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Econometric estimation of groundwater irrigation efficiency of cotton cultivation farms in Pakistan

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ABSTRACT

Study region: Lodhran and Jhang districts in the Central and South Punjab province of Pakistan.
Study focus: Pakistan is amongst the largest groundwater withdrawing countries. With 5.2 million hectares groundwater irrigated area, Pakistan irrigates 4.6% of the global groundwater-fed cropland. However, over the last few decades the groundwater resources are under immense pressure due to overdrafting to meet escalating irrigation water demands. Since most of the groundwater is being extracted for irrigation purposes, examining irrigation water efficiency have become has become inevitable for sustainable groundwater management. This study estimates farm level technical efficiency (TE) and irrigation water-use efficiency (IWE) of groundwater irrigated cotton farms in the Punjab province of Pakistan.
New hydrological insights for the region: Irrigation water-use efficiency (IWE) is generally defined from three perspectives: (i) efficiency of the irrigation system, i.e., water conveyance efficiency; (ii) efficiency in water application at the farm gate and; (iii) the response of a crop to irrigation water application, i.e., the amount of water actually utilized by the crop compared to the amount of water supplied to that crop. These measures of IWE are devoid of economic principles. Hence, irrigation water efficiency has expanded its boundaries from hydrological and engineering principles to economic rationale which is useful to guide targeted farms to improve their irrigation efficiencies. This study advances the frontier of existing economic measure of IWE by employing a restricted production frontier model.

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1. Introduction

Groundwater irrigation is an important factor to agricultural production in large parts of the world especially in South Asian countries (Shah, 2007). In the Indian sub-continent more than 85% of the groundwater extraction is used for irrigation purposes (Mukherjee et al., 2014). India, Pakistan and Bangladesh are the largest groundwater using countries in South Asia. These three countries have 48 million hectares area equipped with groundwater irrigation which constitutes approximately 42% of the global groundwater-fed cropland (Siebert et al., 2010). In Pakistan, irrigated agriculture relies more on groundwater compared to the other South Asian countries due to dwindling surface water resources. Evidences suggest that existing surface water resources are not only deficient but are also highly skewed over time and space. This variation in surface water runoffs has led to the expansion of a large scale groundwater-fed irrigation system in the Indus River Basin of Pakistan. A sharp increase in the groundwater use over the last half-century has evolved as a “silent revolution” carried out by millions of farmers in pursuit of reliable irrigation water supplies. Since 1960, groundwater share to the total irrigation water supply has increased by more than 50% (Byrelle and Siddiq, 1994; Qureshi et al., 2009) and more than one million farmers have installed tube-wells[1] across the country. Fig. 1(a) and (b) shows tube-well development trends and increase in the share of groundwater in irrigation over time. During early 1960s the tube-well adoption was encouraged by the government’s support policies such as rural electrification, subsidization of electricity, diesel and drilling services, supply of free pump sets and easy to get long-term loans. However, higher yields and greater economic returns from groundwater use encouraged farmers to adopt tube-wells in subsequent periods (Falcon and Gotsch, 1968; Johnson, 1989; Papanek, 1968; van Steenbergen and Oliemans, 2002). Limited to less than 30 thousands in 1960s, the number of tube-well has now gone over one million. Although tube-well ownership has been on the increase, thousands of smallholder farmers still do not own tube-wells. Those who do not own tube wells irrigate their lands by informally buying[2] surplus pumped water from their nearby tube-well owners (Meinzen-Dick, 1996; Qureshi et al., 2009).

Although groundwater resources have played a key role to agricultural production, overdrafting of groundwater resources is at critical juncture in Pakistan (Khan et al., 2008a; Kijne, 1999; Qureshi et al., 2009; Shah et al., 2000). The recent groundwater abstraction rates (60 $km^3\ y^{-1}$) have exceeded the recharge rates (55 $km^3\ y^{-1}$) which have resulted into substantial depletion of groundwater aquifers (Giordano, 2009). Wada et al. (2010) mapped out various hot spots of groundwater depletion in different regions of the world and noted that the highest depletion rates are in North-East Pakistan and North-West India. The rapid depletion of groundwater resources is making relative accessibility of groundwater resources economically unviable and is creating many negative environmental and economic externalities with serious repercussions to the sustainability irrigated agriculture in Pakistan (Kahlown and Azam, 2002; Kelleners and Chaudhry, 1998; Khan et al., 2008b; Kijne, 1999; Qureshi et al., 2009; Shah et al., 2000; van Steenbergen et al., 2014).

Although the agrarian economy of Pakistan is dominated by wheat, cotton, rice and sugarcane crops, cotton production remains the most important agricultural commodity due to its export value in the international trade market. Cotton production accounts for 6.9% of the value added in agriculture and contribute 1.4% to the country’s gross domestic production (GDP). Pakistan remained the 4th largest cotton producer with 9.80% share in the global cotton production during the year 2011–12. Over the same period, Pakistan’s yarn and apparel exports contributed 26% and 14% to the global market. At national level, cotton exports accounted for 46% of the country’s entire exports and employed 35% of the total industrial labour force (FAO, 2012; Government of Pakistan, 2011–12).

[1] A tube-well is a type of water well, drilled to extract subsurface water through a pump. In Pakistan, tub-wells of 5–7 in. diameter are usually drilled to extract groundwater. These tube-wells are mounted with either 15–25 horsepower diesel engine or 15–30 horsepower electrical motor depending upon the depth of water table.

[2] In South Asia (Pakistan, India and Bangladesh) informal groundwater markets have evolved over the time for trading groundwater abstractions between the tube-well owners and non-owners (Meinzen-Dick, 1996). Such markets increase access to groundwater and offer opportunities to overcome production uncertainties for tenants and small farmers (Manjunatha et al., 2011; Meinzen-Dick, 1996; Shiferaw et al., 2008). However, such markets do not guarantee access over spatial and temporal crop water requirements (Jacoby et al., 2004).

