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

Jianjun Tang\textsuperscript{a,c,*}, Henk Folmer\textsuperscript{a,b}, Jianhong Xue\textsuperscript{b}

\textsuperscript{a}Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, Landleven 1, 9747 AD Groningen, The Netherlands
\textsuperscript{b}Department of Agricultural Economics, College of Economics and Management, Northwest A\&F University, Yangling, Shaanxi 712100, China
\textsuperscript{c}Centre for Public Health, Queen’s University Belfast, Belfast BT12 6BB, Northern Ireland, United Kingdom

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\textbf{A B S T R A C T}

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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\section*{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 \textit{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 m$^3$ 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 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...
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-Stubman (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 Diewet (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. F1 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 C1, C2 and C3. Point P at C1 is the actual cost at which the producer uses OW1 of input factor W and OE of input factor X. Point E* on C2 denotes the cost where the use of W is technically efficient, given X (OE) and output. The isocost line C3 is drawn tangent to the isoquant F1 at point D where W and X are both allocatively efficient. The slope of C3 (with negative sign) equals the ratio of the prices of W and X. X* and W* are intersections1 of the isocost line C3 and the vertical and horizontal axis, respectively. C4 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 (SFTE) of W is the ratio between the cost when W is technically efficient and actual cost, that is, C2/C1. SFAE of W is the ratio between the cost at point D and the cost at point E*, that is, C3/C2. Finally, MFEE is the product of SFTE and SFAE and equals C4/C3. 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:

\[ Y_i = f(X_{i1}; \beta) \exp(v_i - u_i) \]  (1)

For farmer i, production function (1) describes output Yi as a function of a vector of inputs Xi 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 ith farmer, the translog stochastic frontier production function with 4 inputs, reads:

\[ \ln y_i = \beta_0 + \beta_1 \ln w_i + \sum_{j=1}^{3} \beta_j \ln x_{ij} + \frac{1}{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \beta_{jk} \ln x_{ij} \ln x_{ik} + \frac{1}{2} \beta_{ww}(\ln w_i)^2 + v_i - u_i \]  (2)

where \( y_i \) is output (wheat in the present study). The 4 inputs considered in the application below include: (1) \( x_{i1} \), the sown area (Land); (2) \( x_{i2} \), Labor; (3) \( x_{i3} \), Other inputs; and (4) \( w_i \), Water.

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

\[ \ln S_j - \ln S_w - \ln (p_j x_j) + \ln (p_w w_i) = \tau_j, \quad j = 1, 2, 3 \]  

(3)

where

\[ S_j = \beta_j + \sum_{k=1}^{3} \beta_{jk} \ln x_k + \beta_{wj} \ln w_i, \quad j = \text{Land, Labor and Other inputs} \]  

(4)

In (3), \( p_j \) is the price of the jth input, \( p_w \) is the price of water and \( S_j \) and \( S_w \) are the partial derivatives (elasticity) with respect to input j and w, respectively. \( \tau_j \) is the error term which is normally distributed and can take both positive and negative values. (Note that \( \tau_j \) 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 \( \tau_j > 1 \), input \( x_j \) is underutilized relative to irrigation water; it is overutilized, if \( \tau_j < 1 \).

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 \( w^* \) while producing the same level of output (\( y_i \)).

\[ F(x_i, w_i^*; \beta) \exp(u_i) = F(x_i, w_i; \beta) \exp(u_i - u_i) \]  

(5)

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

\[ \text{IWTE}_i = \exp \left( -\frac{\sigma_i \pm \sqrt{\sigma_i^2 - 2\beta_{wuw} u_i}}{\beta_{wuw}} \right) \]  

(6)

where

\[ \sigma_i = \beta_{ww} + \sum_{j=1}^{3} \beta_{wj} \ln x_j + \beta_{ww} \ln w_i \]  

(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 \( C_2 \)

\[ C_2 = p_w w^* + \sum_{j=1}^{4} p_j x_j \]  

(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:

\[ C'(p, y) = p_w w^* + \sum_{j=1}^{3} p_j x_j' \]  

(9)

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

Finally, from its definition IWAE is

\[ \text{IWAE} = \frac{C'(p, y)}{C_2} \]  

(10)

