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Technical and allocative efficiency of irrigation water use in the Guanzhong Plain, China

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ABSTRACT

Due to increasing water scarcity, accelerating industrialization and urbanization, efficiency of irrigation water use in Northern China needs urgent improvement. Based on a sample of 347 wheat growers in the Guanzhong Plain, this paper simultaneously estimates a production function, and its corresponding first-order conditions for cost minimization, to analyze efficiency of irrigation water use. The main findings are that average technical, allocative, and overall economic efficiency are 0.35, 0.86 and 0.80, respectively. In a second stage analysis, we find that farmers' perception of water scarcity, water price and irrigation infrastructure increase irrigation water allocative efficiency, while land fragmentation decreases it. We also show that farmers' income loss due to higher water prices can be offset by increasing irrigation water use efficiency.

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Introduction

Due to water scarcity, irrigation plays an important role in agricultural production in North China. Huang et al. (2006) points out that widespread irrigation is required to keep up and expand agricultural outputs, particularly wheat and maize, but also to alleviate poverty. However, water scarcity in the region has been worsening due to accelerating industrialization and urbanization, but also because of environmental challenges, such as climate change and water pollution (Jiang, 2009). These developments have led to increased competition among the main water users, i.e. agriculture, industry and households.

Irrigation consumes 60% of total annual water resources in *inter alia* the Guanzhong Plain, which is a region facing severe and increasing water scarcity. In the area, 75% of grain production comes from irrigated land which accounts for 50% of total arable land. Expansion of grain production, and thus of irrigation, is needed to feed China's large and still growing population. However, water has higher marginal returns in industry and the

residential sector. Under such circumstances, it is imperative for agriculture to improve its water use efficiency (Lybbert and Sumner, 2012).

This goal of the paper is to measure the efficiency of farmers' irrigation water use and identify its determinants, based on a sample of 347 farmers in the Guanzhong Plain. The paper contributes to the literature in the following three aspects. First, it focuses on both technical and allocative efficiency. Water use efficiency is commonly defined as yield per m³ water. See, for instance, Wang et al. (2010). This measure is biased and inappropriate, however, because it ignores the fact that yield is not produced by a single input, water, but by multiple inputs including water, but also fertilizers, seeds, machinery and labor. Several researches have recognized this and analyzed technical efficiency of irrigation water use, while controlling for the contributions of all other inputs (Karagiannis et al., 2003; Speelman et al., 2008, among others). For instance, based on data on 50 vegetable farms in Greece, Karagiannis et al. (2003) analyzed input-specific technical efficiency as a measure of water use efficiency. However, technical efficiency analysis does not measure a farmer's ability to allocate irrigation water and other inputs to their cost-minimizing input proportions. For that purpose, allocative efficiency analysis is needed. To the best of our knowledge, there are no analyses of allocative efficiency of irrigation water use. This paper fills this gap by simultaneously estimating a production function, and its corresponding first-order conditions for cost

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minimization, to measure this latter kind of efficiency. In addition, it measures technical and economic efficiency.

Secondly, in a bid to get insight into the determinants of technical and allocative efficiency, the paper does not only consider farm-specific characteristics, like farm size, and socioeconomic features, such as farmer's age and education, but also a farmer's perception of water scarcity. As argued by Folmer (2009) and Folmer and Johansson-Stenman (2011), ignoring the latter kind of variables leads to model under-specification, and thus to biased estimators of the coefficients of the standard explanatory variables, like farm and farmer characteristics, and to invalid inference. Furthermore, if perception turns out to be a determinant of efficiency, it is a potential policy handle in that improving perception via e.g. extension, may induce farmers to reduce their water use. (Note that the literature has so far paid little attention to perception of water scarcity and its potential as a policy instrument.)

Thirdly, the paper provides support to water pricing as a policy handle. In China, the use of this policy instrument is still under debate. Huang et al. (2010) argues that the price of irrigation water in China is too low to induce farmers to save water. However, policymakers fear that higher prices will jeopardize farmers' income and further widen the gap between rural and urban residents (Lohmar et al., 2007). Little research has been conducted to quantify the effect of water price on income. We test whether the income loss due to higher irrigation water price can be offset by more efficient use of water.

The structure of the paper is as follows. Section "Methodology" presents the methodological framework. Sections "The conceptual model and the Structural Equation Model (SEM)" and "Empirical results" discuss the data and the empirical results. Section "Discussion and policy recommendations" presents the conclusions and policy recommendations.

Methodology

Single-factor technical, allocative and economic efficiency

Since Farrell's (1957) pioneering work, the three efficiency measures technical, allocative and economic efficiency, have been extensively used to assess economic performance of various economic sectors. This also applies to agriculture, where a substantial literature on efficiency of agricultural production has developed. Few studies, however, focus on efficiency of a particular input, such as water. To gain insight into the efficiency of the single input irrigation water, we present in this section the notions of *single-factor technical efficiency (SFTE)*, *single-factor allocative efficiency (SFAE)* and *multi-factor economic efficiency (MFEE)*. These concepts, as introduced by Kopp (1981) and Kopp and Diewert (1982), are illustrated in Fig. 1.

In Fig. 1, there is a single output, Y , and two inputs W , i.e. irrigation water, and X , which denotes all other inputs, such as capital, labor, fertilizers and so on. F_1 is an isoquant which represents the production frontier at which a technically, perfectly efficient farmer uses least inputs to produce a given output. Point P is above the production frontier indicating that the farmer who produces at that point is technically inefficient.

Consider the isocost lines C_1 , C_2 and C_3 . Point P at C_1 is the actual cost at which the producer uses OW_1 of input factor W and OE of input factor X . Point E^* on C_2 denotes the cost where the use of W is technically efficient, given X (OE) and output. The isocost line C_3 is drawn tangent to the isoquant F_1 at point D where W and X are both allocatively efficient. The slope of C_3 (with negative sign) equals the ratio of the prices of W and X . X^* and W^* are intersections¹ of the

Fig. 1. Single-factor technical, allocative and multi-factor economic efficiency. Note: Figure is based on Kopp (1981) and Reinhard et al. (1999).

isocost line C_3 and the vertical and horizontal axis, respectively. C_3 is the cost at point D .