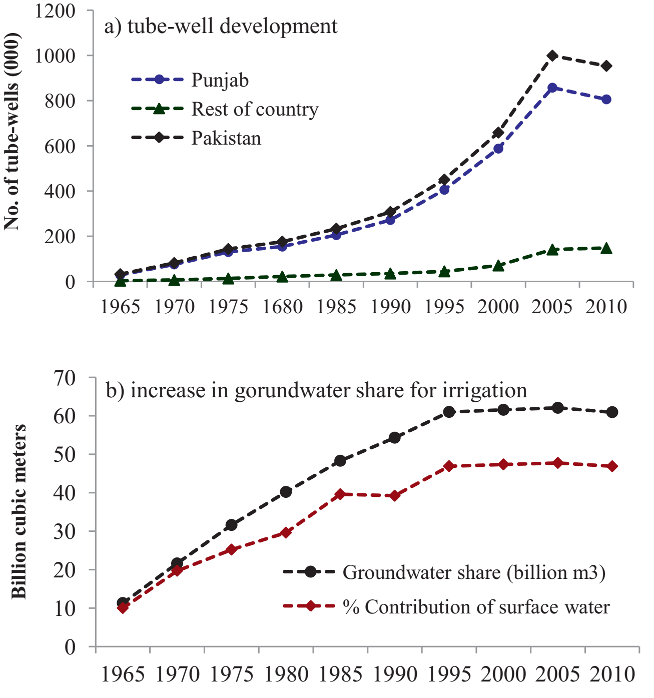

Fig. 1. Technical efficiency estimates of the restricted and unrestricted models.

Hence, national economic growth is greatly influenced by the volume and value of cotton production and its by-products. Thus, cotton production has always been under agricultural policy limelight. As a result of policy support for cotton industry, the area under cultivation and production has increased by 33% and 163% since 1980, while domestic consumption has increased by almost 400% over the same period (Government of Pakistan, 2011–12; USDA, 2012). However, yields in cotton production in per hectare basis have remained low (Watto and Mugera, 2014).

Under the current agricultural policy, the Pakistan Central Cotton Committee (PCCC) aims to increase cotton production by 40–60% as national strategy to achieve the target of 19.1 million bales by 2015. The major components of this strategy include: (1) to increase area under cotton cultivation; (2) to encourage adoption of genetically modified cotton varieties; (3) to improve production technology; (4) to subsidize fertilizers; and (5) to manage integrated pest management (PCCC, 2008). However, on-going water stress may undermine the potential of this policy, which unfortunately has not been taken into consideration in the recent policy. Similarly, despite widespread policy efforts and other encouraging incentives, the expected outcomes did not realize in the past. Because cotton cultivation is associated with excessive water applications, improving cotton productivity should integrate with water saving policies. Evidence suggests that inefficient irrigation water application is one of the major reasons of low water productivity in agricultural production in Pakistan. Farmers generally apply water to uneven bunded fields through flood irrigation, resulting into long irrigation events, over-irrigation and low agriculture water productivity (Kahlown et al., 2007). The estimated cotton water productivity[3] of 0.22 $kg\,m^{-3}$ is much lower compared to the major cotton producing countries (Shabbir et al., 2012). Because of high water requirement, cotton production in Pakistan has prompted research efforts to seek production systems that use inputs in combinations to achieve higher efficiencies.

[3] Water productivity (kg/m^3) is defined as crop yield (kg) per accumulated actual evapotranspiration for the growing season (m^3): $WP = \frac{\text{Crop yield}}{Et_{a,seasonal}}$.

The objective of this paper is to estimate farm level technical efficiency and irrigation water efficiency of groundwater irrigated cotton farms in the Punjab province of Pakistan. The contribution of this study resides in its methodological and empirical applications. Methodologically, this paper advances the frontier of existing input-specific technical efficiency by using the restricted translog model. Empirically, it is the first study which has focused on irrigation water-use efficiency in groundwater irrigated cotton farming in Pakistan.

The rest of the paper is organized as follows. The next section describes the stochastic production frontier to estimate technical and input-specific (irrigation water-use efficiency) technical efficiency. Section 3, describes the data and principle features of the study areas. The results are presented in the Section 4. The final section draws conclusions and provides some policy implications.

2. Methdological framework

2.1. Definition and estimation of technical and irrigation water efficiency

In production economics, technical efficiency is defined as the ability of a firm to produce maximum possible output within the available set of inputs under the given technology (Coelli et al., 2002). Irrigation water-use efficiency is defined as the ratio of minimum feasible water use to observed water, conditional on production technology and observed levels of the output and inputs (Karagiannis et al., 2003). More generally, irrigation water-use efficiency is an input-oriented, single factor measure of technical efficiency.

We explain the theoretical background for technical efficiency following Aigner et al. (1977) and Meeusen and van der Broeck (1977). Let the production technology be described by the stochastic production function as follows:

$$y_i = f(x_i, w_i; \beta)\exp(\varepsilon_i \equiv v_i - u) \tag{1}$$

where y_i denotes the amount of crop output for farm i ($i = 1, \ldots, N$); x_i represents the vector of conventional inputs; w_i is the vector of volume of groundwater used for irrigation for farm i; β is a vector of parameters to be estimated; ε_i is a composed error term consisting of v_i, a symmetric and normally distributed error term that is independently and identically distributed as $N(0, \sigma_v^2)$, intended to capture the exogenous random forces which are beyond the control of the farmers, and $u_i \geq 0$, a non-negative random error term independently and identically distributed as $N^+(0, \sigma_u^2)$, that captures the shortfall of output from the production frontier.

