in East China. Sci. Total Environ. 610–611, 84–93. https://doi.org/10.1016/j.scitotenv.2017.08.011.
Chakraborty, S., Pandey, R.P., Mishra, S.K., Chaube, U.C., 2015. Relation between runoff curve number and irrigation water requirement. Agric. Res. 4 (4), 378–387. https://doi.org/10.1007/ s40003-015-0184-4.
Charnes, A., Cooper, W.W., Rhodes, E., 1978. Measuring the efficiency of decision making units. Eur. J. Oper. Res. 2, 429–444. https://doi.org/10.1016/0377-2217(78)90138-8.
Chen, J.D., Song, M.L., Xu, L., 2015. Evaluation of environmental efficiency in China using data envelopment analysis. Ecol. Indic. 52, 577–583. https://doi.org/10.1016/j.ecolind.2014.05.008.
Coelli, T., 1996. A Guide to DEAP Version 2.1: A data envelopment analysis (computer

program), CEPA Working Papers No. 8/96. University of New England, Australia.
Coelli, T.J., Rao, P.D.S., O'Donnel, C.J., Battese, G.E., 1998. An Introduction to Efficiency and Productivity Analysis. Springer, New York.
Cremades, R., Rothausen, S.G.S.A., Conway, D., Zou, X., Wang, J., Li, Y., 2016. Co-benefits and trade-offs in the water–energy nexus of irrigation modernization in China. 054007. Environ. Res. Lett. 11. https://doi.org/10.1088/1748-9326/11/5/054007.
Deng, G., Li, L., Song, Y., 2016. Provincial water use efficiency measurement and factor analysis in China: based on SBM-DEA model. Ecol. Indic. 69, 12–18. https://doi.org/10.1016/j.ecolind.2016.03.052.
Döll, P., Siebert, S., 2002. Global modeling of irrigation water requirements. Water Resour. Res. 38 (4) 8–1-8-10 10.1029/2001WR000355.
FAO, 2011. The state of the world's land and water resources for food and agriculture: managing systems at risk. Food and Agricultural Organization of the United State, Rome.
FAO, 2010. Land and Water Development Division. CROPWAT Model. Food and Agric. Org. of the U. N, Rome, Italy. (Available from: www.fao.org/nr/water/in-foresdatabasescropwat. html2010 (accessed 18.06.13)).
Fishman, R., Devineni, N., Raman, S., 2015. Can improved agricultural water use efficiency save India's groundwater? Environ. Res. Lett. 10, 084022. https://doi.org/10.1088/1748-9326/10/8/084022.
Frija, A., Chebil, A., Speelman, S., Buysse, J., Van Huylenbroeck, G., 2009. Water use and technical efficiencies in horticultural greenhouses in Tunisia. Agr. Water Manage. 96, 1509–1516. https://doi.org/10.1016/j.agwat.2009.05.006.
Frija, A., Wossink, A., Buysse, J., Speelman, S., Van Huylenbroeck, G., 2011. Irrigation pricing policies and its impact on agricultural inputs demand in Tunisia: a DEA-based methodology. J. Environ. Manage. 92, 2109–2118. https://doi.org/10.1016/j.jenvman.2011.03.013.
Fu, G.B., Chen, S.L., Liu, C.M., Shepard, D., 2004. Hydro-climatic trends of the Yellow River basin for the last 50 years. Climatic Change 65, 149–178. https://doi.org/10.1023/B:CLIM. 0000037491.95395.bb.
Gadanakis, Y., Bennett, R., Park, J., Areal, F.J., 2015. Improving productivity and water use efficiency: a case study of farms in England. Agr. Water Manage. 160 22–32. http://dx.doi. org/10.1016/j.agwat.2015.06.020.
Gleick, P., 2014. The World's Water: The Biennial Report on Freshwater Resources 8 Island Press.
Gong, D.Z., Mei, X.R., Hao, W.P., Wang, H.B., Caylor, K.K., 2017. Comparison of multi-level water use efficiency between plastic film partially mulched and non-mulched croplands at eastern Loess Plateau of China. Agr. Water Manage. 179, 215–226. https://doi.org/10.1016/j.agwat.2016.06.006.
Grassinia, P., Torrion, J.A., Yang, H.S., Rees, J., Andersen, D., Cassman, K.G., Specht, J.E., 2015. Soybean yield gaps and water productivity in the western U.S. Corn Belt. Field Crop. Res. 179, 150–163. https://doi.org/10.1016/j.fcr.2015.04.015.
Hoekstra, A.Y., Mekonnen, M.M., 2012. The water footprint of humanity. Proc. Natl. Acad. Sci. U.S.A. 109, 3232–3237. https://doi.org/10.1073/pnas.1109936109.
Hoff, H., 2010. The global water challenge – modeling green and blue water. J. Hydrol. 384 (3), 175–176. https://doi.org/10.1016/j.jhydrol.2010.02.027.