Finally, from its definition, MFEE is obtained as:

\[ \text{MFEE} = \text{IWTE} + \text{IWAE} \]  

(11)

where \( \text{IWTE} = 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 reference 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). 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 177 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 (Eq. (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 indicators 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:

\begin{equation}
 y = A_y \eta + \varepsilon 
\end{equation}

(11)

\begin{equation}
 x = A_x \zeta + \delta 
\end{equation}

(12)

\begin{equation}
 \eta = B \eta + \Gamma \zeta + \zeta
\end{equation}

(13)

where \( y \) is a \( p \times 1 \) vector of endogenous observed variables, \( x \) a \( q \times 1 \) vector of exogenous observed variables, \( \eta \) an \( m \times 1 \) vector of latent endogenous variables, and \( \zeta \) 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 \( \beta_{ij} \) representing the effect of the \( j \)th endogenous latent variable on the \( i \)th endogenous latent variable, and \( \Gamma \) is an \( n \times n \) matrix with \( \gamma_{ij} \) representing the effect of the \( j \)th exogenous latent variable on the \( i \)th endogenous latent variable. Finally, \( \varepsilon \) and \( \delta \) are \( p \times 1 \) and \( q \times 1 \) vectors of measurement errors of \( y \) and \( x \), with covariance matrices \( \Theta_{\varepsilon} \) and \( \Theta_{\delta} \), respectively. \( \zeta \) is a vector of disturbances of the structural model. Its covariance matrix is \( \Psi \). 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{equation}
\begin{bmatrix}
\text{IWTE} \\
\text{IWAE} \\
\text{Percep1} \\
\text{Percep2} \\
\text{Percep3}
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 \\
\end{bmatrix}
\begin{bmatrix}
\text{IWTE} \\
\text{IWAE} \\
\text{Perception}
\end{bmatrix}
+ 
\begin{bmatrix}
\varepsilon_1 \\
\varepsilon_2 \\
\varepsilon_3 \\
\varepsilon_4 \\
\varepsilon_5
\end{bmatrix}
\end{equation}

(14)
distribution of the \( \psi \).

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

\[ \Psi = \begin{pmatrix} \psi_{11} & 0 & 0 \\ \psi_{21} & \psi_{22} & 0 \\ 0 & 0 & \psi_{33} \end{pmatrix} \]  

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 \( \Psi \).

**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 irrigate\(^9\); 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 m\(^3\)). 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 \( \chi^2 \) 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 (\( \ln \text{Labor} \) and \( \ln \text{Water} \)) in Other inputs) are insignificant. The ratio \( \frac{\sigma^2_1}{\sigma^2_2} = 44.76\% \) 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, IWAIE and MFEE scores are shown in Fig. 3. The IWTE, IWAIE and MFEE distributions are close to normal while the IWTE distribution is skewed to the

\[^9\] We acknowledge one of the reviewers' suggestion to adopt this approach.

\[^10\] 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 \( \chi^2 \) statistics is 322.39. The 1\% significance level with 10 degrees of freedom is 23.21.
The estimated translog production function.