The stochastic version of the output oriented technical efficiency for the ith farm is expressed as:

$$TE_i = \frac{y_i}{[f(x_i, w_i; \beta)\exp(v_i)]} \tag{2}$$

$$TE_i = \exp(-u_i) \tag{3}$$

Since $u_i \geq 0$ and $0 \leq \exp(-u_i) \leq 1$, technical inefficiency has to be separated from statistical noise in the composed error term. Battese and Coelli (1992) propose the technical efficiency estimator as:

$$TE_i = E[\exp(-u_i)|(\varepsilon_i)] \tag{4}$$

The outlined measure of technical efficiency (radial contraction) does not estimate the efficient use of individual inputs which in our case is irrigation water. We explain the idea of technical efficiency and input-specific efficiency (radial and non-radial contraction of input use) in Fig. 2. Let us consider three farms A, B and C using two inputs x_1 (irrigation water) and x_2 (fertiliser) to produce a single output Y_o. Based on the efficiency concept, farms B and C are the best performers or technically efficient because they are located on the frontier. However, farm A is inefficient because it is not located on the frontier. Let the inefficient farm A produce output Y_o using x_{2A} units of fertilizer and w_1 units of irrigation water. The radial contraction of inputs x_1 and x_2 produces a projected point A^o on the frontier which is technically efficient. Hence, technical efficiency of farm A with respect to farms B and C is given by the ratio $TE_A = OA^o/OA$. The irrigation water-use efficiency, however, is based on the non-radial concept of technical efficiency which in case of farm A is given by the ratio $IE = x_{2c}/x_{2A} = w_2/w_1$. This

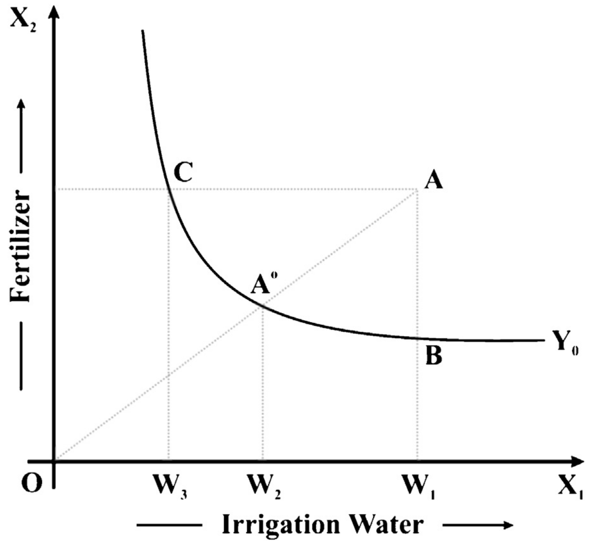

Fig. 2. Irrigation water-use efficiency estimates of the restricted and unrestricted models.
Source: Karagiannis et al. (2003).

measure of irrigation water-use efficiency determines both the minimum feasible irrigation water use (w_2) and the maximum possible reduction in irrigation water use ($w_1 - w_3$) without compromising the existing output level Y_o. Fig. 1 shows that in order to make the *i*th farm technically efficient, the maximum possible reduction required in irrigation water use ($w_1 - w_2$) is always lower than the reduction ($w_1 - w_3$) required to make the *i*th farm irrigation water use efficient.

Conceptually, irrigation water-use efficiency requires an estimate of the quantity (w_2) which is not directly observable as illustrated in Fig. 2. However, using $IWE_i = w_2/w_1$, we can easily observe (w_2) that is $w_2 = w_1 \times IWE_i$. By substituting this ratio into Eq. (1) and by noticing that point C in Fig. 2 lies on the frontier, i.e., $u_i = 0$, Eq. (1) may be expressed as:

$$y_i = f[x_i, w_i^E; \beta] \exp(v_i) \tag{5}$$

where $w_i^E = w_2$ (Reinhard et al., 1999). We can estimate now IWE_i be equating Eq. (1) with Eq. (5) and by using econometrically estimated parameters β.

3. Empirical model

Let the unknown production frontier Eq. (1) be specified by the following translog specification:

$$\begin{aligned}\ln y_i = {} & \beta_0 + \sum_{j=1}^{j} \beta_j \ln x_{ji} + \frac{1}{2}\left(\sum_{j=1}^{j}\sum_{k=1}^{j} \beta_{jk} \ln x_{ji} \ln x_{ki}\right) \\ & + \beta_w \ln w_i + \frac{1}{2}\left(\beta_{ww} \ln w_i^2 + \sum_{j=1}^{j} \beta_{jw} \ln x_{ji} \ln x_{wi}\right) + v_i - u_i\end{aligned} \tag{6}$$

To separate the stochastic and inefficiency effects in the model, we need to impose a distributional assumption. In this study, inefficiency is modelled explicitly as a function of known characteristics and exogenous effects, such that:

$$u_i = \delta_0 + \sum_{j=1}^{j} \delta_j z_{ij} + \lambda_i \tag{7}$$

where z_i is a vector of variables which explain efficiency differentials among farmers; δ is the associated inefficiency parameter coefficient, and λ_i is a random variable defined by the truncation of the normal distribution with mean zero and variance σ^2 where the point of truncation is $-z_i\delta$ such that $\lambda_i \geq z_i\delta$ (Battese and Coelli, 1995).

The translog production function is the best investigated functional form and is widely used in efficiency estimation models. However, there are several concerns about the flexibility and theoretical consistency when estimating a translog production function (Sauer, 2006). Since micro-economic theory requires a production function monotonically increasing in all inputs (Henningsen and Henning, 2009) and quasi-concave (Lau, 1978), it is necessary to test the estimated production frontier for theoretical consistency and, if necessary, to impose them. The monotonicity restrictions require holding $\partial y_i/\partial x_i \geq 0 \; \forall \, i, x$, for all observations (Coelli et al., 2005; Perelman and Santin, 2011). However, imposing global convexity restrictions greatly restrict the flexibility of the functional form (Lau, 1978; Sauer, 2006), and hence, should be applied to ensure local quasi-concavity. Henningsen and Henning (2009) argue that when estimating a production function under the assumption of output maximization, it does not necessarily need to be quasi-concave. Monotonicity can be imposed by using the Bayesian techniques (O'Donnell and Coelli, 2005; Pascoe et al., 2010), non-parametric approach (Grosskopf et al., 1995) or a three-step procedure (Henningsen and Henning, 2009).