EE^* is the minimum feasible use of W conditional on a given level of input X (OE) and actual output. $SFTE$ of W at point P equals EE^*/EP . From a cost perspective, single-factor technical cost efficiency ($SFTCE$) of W is the ratio between the cost when W is technically efficient and actual cost, that is, C_2/C_1 . $SFAE$ of W is the ratio between the cost at point D and the cost at point E^* , that is, C_3/C_2 . Finally, $MFEE$ is the product of $SFTCE$ and $SFAE$ and equals C_3/C_1 . Since $MFEE$ is determined as their product, the focus below will be on $SFTE$ and $SFAE$. Below we label the three types of single factor irrigation water efficiencies as $IWTE$, $IWAE$ and $MFEE$, respectively.

Measurement of irrigation water technical efficiency (IWTE)

Having introduced the concepts of $SFTE$ and $SFAE$ in the previous section, we now turn to the methodology of estimating these measures. In this subsection we pay attention to $SFTE$, in the next to $SFAE$.

Following Aigner et al. (1977), the general stochastic production function for cross sectional data is:

$$Y_i = F(X_i; \beta) \exp(v_i - u_i) \quad (1)$$

For farmer i , production function (1) describes output Y_i as a function of a vector of inputs X_i and an error term made up of two components: $v_i \sim N(0, \sigma_v^2)$, representing the standard error term, and the non-negative error term u_i , which follows a half-normal distribution, reflecting the shortfall of a farmer's output from the production frontier, due to technical inefficiency.

A translog stochastic frontier production function is usually chosen for (1). For the i th farmer, the translog stochastic frontier production function with 4 inputs, reads:

$$\begin{aligned} \ln y_i = & \beta_0 + \beta_w \ln w_i + \sum_{j=1}^3 \beta_j \ln x_{ji} + \frac{1}{2} \sum_{j=1}^3 \sum_{k=1}^3 \beta_{jk} \ln x_{ji} \ln x_{ki} \\ & + \sum_{j=1}^3 \beta_{wj} \ln w_i \ln x_{ji} + \frac{1}{2} \beta_{ww} (\ln w_i)^2 + v_i - u_i \end{aligned} \quad (2)$$

where y_i is output (wheat in the present study). The 4 inputs considered in the application below include: (1) x_{1i} , the sown area (Land); (2) x_{2i} , Labor; (3) x_{3i} , Other inputs; and (4) w_i , Water.

¹ X^* is the quantity of X when cost (C_3) is incurred to purchase X only, while W^* is the quantity of W when cost (C_3) is incurred to purchase W only.

Following Schmidt and Lovell (1979), the first-order conditions of cost minimization imply that the technical rate of substitution equals the factor price ratio. To avoid identification problems, we arbitrarily choose w as numeraire. For farmer i , the first-order conditions are:

$$\ln S_{ji} - \ln S_{wi} - \ln(p_{ji}x_{ji}) + \ln(p_{wi}w_i) = \tau_{ji} \quad j = 1, 2, 3 \quad (3)$$

where

$$S_{ji} = \beta_j + \sum_{k=1}^3 \beta_{jk} \ln x_{ki} + \beta_{wj} \ln w_i, \quad j = \text{Land, Labor and Other inputs} \quad (4)$$

In (3), p_{ji} is the price of the j th input, p_{wi} is the price of water and S_{ji} and S_{wi} are the partial derivatives (elasticity) with respect to input j and w , respectively. τ_{ji} is the error term which is normally distributed and can take both positive and negative values. (Note that τ_{ji} also corresponds to allocative inefficiency which is defined as the extent of failure to choose cost-minimizing factor proportions between the input j and the numeraire w . For further details, see Section “Measurement of Irrigation Water Allocative Efficiency (IWAE)”). If $\tau_{ji} > 1$, input x_i is underutilized relative to irrigation water; it is overutilized, if $\tau_{ji} < 1$.

Following Reinhard et al. (1999), $IWTE$ for farmer i can be obtained by setting actual production equal to production under no technical inefficiency ($u_i = 0$), i.e. when using minimum feasible irrigation water w_i^f while producing the same level of output (y_i).

$$F(x_i, w_i^f; \beta) \exp(v_i) = F(x_i, w_i; \beta) \exp(v_i - u_i) \quad (5)$$

From (5), $IWTE$ for individual farmer i can be obtained as:²

$$IWTE_i = \exp\left(\frac{-\varpi_i \pm \sqrt{\varpi_i^2 - 2\beta_{ww}u_i}}{\beta_{ww}}\right) \quad (6)$$

where

$$\varpi_i = \beta_w + \sum_{j=1}^3 \beta_{wj} \ln x_{ji} + \beta_{ww} \ln w_i \quad (7)$$

Measurement of Irrigation Water Allocative Efficiency (IWAE)

We now turn to IWAE, i.e. irrigation water allocative efficiency when all inputs are adjusted to their respective cost-minimizing input proportions, given prices of all inputs, and output. As shown in Section “Single-factor technical, allocative and economic efficiency”, allocative efficiency of irrigation water is the ratio between the cost at point E^* (C_2 in Fig. 1) and the cost at point D (C_3 in Fig. 1). Suppressing the subscript i , we have for C_2

$$C_2 = p_w w^f + \sum_{j=1}^3 p_j x_j \quad (8)$$

At point D in Fig. 1 the producer is both technically and allocatively efficient. Hence, the minimum feasible cost of producing actual output Y at point D , $C^*(p, y)$, is:

$$C^*(p, y) = p_w w^* + \sum_{j=1}^3 p_j x_j^* \quad (9)$$

The optimal inputs x_j^* and w^* are obtained by solving the Eqs. (2) and (3) with the allocative inefficiency term $\tau_{ji} = 0$, and the technical inefficiency term $u_i = 0$.³

Finally, from its definition $IWAE$ is

$$IWAE = \frac{C^*(p, y)}{C_2} \quad (10)$$

Finally, from its definition, $MFEE$ is obtained as:

$$MFEE = IWTE * IWAE \quad (11)$$

where $IWTCE = C_2/C_1$.⁴

The Conceptual model and the Structural Equation Model (SEM)

Below we first develop the conceptual model, i.e. the model that describes the determinants of $IWTE$ and $IWAE$ (Section “The determinants of $IWTE$ and $IWAE$ ”). Next, in Section “SEM”, we present it as a Structural Equation Model (SEM).