Kang, S., Hao, X., Du, T., Tong, L., Su, X., Lu, H., Li, X., Huo, Z., Li, S., Ding, R., 2017. Improving agricultural water productivity to ensure food security in China under changing environment: from research to practice. Agr. Water Manage. 179, 5–17. https://doi.org/10.1016/j.agwat.2016.05.007.
Lei, H.M., Yang, D.W., 2010. Interannual and seasonal variability in evapotranspiration and energy partitioning over an irrigated cropland in the North China Plain. Agr. Forest Meteorol. 150, 581–589. https://doi.org/10.1016/j.agrformet.2010.01.022.
Li, J.F., Zhang, Q., Chen, Y.D., Singh, V.P., 2015. Future joint probability behaviors of precipitation extremes across China: spatiotemporal patterns and implications for flood and drought hazards. Global Planet Change 124, 107–122. https://doi.org/10.1016/j.gloplacha.2014.11.012.
Li, Z.Z., Sun, Z.H., 2016. Optimized single irrigation can achieve high corn yield and water use efficiency in the Corn Belt of Northeast China. Eur. J. Agron. 75, 12–24. https://doi.org/10.1016/j.eja.2015.12.015.
Lilienfeld, A., Asmild, M., 2007. Estimation of excess water use in irrigated agriculture: a data envelopment analysis approach. Agr. Water Manage. 94, 73–82. https://doi.org/10.1016/j.agwat.2007.08.005.
Liu, J., Wang, Y.B., Yu, Z.B., Cao, X.C., Tian, L., Sun, S.K., Wu, P.T., 2017. A comprehensive analysis of blue water scarcity from the production, consumption, and water transfer perspectives. Ecol. Indic. 72, 870–880. https://doi.org/10.1016/j.ecolind.2016.09.021.
Liu, J., Wu, P.T., Wang, Y.B., Zhao, X.N., Cao, X.C., Sun, S.K., 2014. Assessment of agricultural productive efficiency for Hetao Irrigation District based on data envelopment analysis. Trans. CSAE 30 (9), 110–118 (In Chinese with English abstract) http://dx.doi.org/10.3969/j.issn.1002-6819.2014.09.014.
Liu, J., Zehnder, A.J.B., Yang, H., 2009. Global consumptive water use for crop production: the importance of green water and virtual water. Water Resour. Res. 45 (5) 641–648. http://dx.doi. org/10.1029/2007WR006051.
Manjunatha, A.V., Speelman, S., Chandrakanth, M.G., Van Huylenbroeck, G., 2011. Impact of groundwater markets in India on water use efficiency: a data envelopment analysis approach. J. Environ. Manage. 92, 2924–2929. https://doi.org/10.1016/j.jenvman.2011.07.001.
Pereira, H., Marques, R.C., 2017. An analytical review of irrigation efficiency measured using deterministic and stochastic models. Agri. Water Manage 184, 28–35. https://doi.org/10.1016/j.agwat.2016.12.019.
Porkka, M., Gerten, D., Schaphoff, S., Siebert, S., Kummu, M., 2016. Causes and trends of water scarcity in food production. 015001. Environ. Res. Lett. 11. https://doi.org/10.1088/1748- 9326/11/1/015001.
Ren, C.F., Guo, P., Yang, G.Q., Li, R.H., Liu, L., 2016. Spatial and temporal analyses of water resources use efficiency based on data envelope analysis and malmquist index: case study in Gansu Province, China. J. Water Res. Plan. Man. 142 (12). https://doi.org/10.1061/(ASCE)WR.1943-5452.0000719.
Rockström, J., 1999. On-farm green water estimates as a tool for increased food production in water scarce regions. Phys. Chem. Earth, Part B 24 (4), 375–383. https://doi.org/10.1016/S1464-1909(99)00016-7.
Rockström, J., Barron, J., 2007. Water productivity in rainfed systems: overview of challenges and analysis of opportunities in water scarcity prone savannahs. Irrigation Sci. 25, 299–311. https://doi.org/10.1007/s00271-007-0062-3.
Rockström, J., Falkenmark, M., Karlberg, L., Hoff, H., Rost, S., Gerten, D., 2009. Future water availability for global food production: The potential of green water for increasing resilience to global change. Water Resour. Res. 45 (7), 142–143. https://doi.org/10.1029/2007WR 006767.
Rockström, J., Lannerstad, M., Falkenmark, M., 2007. Assessing the water challenge of a new green revolution in developing countries. Proc. Natl. Acad. Sci. U.S.A. 104, 6253–6260. https://doi.org/10.1073/pnas.0605739104.
Rost, S., Gerten, D., Bondeau, A., Lucht, W., Rohwer, J., Schaphoff, S., 2008. Agricultural green and blue water consumption and its influence on the global water system. Water Resour. Res. 44, 137–148. https://doi.org/10.1029/2007WR006331.
Schaldach, R., Koch, J., der Beek, T.A., Kynast, E., Flörke, M., 2012. Current and future irrigation water requirements in pan-Europe: an integrated analysis of socio-economic and climate scenarios. Global Planet Change 94–95, 33–45. https://doi.org/10.1016/j.gloplacha.2012.06.004.