In this study, we follow a three-step procedure following Henningsen and Henning (2009) to make adjustments in the model. At first, we estimate the translog production frontier and extract the unrestricted parameters and their covariance matrix. Second, we estimate the restricted parameters through a minimum distance approach as follows:

$$\hat{\beta}^0 = arg\,\min(\hat{\beta}^0 - \hat{\beta}) \hat{\sum}_{\beta}^{-1} (\hat{\beta}^0 - \hat{\beta}) \tag{8}$$

Subject to:

$$\frac{\partial f(x, \beta^0)}{\partial x} \geq 0 \quad \forall i, x$$

Eq. (8) is solved using quadratic programming to get the revised set of coefficients $\hat{\beta}^0$ that confirm whether the monotonicity assumption holds. These restricted parameters $\hat{\beta}^0$ are asymptotically equivalent to the restricted parameters of a one-stage maximum likelihood (*ML*) estimation model (Koebel et al., 2003). Finally, the stochastic frontier model (adjusted–restricted) is re-estimated as:

$$\ln y_i = \alpha_0 + \alpha_1 \ln \tilde{y} - v_i + \varepsilon_i \tag{9}$$

where $\tilde{y}_i = f(x, \hat{\beta}^0)$. That is, the only input is the estimated frontier output based on the restricted parameters. The parameters α_0 and α_1 represent final adjustments to the parameter estimates. The advantage of the three step approach is that the parameter values estimated in the first stage provide appropriate starting values where the variance–covariance matrix limits the degree to which these parameters are altered when imposing monotonicity in the non-parametric component (Gedara et al., 2012).

Since the outlined measure of technical efficiency is incapable of identifying the efficient use of individual inputs such as fertilizer or irrigation water, we drive the efficiency of irrigation water use by using Eq. (10). This approach follows Reinhard et al. (1999) who proposed this model to estimate environmental efficiency. The same approach was later adopted by Karagiannis et al. (2003) to estimate irrigation water-use efficiency. We derive irrigation water-use efficiency by using Eq. (5) and the following relation developed by Reinhard et al. (1999) for the translog specification:

$$IWE_i = \exp\left[\frac{\{-\zeta_i \pm (\sqrt{\zeta_i^2 - 2\alpha_{ww}u_i})\}}{\alpha_{ww}}\right] \tag{10}$$

where

$$\zeta_i = \frac{\partial \ln y_i}{\partial \ln w_i} = \alpha_w + \sum_{j=1}^{j} \alpha_{jw} \ln x_{ji} + \alpha_{ww} \ln w_i$$

where w_i represents the irrigation water variable input. Assuming weak monotonicity, a technically efficient farm should also be efficient in its irrigation water use. However, this may not be necessarily true. A technically efficient farm may be inefficient in its individual input use (Karagiannis et al., 2003).

As micro-economic theory requires a production function increasing monotonically in all inputs, satisfying monotonicity assumptions in estimating input-specific efficiency is even more important. A technically efficient farm is supposed to use all inputs efficiently; however, a technical inefficient farm could also use one or more than one inputs efficiently. Hence, if we are concerned about any particular input, we must ensure that monotonicity assumption holds for that input. So, we estimate input-specific technical efficiency in two steps. First, we extract the estimated coefficients and one-sided error term from the unrestricted stochastic frontier model and use them in Eq. (10) to get the irrigation water efficiency estimates. At second, we extract the estimated coefficients and one-sided error term from the restricted model and use them in Eq. (10) to get the restricted irrigation water efficiency estimates.

3.1. *Explaining efficiency differentials*

In explaining efficiency differentials, the commonly used two-stage estimation procedure has been considered inconsistent with the assumption of identically distributed inefficiency effects in the stochastic frontier model, which is necessary in the *ML* estimation (Battese and Coelli, 1995; Kumbhakar et al., 1991; Reifschneider and Stevenson, 1991). However, the two-stage estimation procedure can be used to identify the determinants of irrigation water-use efficiency as irrigation water-use efficiency is estimated from the parameter estimates and the estimated one-sided error component of the stochastic production frontier which is not directly related to distributional assumptions (Karagiannis et al., 2003). Therefore, we choose a two-stage regression model to identify the determinants of TE and IWE. The second-stage regression model takes the following form:

$$\ln IWE_i = h(z_i, \delta) + e_i \tag{11}$$

where $h(\cdot)$ is the deterministic kernel of the regression model, δ is the vector of the parameters to be estimated and e_i is an independently and identically distributed random variable with zero mean and constant variance.[4] The above model is estimated with standard ordinary least squares.

4. Study area and data

4.1. *Characteristics of study areas*

The study is conducted in the *Jhang* and *Lodhran* districts of the Punjab province of Pakistan (Fig. 3). In the study districts, cotton farming heavily relies on groundwater for irrigation purposes due to the arid and semi-arid climate. The selected farms solely depend on groundwater for irrigation purposes in the *Jhang* district while partly on canal water in the *Lodhran* district. In *Lodhran* district canals

[4] Since $0 < IWE \leq 1$, the dependent variable should be transformed before estimation if OLS is to be applied (Kumbhakar and Lovell, 2000).