The determinants of $IWTE$ and $IWAE$

The scores for $IWTE$ and $IWAE$ are obtained from the Eqs. (6) and (10) in Section “Methodology”. We assume that the explanatory variables discussed below apply to each of the two types of efficiencies, though possibly with different coefficients. Therefore, we use the catch-all label *Efficiency* in this section.

Endogenous explanatory variables

As an explanatory variable of both types of efficiency, we postulate Perception of water scarcity (*Perception*). This assumption is based on the growing evidence that economic behavior is strongly influenced by psychological factors including perceptions, expectations and habits (Folmer (2009), Folmer and Johansson-Stenman (2011) and the reference therein). The underlying mechanism is that perception increases intrinsic motivation which enhances environmentally friendly behavior (Lindenberg, 2001).

We take *Perception* as a latent variable or theoretical construct, i.e. a variable that refers to a phenomenon that is supposed to exist but cannot be directly observed (see e.g. Folmer (1984) and the references therein).⁵ We measure the latent variable *Perception* by the following three items (observed variables), each measured at a 5 points scale:⁶

- (i) *Perception 1 (Percep1)*: Irrigation water is scarce in my village.
- (ii) *Perception 2 (Percep2)*: Irrigation water scarcity is worse now than before.
- (iii) *Perception 3 (Percep3)*: Irrigation water will be scarcer in the next two years than it is now.

We expect a positive impact of *Perception* on *Efficiency*. This expectation is based on the assumption that farmers who clearly perceive water as a scarce input are likely to be intrinsically motivated to be efficient.

We do not only hypothesize an impact of *Perception* on *Efficiency*, but also vice versa. That is, we assume that efficient farmers perceive water scarcity less as a problem. We have not been able to find evidence for this hypothesis in the social science and economics literature. However, experts on irrigation in the Guanzhong Plain have pointed out in various in-depth interviews that efficient farmers have a more optimistic view on water scarcity (as measured by the above three observed variables) than less efficient farmers. Therefore, we test this hypothesis in the empirical analysis below.

² For details, see Reinhard et al. (1999) and Tang et al. (2013a).

³ Eqs. (2) and (3) make up a system of 4 nonlinear equations with 4 unknown optimal inputs x_1^* , x_2^* , x_3^* and w^* . We solved them using Matlab by setting the actual values as starting values (Rodríguez-Álvarez et al., 2004).

⁴ Here C_1 is the actual cost.

⁵ See Section “SEM” for the econometrics of handling latent and observed variables.

⁶ Each item is presented as a statement with response categories ranging from fully disagree to fully agree.

Exogenous variables

We first discuss the exogenous explanatory variables of *Efficiency* and next those of *Perception*.

Age. Chen et al. (2009) shows that older farmers are more technically efficient than younger farmers. The explanation is that older farmers have more farming experience and thus have developed more efficient irrigation practices. Hence, we expect a positive effect on *Efficiency*.

Time spent on farming (Time). In the Guanzhong Plain, there is a growing number of part-time farmers who spend less time on irrigation; particularly they irrigate less frequently than their full time peers. This restriction reduces the possibilities for “precise irrigation” (right moment and adequate amount). Moreover, since they have off-farm income, farming activities, including irrigation, are likely to be less important to them than to full time farmers. Hence, we assume that part-time farmers are less efficient than their full time peers.

Land Fragmentation (Fragmentation). This variable is measured by the number of different plots a farmer cultivates. A large number of different plots indicates a high level of land fragmentation. The impact of land fragmentation on efficiency of agricultural production in general has been empirically investigated in China. Based on a sample of 1093 rice producers in South-east China, Tan et al. (2010) showed that land fragmentation is an important, negative, determinant of technical efficiency. For 339 rice producers in Zhejiang, Hubei, and Yunnan Provinces, Zhang et al. (2011) found that land fragmentation is hindering technical efficiency. To the best of our knowledge, the impact on irrigation water efficiency has not been investigated yet. We hypothesize that land fragmentation decreases *Efficiency*.

Irrigation infrastructure (Infrastructure). At the termination of the collective agricultural system in 1978, irrigation canals started to deteriorate due to reduced maintenance which, *inter alia*, has led to seepage (Wang et al., 2006).⁷ In 1999, the World Bank started an irrigation infrastructure repair project in the Guanzhong Plain. However, not all canals have been repaired and presently there exist differences in irrigation infrastructure quality. We expect farmers located at repaired (cement) canals to be more efficient. Infrastructure takes the value 1 if the farmer is connected to a cement irrigation canal and 0 otherwise.

Income. Liu et al. (2008) found a positive impact of net per capita income on water-saving technology adoption in 10 provinces in China. The explanation is that possibilities to purchase and use more advanced technology increase with income. We thus assume a positive impact on *Efficiency*.

We now turn to the exogenous explanatory variables of *Perception*.

Income. We also hypothesize a positive income effect on *Perception* in that higher income allows the acquisition of information which in its turn may promote clearer perception.

Education. Education is measured as years of schooling in this study. We assume that educated farmers have clearer perceptions of irrigation water scarcity than uneducated because education

makes individuals more knowledgeable and able to interpret a complex phenomenon like the environment (Stapp, 1969). We hypothesize a positive impact on *Perception*.

Water price. Irrigation water price varies in the Guanzhong Plain, mainly because of scarcity. Wang et al. (2009) found that farmers respond to higher water prices by reducing water use. The reason is that water price signals the value of water. We therefore expect *Water price* to have a positive impact on *Perception*.