Scheierling, S.M., Treguer, D.O., Booker, J.F., Decker, E., 2014. How to assess agricultural water productivity? looking for water in the agricultural productivity and efficiency literature. Policy Res. Working Papers. https://doi.org/10.1596/1813-9450-6982.
Singh, P., Wani, S., Pathak, P., Singh, A., 2011. Increasing crop water productivity and water use efficiency in rainfed agriculture. In: Suhas, P.W., Rockestrom, J., Sahrawat, K.L. (Eds.), Integrated watershed management in rainfed agriculture. A Balkeman Book. CRC Press, ICRISAT, India, pp. 315–348.
M. Smith Irrigation and Drainage Pap. 46, CROPWAT—A Computer Program for Irrigation Planning and Management. Food and Agric. Org. of the U. N 1992 Rome, Italy.
Soltani, G., 2013. Agricultural water-use efficiency in a global perspective: the case of iran. Economic Research Forum Working Papers.
Song, J.F., Wang, Y.B., Wu, P.T., 2017. A reviews on irrigation water rebound effect. Adv. Water Sci. 28, 452–461 (in Chinese with English abstract).
Speelman, S., D'Haese, M., Buysse, J., D'Haese, L., 2008. A measure for the efficiency of water use and its determinants, a case study of small-scale irrigation schemes in North-West Province, South Africa. Agr. Syst. 98, 31–39. https://doi.org/10.1016/j.agsy.2008.03.006.
Sun, S.K., Wang, Y.B., Liu, J., Cai, H.J., Wu, P.T., Geng, Q.L., Xu, L.J., 2016. Sustainability assessment of regional water resources under the DPSIR framework. J. Hydrol. 532, 140–148. https://doi.org/10.1016/j.jhydrol.2015.11.028.
Sun, S.K., Wu, P.T., Wang, Y.B., Zhao, X.N., Liu, J., Zhang, X.H., 2013. The impacts of interannual climate variability and agricultural inputs on water footprint of crop production in an irrigation district of China. Sci. Total Environ. 444, 498–507. https://doi.org/10.1016/j.scitotenv.2012.12.016.
Susaeta, A., Adams, D.C., Carter, D.R., Dwivedi, P., 2016. Climate change and ecosystem services output efficiency in southern loblolly pine forests. Environ. Manage. 58, 417–430. https://doi.org/10.1007/s00267-016-0717-z.
Tang, J., Folmer, H., Xue, J., 2015. Technical and allocative efficiency of irrigation water use in the Guanzhong Plain, China. Food Policy 50, 43–52. https://doi.org/10.1016/j.foodpol. 2014.10.008.
Toma, P., Miglietta, P.P., Zurlini, G., Valente, D., Petrosillo, I., 2017. A non-parametric bootstrap-data envelopment analysis approach for environmental policy planning and management of agricultural efficiency in EU countries. Ecol. Indic. 83, 132–143. https://doi.org/10.1016/j.ecolind.2017.07.049.
Vanham, D., Bidoglio, G., 2013. A review on the indicator water footprint for the EU28. Ecol. Indic. 26, 61–75. https://doi.org/10.1016/j.ecolind.2012.10.021.
Veettil, A.V., Mishra, A.K., 2016. Water security assessment using blue and green water footprint concepts. J. Hydrol. 542, 589–602. https://doi.org/10.1016/j.jhydrol.2016.09.032.
Wang, G., Chen, J., Wu, F., Li, Z., 2015a. An integrated analysis of agricultural water-use efficiency: a case study in the Heihe River Basin in Northwest China. Phys. Chem. Earth 89V90, 3–9. https://doi.org/10.1016/j.pce.2015.10.009.
Wang, X.J., Yang, H., Shi, M.J., Zhou, D.Y., Zhang, Z., 2015b. Managing stakeholders' conflicts for water reallocation from agriculture to industry in the Heihe River Basin in Northwest China. Sci. Total Environ. 505, 823–832. https://doi.org/10.1016/j.scitotenv.2014.10.063.
Ward, F.A., 2014. Economic impacts on irrigated agriculture of water conservation programs in drought. J. Hydrol. 508, 114–127. https://doi.org/10.1016/j.jhydrol.2013.10.024.
Ward, F.A., Pulido-Velazquez, M., 2008. Water conservation inirrigation can increase water use. Proc. Natl. Acad. Sci. U.S.A. 105, 18215–18220. https://doi.org/10.1073/pnas.0805554105.
Xu, C.L., Tao, H.B., Tian, B.J., Gao, Y.B., Ren, J.H., Wang, P., 2016. Limited- irrigation improves water use efficiency and soil reservoir capacity through regulating root and canopy growth of winter wheat. Field Crop. Res. 196, 268–275. https://doi.org/10.1016/j.fcr.2016.07.009.
Xue, J., Ren, L., 2016. Evaluation of crop water productivity under sprinkler irrigation regime using a distributed agro-hydrological model in an irrigation district of China. Agr. Water Manage. 178, 350–365. https://doi.org/10.1016/j.agwat.2016.10.003.