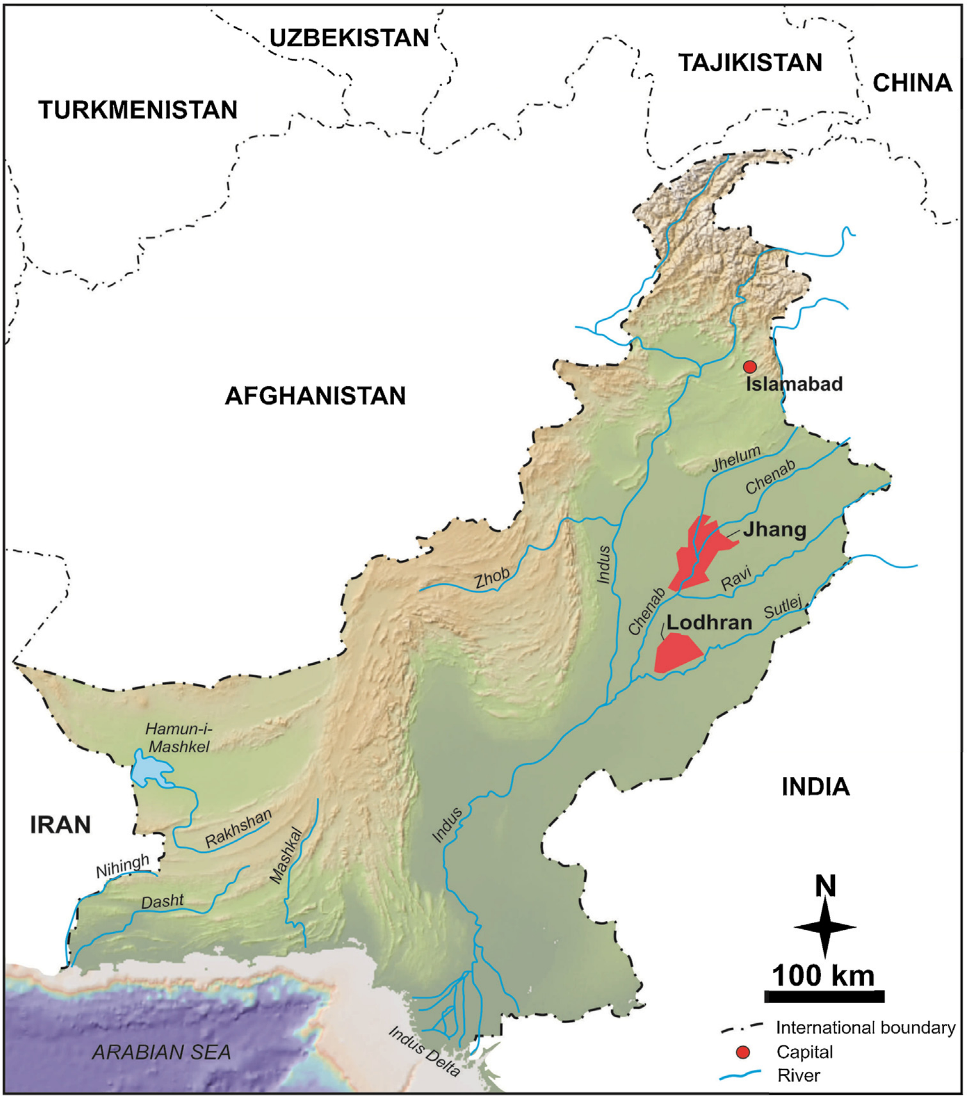

Fig. 3. Map showing study districts (*Jhang and Lodhran*) in red colour.

supply water only during the *Kharif*[5] season. The canal water[6] contribution during the *Kharif* season of 2010–11 was observed to range between 20% and 44% of the total irrigation requirements for cotton crop. Besides limited canal water supplies, both districts receive very little rainfall. The average precipitation rate in *Lodhran* district is 71 mm^{-1} while it is 180 mm^{-1} in the *Jhang* district. Therefore,

[5] There are two cropping seasons in Pakistan, *Kharif* and *Rabi*. *Kharif* starts from June, July and goes to October, November, while the *Rabi* season starts from September, October and continues to April, May. However, cropping time varies geographically across the country. Cotton is a *Kharif* crop.

[6] In Punjab canal water is distributed equitably proportional to the farm size as a fixed weekly rotation which is allocated through a calibrated orifice from the watercourse. Water management department has computed a common conversion factor of 102.98 to convert the discharge water into cubic metres.

majority of the irrigation water comes from groundwater which is extracted mainly through deep tube-wells.

Our sample data show large variation in the depths of installed tube-wells. In the *Lodhran* district, the variation was observed to be between 60 and 99 m compared to the *Jhang* district where it was between 33 and 57 m. Low water tables not only contribute to high groundwater extraction costs but also to high tube-well installation costs. The total installation cost to bore a 24 m deep tube-well is seven times higher compared to boring a tube-well at a depth of 6 m (Qureshi et al., 2003). We found that due to deep groundwater tables and the high installation cost, tube-well population is relatively less dense in the Northern part of the *Jhang* and Southern part of the *Lodhran* district. As a result, farmers generally engage in informal groundwater trading. Such informal groundwater transactions increase access to irrigation water for tenants and smallholder farmers who do not own tube-wells. Since these markets are not formally regulated, sometimes tube-well owners prefer certain water buyers due to social ties with them, thus discriminating to whom to sell water (Jacoby et al., 2004; Khanna, 2007; Shah, 1993). Despite the fact that the cost of buying water for non-tube-well owners is 3–4 times more than that of extracting groundwater for tube-well owners, water buyer often cannot get water in time (Jacoby et al., 2004; Khanna, 2007; Shah, 1993).

4.2. Data collection and variable definition

A multi-stage sampling technique was used in data collection. In the first stage, one *tehsil*[7] was selected purposively from the *Lodhran* and the *Jhang* district. In the next stage, 10 villages were selected at random from each purposively selected *tehsil*. Then, from each village 10 groundwater users (5 tube-well owners and 5 water buyers) were selected randomly to obtain the differential impact of tube-well ownership and to reveal the difference of amount of irrigation water applied and production gains for tube-well owners and water buyers. A village is usually comprised of 60–70 farming households in the study areas. Finally, we collected farm level data from 200 groundwater-fed agricultural farms. However, only 92 tube-well owners and 80 water buyers cultivated cotton crop during the cropping season of 2010–11. The dataset used in this study is relatively small and is collected from one *tehsil* in two districts. However, the sample farms reflect the typical situation of groundwater irrigated farms in the study districts in particular and in the rural areas of the Punjab in general.

The data were collected using an interview schedule. We collected information on various inputs and output quantities. The inputs were measured as: (1) seed and fertiliser in kg/acre; (2) total labour, consisting of hired (casual and permanent) and family labour in h/acre; (3) farm operations as number of applications/acre; and (4) groundwater use in cubic metres/acre. Cotton yield (output) is measured in kg/acre as well.