Precipitation. People form perceptions of their environment via signals and stimuli that they receive from it (Sudarmadi et al., 2001). In the case of irrigation water, *Precipitation* is an important signal. In the study area, precipitation, ranges from 137 mm to 220 mm during the growing season (from October to May). We hypothesize that *Perception* varies inversely with *Precipitation* in that in areas with more rainfall perception of water scarcity is lower.

SEM

The conceptual model above contains the latent variable *Perception* as well as several observed variables including the indicators that measure *Perception*. Both types of variables can be simultaneously handled by means of a Structural Equation Model (SEM). A SEM consists of two sub-models: two measurement models (Eqs. (11) and (12)) and a structural model (Eq. (13)) (Jöreskog, 1977; Jöreskog and Sörbom, 2001). The measurement models specify the relationship between the latent variables and their observed indicators⁸ while the structural model represents the relationships between the latent exogenous and latent endogenous variables as well as the relationships among the latent endogenous variables. Specifically:

$$y = A_y \eta + \varepsilon \quad (11)$$

$$x = A_x \xi + \delta \quad (12)$$

$$\eta = B\eta + \Gamma\xi + \zeta \quad (13)$$

where y is a $p \times 1$ vector of endogenous observed variables, x a $q \times 1$ vector of exogenous observed variables, η an $m \times 1$ vector of latent endogenous variables, and ξ a $n \times 1$ vector of latent exogenous variables. A_y and A_x are $p \times m$ and $q \times n$ matrices of regression coefficients or loadings. B is an $m \times m$ matrix with β_{ij} representing the effect of the j th endogenous latent variable on the i th endogenous latent variable, and Γ is an $m \times n$ matrix with γ_{ij} representing the effect of the j th exogenous latent variable on the i th endogenous latent variable. Finally, ε and δ are $p \times 1$ and $q \times 1$ vectors of measurement errors of y and x , with covariance matrices θ_ε , and θ_δ , respectively. ζ is a vector of disturbances of the structural model. Its covariance matrix is Ψ . For identification, estimation, testing and modification indices we refer to Jöreskog and Sörbom (2001). Folmer and Oud (2008) discuss the theoretical and empirical advantages of using SEM.

In SEM notation the conceptual model presented in Fig. 2 reads:

$$\begin{bmatrix} IWTE \\ IWAE \\ Percp1 \\ Percp2 \\ Percp3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \lambda_{3,1} \\ 0 & 0 & \lambda_{4,1} \\ 0 & 0 & \lambda_{5,1} \end{bmatrix} \begin{bmatrix} IWTE \\ IWAE \\ Perception \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \end{bmatrix} \quad (14)$$

⁷ In the Guanzhong Plain, a canal is used by a group of farmers. Irrigation water flows from the canal to the farmlands. Farmers are charged for the total amount of water withdrawn, including water lost during transportation due to seepage. If a canal is totally destroyed, the farmers who use it, have no longer access to irrigation water.

⁸ Note that directly observed variables can be conveniently handled in the SEM framework by specifying an identity relationship in the measurement model between the latent variable and the corresponding observed variable.

Fig. 2. The efficiency-perception model. (Error terms not included.)

$$\begin{bmatrix} \text{Age} \\ \text{Time} \\ \text{Fragmentation} \\ \text{Infrastructure} \\ \text{Income} \\ \text{Education} \\ \text{Waterprice} \\ \text{Precipitation} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \text{Age} \\ \text{Time} \\ \text{Fragmentation} \\ \text{Infrastructure} \\ \text{Income} \\ \text{Education} \\ \text{Water price} \\ \text{Precipitation} \end{bmatrix} \quad (15)$$

$$\begin{bmatrix} \text{IWTE} \\ \text{IWAE} \\ \text{Perception} \end{bmatrix} = \begin{bmatrix} 0 & 0 & \beta_{1,3} \\ 0 & 0 & \beta_{2,3} \\ \beta_{3,1} & \beta_{3,2} & 0 \end{bmatrix} \begin{bmatrix} \text{IWTE} \\ \text{IWAE} \\ \text{Perception} \end{bmatrix} + \begin{bmatrix} \gamma_{1,1} & \gamma_{1,2} & \gamma_{1,3} & \gamma_{1,4} & \gamma_{1,5} & 0 & 0 & 0 \\ \gamma_{2,1} & \gamma_{2,2} & \gamma_{2,3} & \gamma_{2,4} & \gamma_{2,5} & 0 & 0 & 0 \\ 0 & 0 & 0 & \gamma_{3,5} & \gamma_{3,6} & \gamma_{3,7} & \gamma_{3,8} & 0 \end{bmatrix} \begin{bmatrix} \text{Age} \\ \text{Time} \\ \text{Fragmentation} \\ \text{Infrastructure} \\ \text{Income} \\ \text{Education} \\ \text{Waterprice} \\ \text{Precipitation} \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \zeta_3 \end{bmatrix} \quad (16)$$

$$\Psi = \begin{pmatrix} \psi_{11} & 0 & 0 \\ \psi_{21} & \psi_{22} & 0 \\ 0 & 0 & \psi_{33} \end{pmatrix} \quad (17)$$

Eqs. (14) and (15) are the endogenous and exogenous measurement models, respectively, and Eq. (16) is the structural model. (17) is the covariance matrix of the vector of structural error terms ζ .

From the conceptual model presented in Section “The determinants of IWTE and IWAE”, it follows that there may be some common factors influencing the disturbances of IWTE and IWAE. To account for this, we specify ψ_{21} as a free parameter that is to be estimated. (Note the similarity to Seemingly Unrelated Regressions (SUR)).⁹

Empirical results

Data collection and descriptive statistics

The analysis is based on a cross-sectional dataset collected in a survey among 446 farmers in the Guanzhong Plain, for the crop year 2011, which runs from October 2010 to May 2011. Although

virtually all farmers produce several crops, we only consider wheat farmers which is the main crop irrigated. Other crops such as corn and apple require no or little irrigation. Output is measured as yield of wheat times price.