Table 1
Descriptive statistics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit of measurement</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>S.D.</th>
<th>Coefficient of variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield</td>
<td>kg</td>
<td>200</td>
<td>20,000</td>
<td>2582</td>
<td>1820</td>
<td>0.70</td>
</tr>
<tr>
<td>Price of yield</td>
<td>Yuan/kg</td>
<td>1.5</td>
<td>3</td>
<td>2.02</td>
<td>0.10</td>
<td>0.05</td>
</tr>
<tr>
<td>Output</td>
<td>Yuan</td>
<td>400</td>
<td>38,800</td>
<td>5209</td>
<td>3659</td>
<td>0.70</td>
</tr>
<tr>
<td>Land</td>
<td>Mu</td>
<td>0.40</td>
<td>40.00</td>
<td>5.71</td>
<td>3.86</td>
<td>0.68</td>
</tr>
<tr>
<td>Labor</td>
<td>man-days</td>
<td>3.8</td>
<td>38</td>
<td>15.35</td>
<td>14.06</td>
<td>0.95</td>
</tr>
<tr>
<td>Other inputs</td>
<td>Yuan</td>
<td>157</td>
<td>20,100</td>
<td>2156</td>
<td>1612</td>
<td>0.75</td>
</tr>
<tr>
<td>PriceLand</td>
<td>Price of land in Yuan/mu</td>
<td>40.00</td>
<td>1500.00</td>
<td>241.99</td>
<td>193.65</td>
<td>0.80</td>
</tr>
<tr>
<td>PriceLabor</td>
<td>Price of labor in Yuan/day</td>
<td>30.00</td>
<td>200.00</td>
<td>73.25</td>
<td>27.25</td>
<td>0.37</td>
</tr>
<tr>
<td>Age</td>
<td>Years</td>
<td>26</td>
<td>77</td>
<td>53.08</td>
<td>10.07</td>
<td>0.19</td>
</tr>
<tr>
<td>Education</td>
<td>Years</td>
<td>0</td>
<td>12</td>
<td>6.64</td>
<td>1.70</td>
<td>0.26</td>
</tr>
<tr>
<td>Income</td>
<td>Yuan</td>
<td>1000</td>
<td>195,000</td>
<td>26,941</td>
<td>25,103</td>
<td>0.93</td>
</tr>
<tr>
<td>Time</td>
<td>—</td>
<td>1</td>
<td>5</td>
<td>3.80</td>
<td>1.44</td>
<td>0.38</td>
</tr>
<tr>
<td>Water price</td>
<td>Yuan/m³</td>
<td>0.02</td>
<td>1.00</td>
<td>0.32</td>
<td>0.13</td>
<td>0.41</td>
</tr>
<tr>
<td>Fragmentation</td>
<td>—</td>
<td>1</td>
<td>15</td>
<td>2.74</td>
<td>1.75</td>
<td>0.64</td>
</tr>
<tr>
<td>Precipitation</td>
<td>mm</td>
<td>137</td>
<td>220</td>
<td>174.31</td>
<td>17.07</td>
<td>0.10</td>
</tr>
<tr>
<td>Infrastructure</td>
<td>—</td>
<td>0</td>
<td>1</td>
<td>0.52</td>
<td>0.49</td>
<td>0.94</td>
</tr>
<tr>
<td>IWTE</td>
<td>—</td>
<td>0.06</td>
<td>0.76</td>
<td>0.35</td>
<td>0.14</td>
<td>0.40</td>
</tr>
<tr>
<td>IWTC</td>
<td>—</td>
<td>0.75</td>
<td>0.99</td>
<td>0.93</td>
<td>0.04</td>
<td>0.04</td>
</tr>
<tr>
<td>IWA</td>
<td>—</td>
<td>0.64</td>
<td>0.98</td>
<td>0.86</td>
<td>0.07</td>
<td>0.08</td>
</tr>
<tr>
<td>MFEE</td>
<td>—</td>
<td>0.60</td>
<td>0.93</td>
<td>0.80</td>
<td>0.07</td>
<td>0.09</td>
</tr>
</tbody>
</table>

Note:
*p < 0.10.
**p < 0.05.
***p < 0.01.

Table 2
Descriptive statistics for indicators of Perception.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Strongly disagree (%)</th>
<th>Disagree (%)</th>
<th>Neither disagree nor agree (%)</th>
<th>Agree (%)</th>
<th>Strongly agree (%)</th>
<th>In total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percep1</td>
<td>30.55</td>
<td>31.99</td>
<td>1.44</td>
<td>18.16</td>
<td>17.87</td>
<td>100</td>
</tr>
<tr>
<td>Percep2</td>
<td>14.12</td>
<td>42.36</td>
<td>10.09</td>
<td>19.02</td>
<td>14.41</td>
<td>100</td>
</tr>
<tr>
<td>Percep3</td>
<td>7.78</td>
<td>17.87</td>
<td>44.96</td>
<td>17.29</td>
<td>12.10</td>
<td>100</td>
</tr>
</tbody>
</table>