Various studies have used different approaches to compute the volume of irrigation water. However, they do not give actual estimates of water used. For example, Gedara et al. (2012) measured the quantity of water used in rice production in Sri Lanka, which was related to the proportion of total land owned by the farmer and the total quantity of water released, assuming that this was distributed evenly across the irrigated area. Sharma et al. (2001) measured water by the number of times water was released for the farm from the main water course in the Tarai of Nepal. In contrast to the surface water volumes, groundwater use estimates are more realistic and reliable. In Pakistan information on groundwater utilization does not exist at the district level due to the large number of non-registered small scale and fragmented groundwater users (Qureshi et al., 2003). Further, at farm level groundwater extractions are not monitored as metres are not installed on tube-wells. In this study, we computed groundwater volume by collecting information about the number of irrigations for applied to cotton crop, duration of water application per irrigation event, borehole depth, diameter of suction pipe, and power of the engine used to pump groundwater. Using this information in an approximate estimation model, as used by Eyhorn et al. (2005) and Srivastavaa et al. (2009), we measured groundwater extraction in litres using the following formula and then converted into m^3. This approximation formula for

[7] *Tehsil is* an administrative unit. A district usually comprise of 5–6 tehsils (sub-districts). *Lodhran* district is comprised of three tehsils, i.e., *Dunyapur*, *Kahror Pakka* and *Lodhran* while *Jhang* district is comprised of four tehsils i.e., *Athara Hazari*, *Shorkot*, *Ahmad Pur Sial* and *Jhang*.

Table 1
Summary statistics of the variables used in the empirical model.

Variable	Tube-well owners		Water buyers	
	Mean	Std. Dev.	Mean	Std. Dev.
Economic data				
Farm production (kg)	8473	6199	4598	3811
Seed quantity (kg)	88.75	65.94	48.56	42.27
Labour (h)	3396.75	2522.90	1814.45	1549.29
Fertilizer (kg)	2300.88	1866.25	1231.02	1226.89
Machinery cost (Rs.)	39,027.80	25,896.19	22,303.19	18,785.18
Irrigation water (m^3)	24,074.09	17,842.71	12,143.78	10,084.01
Farm characteristics				
Farmers age (years)	45.435	8.961	42.363	8.138
Farmers education (years of schooling)	5.674	4.401	3.750	3.733
	Proportion of farmers with dummy variables			
	0	1	0	1
Land tenureship (0 = *tenants*, 1 = *owners*)	18.48	81.52	18.75	81.25
Off-farm income (0 = *no*, 1 = *yes*)	82.61	17.39	88.75	11.25
Seed (0 = *not-improved*, 1 = *improved*)	73.91	26.09	73.75	26.25
Extension services (0 = *no*, 1 = *yes*)	66.30	33.70	73.75	26.25
Water shortage perceptions				
Salinity perception (0 = *no*, 1 = *yes*)	73.91	26.09	80	20
Is water table declining? (0 = *no*, 1 = *yes*)	25.00	75.00	76.25	23.75
Effect on cropping patterns (0 = *no*, 1 = *yes*)	44.57	55.43	46.25	53.75

groundwater extractions is based on the assumptions that the lifting head is equal to the depth of the tube-well. It does not consider pump efficiency differences due to maintenance conditions and mode of operation, i.e., diesel operated or electricity operated. However, it does consider efficiency differences due to voltage variations in electrical power supply.

$$Q = \frac{t \times 129574.1 \times BHP}{[d + (255.5998 \times BHP^2)/d^2 \times D^4)]} \qquad (12)$$

where Q represents the volume of water in litres, t is the total irrigation time, d is the depth of bore, D is the diameter of the suction pipe, and BHP is the power of the engine.

The descriptive statistics of the variables used in the SFA model are presented in Table 1.

Table 1 compares selected variables for both tube-well owners and water buyers used in the analysis. It is evident from the descriptive statistics that on average there is no considerable variation in the use of farm inputs including per acre seed rate, labour use and fertilizer application. Similarly, output produced by tube-well owners and water buyers do not vary considerably. In contrast, there is some variation in the number of farm operations and irrigation water applied by tube-well owners and water buyers. On average, tube-well owners used 7% more groundwater than water buyers. The average cotton yield is 836 kg/acre, with a maximum of 1400 kg/acre for tube-well owners and 821 kg/acre, with a maximum of 1200 kg/acre for water buyers.

The average farmer's age is 45 years for tube-well owners and 42 for water buyers, ranging from 27 to 60 years. The statistics on education reflect lack of education with 27% of tube-well owners and 43% water buyers had no formal education. Amongst tube-well owners and water buyers the vast majority of the surveyed farms cultivate their own land. Difference in the off-farm income depicts that tube-well owners on average generate 45% more from off-farm business compared to water buyers. We see that 17% of tube-well owners while 11% of water buyers have off-farm business activities. Almost the same proportion of tube-well owners and water buyers among the surveyed cotton farms used improved quality seed. Access to extension advice and to other information sources, e.g., radio, television and newspaper, etc. indicate that tube-well owners relatively seek more extension advice compared to water buyers. There is a very little difference in the perception of tube-well owners and water buyers about the salinity level and its impact on future cropping patterns. However, more tube-well owners perceive that groundwater tables are lowering compared to water buyers.

5. Estimation results and discussion

The parameter estimates of the stochastic frontier model are presented in Table 2a whereas the estimates of the inefficiency model are presented in Table 2b. The estimated parameters of the unrestricted and restricted models show clear differences; however, these differences are less than standard errors of two, as can be seen from the 'difference/standard error' column in Table 2a.

The initial maximum likelihood estimates indicate that none of the variables fully satisfy monotonicity conditions for all observations (Table 3). Irrigation water which we are particularly concerned about satisfies monotonicity conditions for only 78% of the total observations. Similarly, quasi-concavity is satisfied for only 29% of the total observations in the initial model. Monotonicity conditions are fully satisfied for all observations and all variables in the adjusted model. Likewise, quasi-concavity is also improved in the final adjusted model where 95% of the observations satisfied the conditions.

We can interpret this scenario as, for the remaining 5% of observations that are not quasi-concave, the individual inefficiency scores may be either over or under estimated (Sauer, 2006). Since the standard micro-economic theory requires satisfying quasi-concavity under the profit-maximizing assumption, Henningsen and Henning (2009) argue that technical efficiency concept assumes that producers tend to maximize their output given their input quantities rather than to maximize profit. Thus, in contrast to monotonicity condition, satisfying quasi-concavity assumption is not necessarily important. We see that the intercept term in the final step is not significantly different from zero, while the scaling coefficient is not significantly different from 1. From these results we can infer that the three-step procedure has not introduced substantial bias in the model (Gedara et al., 2012).