The following multi-stage sampling procedure was applied. First, since irrigation in the Guanzhong Plain is organized by irrigation districts (ID), we sampled IDs at the first stage. Among the approximately 100,000 IDs, we chose the nine largest because of their well-structured irrigation infrastructure and substantial area coverage of approximately 80%. At the next stage, we sampled canals within the selected IDs. For each ID, we randomly sampled 2–12 canals proportional to its total number of canals. At the third stage, we sampled villages per canal. To account for differences in water availability between upstream and downstream areas, we randomly sampled 1 village from each stratum. The total number of villages sampled was 66. At the final stage, we randomly sampled 5–7 wheat farmers per village, resulting in 405 wheat farmers. Among them, 58 did not irrigate¹⁰; they were excluded from the sample which resulted in a sample of 347 farmers.

Face-to-face interviews were conducted by a group of interviewers consisting of Master and Ph.D students at Northwest A&F University majoring in agricultural economics. Before the interviews, a preliminary survey was held to test the structure of the questionnaire and the clarity of the questions. Based on the outcome of this survey, the ambiguous and unclear questions were revised. The interview was carried out in October, 2011 when the harvest was finished.

Data used in the stochastic frontier analysis include the quantity and price for each of the following inputs: (1) *Land* (measured in mu); (2) *Labor* (measured in man-days); (3) *Other inputs* (the sum of the monetary value of all other inputs including seeds, fertilizers, machinery and pesticides); and (4) *Water* (measured in m³). Table 1 presents descriptive statistics for the key variables included in the analysis and Table 2 for the indicators of perception.

The frontier model

The simultaneous Eqs. (3) and (4) were estimated by the Stata program by Kumbhakar and Wang (2006). We first tested the Cobb-Douglas versus the translog production function. The difference of the log likelihood test statistics follows a χ^2_{10} distribution (Battese and Coelli, 1995). We rejected the Cobb-Douglas specification at 1% significance level.¹¹

The estimates of the translog model are reported in Table 3. Only 2 of the 14 variables ($\ln \text{Labor} * \ln \text{Water}$ and $\ln \text{Water} * \ln (\text{Other inputs})$) are insignificant. The ratio $\frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} = 44.76\%$ indicates that technical efficiency contributes 44.76% to the total variance of output.

The output elasticities of wheat yield with respect to each input are reported in Table 4. The results are in line with Tang et al. (2013a). The highest elasticity is for *Other inputs* (0.46), followed by *Land* (0.44) and *Labor* (0.1132). The elasticity of *Water* is 0.0812 indicating that a 1% increase in irrigation water leads to only a 0.0812% increase of output. The sum of elasticities with respect to the four inputs equals 1.09, indicating a (slightly) increasing return to scale.

The estimated distributions of the IWTE, IWTE, IWAE and MFEE scores are shown in Fig. 3. The IWTE, IWAE and MFEE distributions are close to normal while the IWTE distribution is skewed to the

¹⁰ The main reasons for the 58 farmers to abstain from irrigating are: (1) they are absent from the farm for most of the irrigation season; (2) they think there is no need for irrigation because rainfall is sufficient and (3) there is no irrigation infrastructure.

¹¹ The log likelihood for the Cobb-Douglas specification was −455.77; for the translog specification it was −133.38. So the χ^2_{10} statistics is 322.39. The 1% significance level with 10 degrees of freedom is 23.21.

⁹ We acknowledge one of the reviewers' suggestion to adopt this approach.

Table 1
Descriptive statistics.

Variable	Unit of measurement	Min.	Max.	Mean	S.D.	Coefficient of variation
Yield	kg	200	20,000	2582	1820	0.70
Price of yield	Yuan/kg	1.5	3	2.02	0.10	0.05
Output	Yuan	400	38,800	5209	3659	0.70
Land	Mu	0.40	40.00	5.71	3.86	0.68
Labor	man-days	0.45	46.00	8.26	6.30	0.76
Water	m ³	38	9389	1535	1406	0.92
Other inputs	Yuan	157	20,100	2156	1612	0.75
PriceLand	Price of land in Yuan/mu	40.00	1500.00	241.99	193.65	0.80
PriceLabor	Price of labor in Yuan/day	30.00	200.00	73.25	27.25	0.37
Age	Years	26	77	53.08	10.07	0.19
Education	Years	0	12	6.64	1.70	0.26
Income	Yuan	1000	195,000	26,941	25,103	0.93
Time	—	1	5	3.80	1.44	0.38
Water price	Yuan/m ³	0.02	1.00	0.32	0.13	0.41
Fragmentation	—	1	15	2.74	1.75	0.64
Precipitation	mm	137	220	174.31	17.07	0.10
Infrastructure	—	0	1	0.52	0.49	0.94
IWTE	—	0.06	0.76	0.35	0.14	0.40
IWTCE	—	0.75	0.99	0.93	0.04	0.04
IWAE	—	0.64	0.98	0.86	0.07	0.08
MFEE	—	0.60	0.93	0.80	0.07	0.09

Table 2
Descriptive statistics for indicators of Perception.

Indicators	Strongly disagree (%)	Disagree (%)	Neither disagree nor agree (%)	Agree (%)	Strongly agree (%)	In total
Percep1	30.55	31.99	1.44	18.16	17.87	100
Percep2	14.12	42.36	10.09	19.02	14.41	100
Percep3	7.78	17.87	44.96	17.29	12.10	100

Table 3
The estimated translog production function.

Variable	Coefficient	S.E.
Constant	−8.0383***	0.9090
lnLand	−3.7634***	0.3023
lnLabor	0.4180***	0.1180
lnWater	0.3432***	0.0497
ln(Other inputs)	4.1463***	0.2881
lnLand*lnLand	−0.7910***	0.0605
lnLabor*lnLabor	−0.0601***	0.0089
lnWater*lnWater	−0.0423***	0.0050
ln(Other inputs)*ln(Other inputs)	−0.6157***	0.0487
lnLand*lnLabor	0.0955***	0.0139
lnLand*lnWater	0.0375***	0.0052
lnLand*ln(Other inputs)	0.6696***	0.0529
lnLabor*lnWater	0.0073	0.0072
lnLabor*ln(Other inputs)	−0.0527***	0.0189
lnWater*ln(Other inputs)	−0.0052	0.0073
σ_u^2	0.0329***	0.0082
σ_v^2	0.0406***	0.0035
Log likelihood	−133.38	

Note:

* $p < 0.10$.** $p < 0.05$.*** $p < 0.01$.**Table 4**
Output elasticities.