Table 3
The estimated translog production function.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>S.E.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-8.0383***</td>
<td>0.9090</td>
</tr>
<tr>
<td>lnLand</td>
<td>-3.7634***</td>
<td>0.3023</td>
</tr>
<tr>
<td>lnLabor</td>
<td>0.4180***</td>
<td>0.1180</td>
</tr>
<tr>
<td>lnWater</td>
<td>0.3432***</td>
<td>0.0497</td>
</tr>
<tr>
<td>ln(Other inputs)</td>
<td>4.1463***</td>
<td>0.2881</td>
</tr>
<tr>
<td>lnLand*lnLand</td>
<td>-0.7910***</td>
<td>0.0605</td>
</tr>
<tr>
<td>lnLabor*lnLabor</td>
<td>-0.0601***</td>
<td>0.0089</td>
</tr>
<tr>
<td>lnWater*lnWater</td>
<td>-0.0423***</td>
<td>0.0050</td>
</tr>
<tr>
<td>ln(Other inputs)*ln(Other inputs)</td>
<td>-0.6157***</td>
<td>0.0487</td>
</tr>
<tr>
<td>lnLand*lnLabor</td>
<td>0.0955***</td>
<td>0.0139</td>
</tr>
<tr>
<td>lnLand*lnWater</td>
<td>0.0375***</td>
<td>0.0052</td>
</tr>
<tr>
<td>lnLand*ln(Other inputs)</td>
<td>0.0696***</td>
<td>0.0529</td>
</tr>
<tr>
<td>lnLabor*lnWater</td>
<td>0.0073</td>
<td>0.0072</td>
</tr>
<tr>
<td>lnLabor*ln(Other inputs)</td>
<td>-0.0527***</td>
<td>0.0189</td>
</tr>
<tr>
<td>lnWater*ln(Other inputs)</td>
<td>-0.0052***</td>
<td>0.0073</td>
</tr>
<tr>
<td>σ²</td>
<td>0.0329***</td>
<td>0.0082</td>
</tr>
<tr>
<td>σ²</td>
<td>0.0406***</td>
<td>0.0035</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-133.38</td>
<td></td>
</tr>
</tbody>
</table>

Note:
*p < 0.10.
**p < 0.05.
***p < 0.01.

Table 4
Output elasticities.

<table>
<thead>
<tr>
<th>Input</th>
<th>Land</th>
<th>Labor</th>
<th>Water</th>
<th>Other inputs</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elasticity</td>
<td>0.4444</td>
<td>0.1132</td>
<td>0.0812</td>
<td>0.4561</td>
<td>1.0949</td>
</tr>
</tbody>
</table>

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. IWTE 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 IWTE 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.

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. 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.
The measures of model fit are presented in Table 5. The p-values corresponding to the $\chi^2$ 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 $\chi^2$ 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 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 $\Psi$ matrix are shown in Table 8. The non-zero estimates in the $\Psi$ matrix are shown in Table 8. Element $\psi_{21}$ is positive and significant, indicating that the error terms in the IWTE and IWAE equation are correlated, thus

---

**Table 5**

<table>
<thead>
<tr>
<th>Statistics</th>
<th>$\chi^2$</th>
<th>NFI</th>
<th>GFI</th>
<th>AGFI</th>
<th>RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Values</td>
<td>34.54(df = 28, p = 0.1835)</td>
<td>0.926</td>
<td>0.985</td>
<td>0.951</td>
<td>0.026</td>
</tr>
</tbody>
</table>

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**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Indicators</th>
<th>Coefficient</th>
<th>t-value</th>
<th>R$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perception</td>
<td>Percep1</td>
<td>0.834</td>
<td>6.682</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>Percep2</td>
<td>0.529</td>
<td>6.174</td>
<td>0.29</td>
</tr>
<tr>
<td></td>
<td>Percep3</td>
<td>0.473</td>
<td>5.826</td>
<td>0.23</td>
</tr>
</tbody>
</table>

**Table 8**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Indicators</th>
<th>Coefficient</th>
<th>t-value</th>
<th>R$^2$</th>
</tr>
</thead>
</table>
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.11 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 (−0.149) and Infrastructure (−0.115) have negative total impacts on Perception while Income 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 on itself, i.e. the inefficiency variance (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 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.

Infrastructre 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 IWAE equals its direct effect (−0.143) plus the dampening effect of 0.080 that derives from the effect of IWAE on itself.
the possibilites for manipulation also 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 IWATE. Since Water price can be easily manipulated, i.e. can be easily changed over time, it is a powerful policy handle to improve IWATE. 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 the ‘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 the 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.

**Reference**