The partial production elasticities with respect to all inputs are reported in Table 4. It is evident from the results that production is inelastic with respect to each of the inputs included in the model. The elasticities at the sample mean are almost identically ranked under both estimations. Seed variable

Table 2a
Restricted and unrestricted model parameter estimate.

Parameters	MLE estimates		Minimum distance estimates			Final SFA estimates	
	Estimate	SE	Coefficient	Difference	Diff/SE	Estimate	SE
Constant	−13.523*	7.351	−13.236	0.287	0.039	−13.534	
Ln seed (kg)	1.108	1.946	0.962	−0.146	−0.075	0.944	
Ln labour (h)	−1.990*	1.145	0.059	2.049	1.790	0.023	
Ln fertilizer (kg)	0.480	1.615	0.524	0.044	0.027	0.497	
Ln machinery (No. of farm operation)	1.936	2.186	1.344	−0.592	−0.271	1.334	
Ln water (m^3)	1.071	1.023	0.345	−0.727	−0.711	0.315	
Ln seed × seed	−0.549	0.427	−0.538	0.012	0.027	−0.585	
Ln seed × labour	−0.545**	0.195	−0.128	0.417	2.138	−0.167	
Ln seed × fertilizer	0.423	0.286	0.342	−0.081	−0.283	0.312	
Ln seed × machinery	0.004	0.295	0.014	0.010	0.035	−0.022	
Ln seed × water	0.348	0.219	0.120	−0.228	−1.041	0.086	
Ln labour × labour	−0.218	0.220	−0.004	0.215	0.975	−0.040	
Ln labour × fertilizer	0.370**	0.172	0.094	−0.276	−1.607	0.059	
Ln labour × machinery	0.561**	0.272	0.030	−0.530	−1.948	−0.006	
Ln labour × water	−0.195	0.168	−0.016	0.179	1.063	−0.053	
Ln fertilizer × fertilizer	−0.604**	0.257	−0.444	0.160	0.623	−0.490	
Ln fertilizer × machinery	0.011	0.265	0.037	0.027	0.101	0.001	
Ln fertilizer × machinery	−0.102	0.188	−0.020	0.082	0.436	−0.057	
Ln machinery × machinery	−0.332	0.361	−0.110	0.222	0.614	−0.149	
Ln machinery × water	−0.194	0.194	−0.050	0.144	0.742	−0.088	
Ln water × water	0.088	0.252	−0.030	−0.118	−0.470	−0.068	
Model variance $\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.055***	(0.011)				0.058***	(0.012)
Variance ratio $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	0.833***	(0.107)				0.827***	(0.100)
Intercept						−0.036	(0.541)
IcFitted						1.000***	(0.234)

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table 2b
Inefficiency model estimates.

Parameter	Initial estimates (MLE)		Final estimates (adjusted model)	
	Coefficient estimate	Std. Error	Coefficient estimate	Std. Error
δ_{AGE}	0.007***	(0.002)	0.007***	(0.002)
δ_{EDC}	−0.003	(0.007)	−0.001	(0.007)
δ_{OFIN}	−0.131	(0.102)	−0.168	(0.112)
δ_{LTS}	0.173**	(0.088)	0.149*	(0.099)
δ_{SDQ}	−0.221**	(0.088)	−0.176**	(0.088)
δ_{TWO}	−0.027	(0.064)	−0.053	(0.065)
δ_{EXT}	−0.282***	(0.097)	−0.294***	(0.102)
δ_{WTD}	0.001	(0.065)	0.003	(0.065)
δ_{SPER}	−0.048	(0.074)	−0.030	(0.073)
δ_{GWSH}	−0.254***	(0.092)	−0.262***	(0.100)

Note: *AGE*, farmer's age in years; *EDC*, dummy variable indicating farmer's education level; *OFIN*, dummy variable indicating farmer's off-farm business activities; *LTS*, dummy variable representing land tenure status; *SDQ*, dummy variable for seed quality; *TWO*, dummy variable indicating tube-well ownership; *EXT*, dummy variable representing access to extension services; *WTD*, dummy variable indicating farmer's perception about decline in groundwater table; *SPER*, dummy variable indicating farmer's perception about salinity perception.

* Significant at 10%.

** Significant at 5%.

*** Significant at 1%.

Table 3
Proportion of farms satisfying the monotonicity and quasi-concavity conditions.

Variables	Maximum likelihood model (%)	Final adjusted model (%)
Monotonicity		
Seed	93.1	100
Labour	67.7	100
Fertilizer	94.2	100
Farm machinery	97.7	100
Irrigation water	78	100
Quasi-concavity	28.9	95.4

Table 4
Partial production elasticities for the sample mean from the unrestricted and restricted models.

Variables	Maximum likelihood model	Final adjusted model
Seed	0.409	0.455
Labour	0.039	0.079
Fertilizer	0.288	0.273
Farm machinery	0.359	0.323
Irrigation water	0.079	0.079

exhibits the largest partial production elasticity while labour displays the lowest. The elasticities relating to seed and labour were slightly lower in the unrestricted estimation compared to the restricted estimation. Irrigation water with an elasticity of 0.079 is ranked 4th out of the five variables included in the model. Similar results were reported by Karagiannis et al. (2003) in his study for out-of-season Greek vegetable farms. Regardless of the impact of measurement units, cotton production is highly responsive to the type and quality of seed (0.41) while it is least responsive to labour (0.039) and irrigation water (0.079), respectively. The returns to scale, derived from the sum of input elasticities, is estimated to be 1.174, suggesting that cotton farms on average are operating under increasing return to scales. The cross-product of the input elasticities are relatively small, suggesting that there is limited opportunity for input substitution.

Table 5 presents technical efficiency and irrigation water-use efficiency estimates derived from both the unrestricted and restricted models. The average TE score is 81% under the both unrestricted and restricted estimates for tube-well owners while the average IWE scores are 61% and 56% under the

Table 5
Frequency distribution of technical and irrigation efficiency for tube-well owners from the unrestricted and restricted models.