Input	Land	Labor	Water	Other inputs	Sum
Elasticity	0.4444	0.1132	0.0812	0.4561	1.0949

right limit of 1. The mean value of *IWTE* is 0.35, indicating that given current technology and keeping other inputs constant, the same output can be produced by using 65% less water. This means that a large proportion of irrigation water is wasted. However, it

also indicates a substantial saving potential. *IWTCE* has a mean value of 0.93, which means that the inefficient use of water leads to a 7% increase of total cost.

IWAE measures farmers' ability to minimize cost using the optimal level of inputs. Its mean value is 0.86, indicating that not allocating the inputs at cost-minimizing proportions has led to a total cost increase by 14%. *MFEE*, which is the product of *IWTCE* and *IWAE*, has a mean value of 0.80. It shows that the total cost can be feasibly decreased by 20% while keeping output at the observed level.

On the basis of the above, we can draw the following conclusion. Since its cost accounts for only 9.85% of total cost, the price of irrigation water can be more than doubled (i.e. increased by the factor 2.03 to give the feasible cost decrease of 20%), without hampering farmers' income, if they improve efficiency by using irrigation water technically efficiently, and optimally allocating their inputs.

SEM

Before going into detail, we make the following observations. First, we assigned a measurement scale to the latent variable *Perception* (which is a prerequisite for identification) by fixing its variance (at 1). Secondly, the coefficients presented below are standardized.¹² (Finally, we estimated the model by means of LISREL 8.8 (Jöreskog and Sörbom, 2001). Because of the presence of ordinal variables, we analyzed a polychoric correlation matrix.

¹² A standardized coefficient gives the standard deviation change in a dependent variable due to a standard deviation change in an explanatory variable. They are obtained by computing the z-scores and running the analysis using the z-scores, rather than the original scores of the variables. Standardized coefficients allow direct comparisons of the effects of the explanatory variables because their relative movements are the same. For variables measured in other units than z-scores, this does not hold.

Fig. 3. Distribution of IWTE, IWTC, IWAE and MFEE scores.

The measures of model fit are presented in Table 5. The p -values corresponding to the χ^2 statistics indicate the probability of obtaining a sample as the one at hand, if the hypothesized conceptual model is true. Since the p -value corresponding to the χ^2 statistic tends to be depressed, if the distribution of the observed variables deviates from normality (Bollen, 1989), we may take the p -value obtained here to indicate a good fit. The other statistics in Table 5 also indicate good overall fit, since they meet their critical values by wide margins.

We now discuss the estimated measurement model in Table 6. The standardized coefficients of the indicators of *Perception* are all significant. Moreover, the reliabilities (R^2) are above the recommended level of 0.20 (Jöreskog and Sörbom, 2001), indicating that the three indicators measure *Perception* well. The most reliable indicator is *Percep1*, followed by *Percep2*, and *Percep3*. Apparently, perceptions of the present and past situation, as measured by the first 2 indicators, is more reliable than perception of the future, as expected.

The structural models are presented in Table 7. We first discuss the efficiency sub-models, next the perception sub-model. In line with the conceptual model, *Perception* impacts positively and significantly on *IWAE*. The impact on *IWTE* is positive, though insignificant at conventional levels. These results indicate that farmers with better perception of water scarcity use irrigation water more efficiently. The impact of *Age* is not significant in the *IWTE* and

Table 5
Goodness of fit statistics.

Statistics	χ^2	NFI	GFI	AGFI	RMSEA
Values	34.54($df = 28$, $p = 0.1835$)	0.926	0.985	0.951	0.026

Note: The cut-off values for NFI, GFI, AGFI and RMSEA indicating a good fit are 0.90, 0.95, 0.90 and 0.06, respectively (Hooper et al., 2008). Put differently, the higher the NFI, GFI and AGFI values and the smaller the RMSEA, the better the fit.

Table 6
The measurement model (standardized coefficients).

Variables	Indicators	Coefficient	t -value	R^2
<i>Perception</i>	<i>Percep1</i>	0.834	6.682	0.66
	<i>Percep2</i>	0.529	6.174	0.29
	<i>Percep3</i>	0.473	5.826	0.23

IWAE equations although its sign is as expected. This outcome is probably due to the fact that irrigation requires few skills and little farming experience. *Time* has a negative and significant impact on *IWTE* while its negative impact on *IWAE* is insignificant. *Fragmentation* on the other hand reduces *IWAE* at 10% significance level and *IWTE* at 11% significance level. The positive and significant coefficients of *Infrastructure* in the *IWTE* and *IWAE* equations indicate that repaired canals reduce leakage of irrigation water and improve accessibility. *Income* positively and significantly impacts on *IWTE*, and on *IWAE*.

We now turn to the *Perception* sub-model. The impacts of *IWAE* and *IWTE* are negative and significant indicating that efficient farmers perceive water scarcity less as a problem. As postulated in the conceptual model, a likely explanation is that efficient farmers are of the opinion that water scarcity can be reduced by improving efficiency. The impact of *Education* is positive, though insignificant. Apparently, perception of water scarcity does not require much education. The impact of *Income* is negative, though insignificant. The outcome indicates that access to information as facilitated by *Income*, does not play much of a role. *Water price* has a positive and significant impact, indicating that *Water price* is an important signaling mechanism. Finally, *Precipitation* impacts *Perception* negatively and significantly, as assumed.

The non-zero estimates in the Ψ matrix are shown in Table 8. Element ψ_{21} is positive and significant, indicating that the error terms in the *IWTE* and *IWAE* equation are correlated, thus

Table 7
The structural model (standardized coefficients).

Variables	Perception	IWTE	IWAE
<i>IWTE</i>	−0.361* (0.202)	—	—
<i>IWAE</i>	−0.568*** (0.186)	—	—
<i>Perception</i>	—	0.326 (0.246)	0.770** (0.360)
<i>Age</i>	—	0.071 (0.064)	0.093 (0.075)
<i>Education</i>	0.036 (0.067)	—	—
<i>Time</i>	—	−0.135** (0.065)	−0.104 (0.076)
<i>Fragmentation</i>	—	−0.108 (0.066)	−0.143* (0.078)
<i>Infrastructure</i>	—	0.172* (0.072)	0.205** (0.086)
<i>Income</i>	−0.095 (0.074)	0.145** (0.071)	0.162* (0.084)
<i>Waterprice</i>	0.179*** (0.068)	—	—
<i>Precipitation</i>	−0.300*** (0.070)	—	—
<i>R</i> ²	0.496	0.128	0.385

Note: Standard errors are in parentheses.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Table 8
Estimated Ψ matrix.

Element	Coefficient	t-value	Element	Coefficient	t-value
ψ_{11}	1.182***	4.688	ψ_{22}	1.499***	3.736
ψ_{21}	0.636***	2.459	ψ_{33}	1.000	—

Note:

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

confirming the use of the SUR structure. Note that ψ_{33} is 1, because the variance of the latent variable *Perception* is fixed at 1 to fix its measurement scale.

Table 9 shows the total effects of all variables on *Perception*, *IWTE* and *IWAE*. The total effect of a variable on an endogenous variable is the sum of its direct effect (in Table 7) and its indirect effects which are its effects on the endogenous variable via intervening endogenous variables.¹³ Note that an endogenous variable can have a total effect on itself due to reciprocal or circular paths. The system is stable and the total effects are finite if the stability index is less than 1. For the present case study it is 0.847.

IWAE (−0.365), *IWTE* (−0.232), *Precipitation* (−0.193), *Income* (−0.154) and *Infrastructure* (−0.115) have negative total impacts on *Perception* while it also has a negative effect on itself via various cycles (−0.357). The total effects of −0.232 and −0.365 of *IWTE* and *IWAE* on *Perception* are equal to their anxiety dampening direct effects (−0.361 and −0.568, respectively) plus the anxiety increasing effects that arise via the efficiency increasing impacts of *Perception* itself on each efficiency variable (0.129 and 0.203, respectively). The total effect of *Perception* on itself is the sum of the total effects of the cycles via *IWTE* and *IWAE*. Similarly, the insignificant direct impact of *Income* on *Perception* (−0.095) is

Table 9
Estimated total effects (standardized coefficients).

Variables	Perception	IWTE	IWAE
<i>IWTE</i>	−0.232* (0.141)	−0.076 (0.087)	−0.179* (0.093)
<i>IWAE</i>	−0.365*** (0.078)	−0.119 (0.074)	−0.281* (0.157)
<i>Perception</i>	−0.357** (0.150)	0.210 (0.133)	0.495*** (0.123)
<i>Age</i>	−0.051 (0.037)	0.054 (0.055)	0.055 (0.050)
<i>Education</i>	0.023 (0.043)	0.008 (0.016)	0.018 (0.033)
<i>Income</i>	−0.154** (0.064)	0.095* (0.053)	0.043 (0.053)
<i>Time</i>	0.069* (0.039)	−0.112** (0.056)	−0.051 (0.051)
<i>Water price</i>	0.115** (0.054)	0.037 (0.027)	0.089** (0.038)
<i>Infrastructure</i>	−0.115*** (0.040)	0.134** (0.052)	0.116** (0.047)
<i>Fragmentation</i>	0.077** (0.037)	−0.082 (0.052)	−0.083* (0.046)
<i>Precipitation</i>	−0.193* (0.070)	−0.063 (0.042)	−0.149*** (0.045)

Note: Standard errors are in parentheses.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

strengthened by the indirect effects mediated by the two efficiency variables (*IWTE* and *IWAE*). There is no direct effect of *Infrastructure* on *Perception*. However, there is a significant total effect (−0.115) via the mediation of *IWTE* and *IWAE*. *Water price*, *Fragmentation* and *Time* have significant, positive effects of 0.115, 0.077 and 0.069, respectively. The direct effect of *Water price* (0.179), is smaller than its total effect (0.115) because *Perception* has a negative effects on the efficiency variables which feedback on *Perception*. *Fragmentation* and *Time* do not directly affect *Perception*. Therefore, their significant total effects are from indirect effects, i.e. via the intervening endogenous variables *IWAE* and *IWTE*. *Age* has an insignificant total effect on *Perception* because its direct impacts on the efficiency variables are insignificant and there is no direct effect on *Perception*. The total effect of *Education* is also insignificant because its direct impacts on the efficiency variables and on *Perception* are both insignificant.

Infrastructure and *Income* have positive and significant total effects on *IWTE* of 0.134 and 0.095, respectively, which are smaller than their direct effects of 0.172 and 0.145, respectively. The impact reducing effects follow from the negative relationship between *IWTE* and *Perception*. In a similar vein, the negative direct effect of *Time* on *IWTE* (−0.135) is slightly dampened by the *IWTE*–*Perception* interaction effect giving a total effect of −0.112. The total effects of other variables on *IWTE* are insignificant, in line with their direct effects.

The variables with significant positive total effect on *IWAE* are *Perception* (0.495), *Infrastructure* (0.116) and *Water price* (0.089). The positive total effects of the first two variables are smaller than their direct effects because of the negative *Perception*–*IWAE* interaction effects. *Water price* has no direct effect on *IWAE*, thus its total effect equals its indirect effect (0.089) mediated by *Perception*. Similar to *Perception*, *IWAE* has a negative effect on itself because its direct impact on *Perception* is negative while the reverse impact is positive. *IWTE*, *Precipitation* and *Fragmentation* have significant negative total effects on *IWAE* of −0.179, −0.149 and −0.083, respectively. The total effects of *IWTE* and *Precipitation* are indirect via *Perception*. For *Fragmentation*, its total effect on *IWTE* equals its direct effect (−0.143) plus the dampening effect of 0.060 that derives from the effect of *IWAE* on itself.

¹³ For an overview of the calculation of the total effects of a SEM/LISREL model, see Jöreskog and Sörbom (2001). Particularly, the total effects of the endogenous variables η on themselves are given by equation 1.25 and the total effects of ξ on η by equation 1.26.

From the above it follows that most variables in the *Perception–IWTE–IWAE* model are linked in multiple direct and indirect ways. For a full understanding of the impacts of a variable both the direct and the indirect effects have to be taken into account. Focusing on the direct impacts may be misleading because a given direct effect may be strengthened or weakened depending on its indirect links and feedbacks. Insight into the total effects is especially relevant from a policy point of view because it shows which variable has the largest impact on a goal variable. However, for policy design, the possibilities for manipulation also have to be taken into account. For instance, the results in Table 9 show that *Water price* has the largest positive impact on *Perception* which in its turn has the largest positive impact on *IWAE*. Since *Water price* can be easily manipulated, i.e. can be easily changed over time, it is a powerful policy handle to improve *IWAE*. *Infrastructure* on the other hand has the largest impact on *IWTE*. However, it is more difficult to manipulate than *Water price* in that it requires investments which require time to materialize. Judged by their total effects, *Fragmentation* is a much less powerful policy handle than both *Water price* and *Infrastructure*. Moreover, it requires a long term perspective.

Discussion and policy recommendations

Due to reduced precipitation, accelerating industrialization and urbanization, improvement of efficiency of irrigation water use is crucial for sustainable development and food security in the Guanzhong Plain (and other arid regions in China), because irrigation consumes about 60% of total water resources. By simultaneous estimation of a translog production function and its associated cost-minimizing conditions, we obtained farmers' irrigation water technical, allocative and economic efficiency, based on data collected from 347 wheat farmers. In a second stage analysis we examined the determinants of irrigation water technical and allocative efficiencies by means of a structural equation model. The main results are as follows.

Overall economic efficiency is estimated at 0.80 on average, indicating a substantial (cost) saving potential via optimization of water usage and management. Irrigation water technical efficiency is low at 0.35 which indicates a potential for substantial water saving. Improving technical efficiency of irrigation water use could lead to 7% total costs saving. In addition, improvement of allocative efficiency could lead to a further total cost saving of 14%.

The above results clear the way for the introduction of water pricing as a policy handle. As shown in Section "Empirical results", higher water prices improve perception of water scarcity and enhance allocative efficiency. So far the impact of water price on water saving has been very modest. The reason is that the price charged is far below the marginal value. The rationale for sub-optimal prices is income policy. There is a widespread belief among Chinese policy-makers that a higher price for irrigation water is at odds with the objective of narrowing the rural–urban income gap which has been widening substantially over the past decades (Johansson et al., 2002; Tsur et al., 2004). The results obtained in this study show that under current technology, farmers' income losses due to higher water prices can be offset by increasing water use efficiency.

There is another compelling reason for the introduction of 'right' irrigation water prices and improving irrigation water efficiency, viz. long run agriculture sustainability. As mentioned above, water demand in China has been rapidly increasing due to rapid industrialization and urbanization, population growth and dietary shift while the already limited water resources are expected to decrease due to water pollution and climate change. Hence, increasingly less water will be available to the agricultural sector. Higher water prices help reducing dissipation of water

which has been prevalent in agricultural production. Furthermore, awareness of irrigation water use efficiency as a prerequisite for agriculture sustainability is likely to (further) contribute to the acceptance of higher water prices. Summarizing, water prices should be revised towards prices that reflects the marginal value of water.

The analysis of the determinants of efficiency reveals that perception has the largest, positive impact on efficiency. Hence, extension is a major policy handle. Tang et al. (2013b) shows that extension should be aimed at social networks. Another reason to focus on extension is that perception sets in motion an iterative process in which perception improves efficiency, but also vice versa: efficient farmers have a more optimistic view of combating water scarcity via improved efficiency.

The results of the paper furthermore confirm the importance of improving irrigation infrastructure at village level. Half of the irrigation canals in China are in a poor state which leads to poor accessibility and substantial loss of irrigation water. However, in spite of the fact that due to canal leakage only 45% of the irrigation water withdrawn reaches the fields, investment in repairing and improving existing aging canals is low on the political agenda. On the other hand, investment in new, prestigious projects like dams, reservoirs, and water transfer projects is substantial. Particularly, the latter accounts for 77% of total annual water-project investments while the figure for rehabilitation of existing projects is 20% only (China Water Statistical Yearbook, 2012). What's more, half of world's dams are in China already and are sufficient for existing and future demand (Liu et al., 2013). Rehabilitation and improving the existing village-level irrigation infrastructure and reduction of agricultural water demand so that more water becomes available for households, industry and ecological purposes is far more economical than investing in prestigious new projects. (Note that such projects would not only improve farmer technical efficiency, but also canal-wide efficiency.)

We also found evidence in this paper that land fragmentation decreases efficiency. After the introduction of Household Responsibility System in 1978, collectively managed land was allocated to individual farmers. Implementation of the policy brought with it the division of plots homogenous in amongst others soil type or irrigation accessibility, into several plots such that each household was allocated at least one plot of a certain kind. This led to irregularly shaped and spatially dispersed plots which increased irrigation time and made it difficult to apply water-saving techniques. The decline of the frequency and magnitude of land reallocation after the introduction of the "Rural Land Contract Law" in 2002 has not been enough to reverse the situation (Wang et al., 2011). Instead, a land rental market is needed at which farmers are allowed to freely trade their user rights. This institutional change would contribute to achieving land consolidation and thus higher water use efficiency, especially in an era when off-farm employment is rapidly developing. As a first step, integrated management of fields could be encouraged to facilitate the introduction of improved irrigation technology such as tubes which would reduce seepage during transportation, particularly to distant plots. It would also reduce labor input into irrigation and thus reduce low efficiency due to part time farming.

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