Efficiency range	Tube-well owners			
	TE (unrestricted)	TE (restricted)	IWE (unrestricted)	IWE (restricted)
<30	0	0	9	14
30–40	0	0	7	11
40–50	1	2	16	11
50–60	7	5	12	17
60–70	12	12	7	21
70–80	16	15	15	18
80–90	28	31	18	0
90–100	28	27	8	0
Mean	0.810	0.810	0.614	0.558
Std. Dev.	0.133	0.131	0.225	0.223
Minimum	0.405	0.412	0.079	0.124
Maximum	0.966	0.967	0.943	0.893
Water buyers				
<30	0	0	20	24
30–40	0	0	18	16
40–50	7	7	10	9
50–60	10	9	9	9
60–70	19	19	6	8
70–80	14	20	13	8
80–90	19	14	4	7
90–100	12	12	1	0
Mean	0.729	0.725	0.471	0.459
Std. Dev.	0.146	0.146	0.219	0.221
Minimum	0.405	0.413	0.041	0.111
Maximum	0.962	0.959	0.932	0.895

unrestricted and restricted estimations. For water buyers, the average TE score is 71% under the both unrestricted and restricted estimations while the average IWE scores are 47% and 46% for the unrestricted and restricted models. The equality of means test (*t-test*) for the unrestricted and restricted TE estimates cannot be rejected at 1%. However, we reject the null hypothesis that mean IWE estimates derived from the unrestricted and restricted models are not significantly different from zero. Figs. 4 and 5 also illustrate that estimates of TE based on the unrestricted and restricted model are highly correlated; the coefficient of correlation for TE is 0.99 and that for IWE is 0.80.

The estimated results suggest taking measures can potentially increase cotton production given the existing resource endowments. Of particular interest is the irrigation water efficiency which is very low given the depleting groundwater resources in Pakistan. Our results indicate that cotton growers on average produce 0.67 kg of cotton using one m^{-3} of groundwater. Although these estimates are fairly higher than the previous estimate of 0.22 kg m^{-3} by Shabbir et al. (2012), yet there is considerable scope for improving water productivity and efficiency when compared to major cotton producing countries. We estimated that 173 cotton farms can save a total of 1.06 million m^3 of groundwater if they achieve 100% efficiency in irrigation water applications. We find that water buyers despite paying more cost for irrigation water remain more technically and irrigation water use inefficient than tube-well owners. Meinzen-Dick (1996) found that tube-well owners were better-off in terms of farm productivity compared to water buyers, presumably as a result of greater control over groundwater access and supplies. Nevertheless, water buyers are risk-prone to uncertain and delayed irrigation supplies. As groundwater trading is informal, it is highly influenced by the social ties between tube-well owners and water buyers. Hence, the absence of a formal contract, sometimes lead to inequities in water allocation and distribution among water buyers (Jacoby et al., 2004; Rinaudo et al., 1997). Moreover, due to on-going energy crises water buyers face more uncertainties and delays in obtaining water for irrigation and it is highly likely that the delayed water application may decrease the marginal product of other inputs such as fertilizer, labour and chemical inputs. Consequently, water buyers remain technically and irrigation water use inefficient.

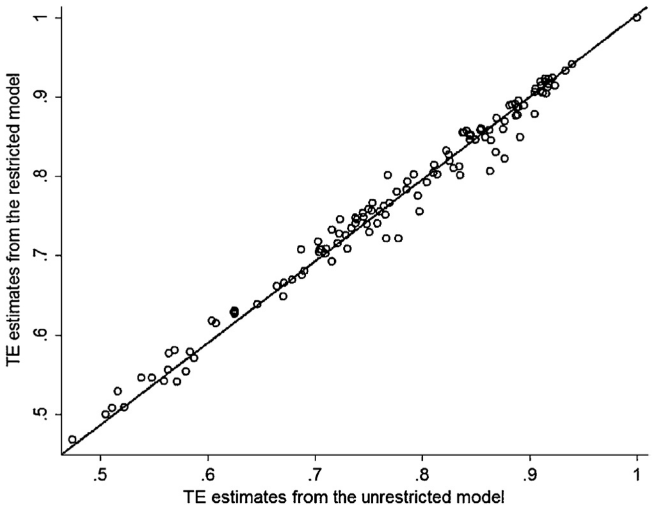

Fig. 4. Technical efficiency estimates of the restricted and unrestricted models.

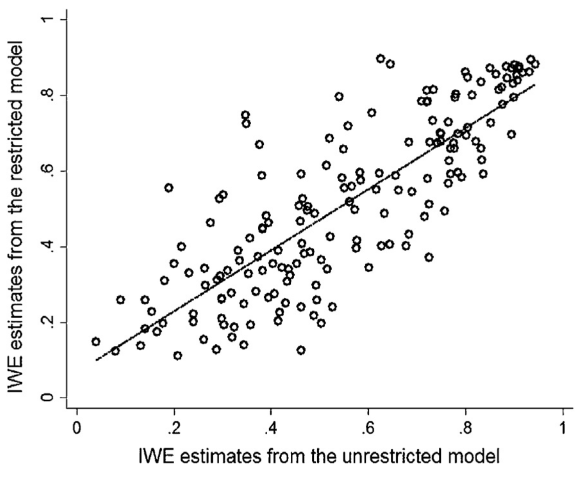

Fig. 5. Irrigation water use efficiency estimates of the restricted and unrestricted models.

Our estimates of IWE are generally lower than various studies on irrigation water-use efficiency in many other water stressed regions such as Speelman et al. (2008) for small-scale irrigation schemes in South Africa, Frija et al. (2009) for small-scale greenhouse farms in Tunisia and Manjunatha et al. (2011) for irrigated agriculture in India. The average scores are higher than those in Karagiannis et al. (2003) for out-of season vegetable farming in Greece. However, in contrast to our work, these studies have included multiple crops mainly fruits and vegetables in their analysis to assess irrigation water-use efficiency.

As far as estimates of the inefficiency[8] model (Table 2b) are concerned, the estimated coefficients and standard errors of the unrestricted and restricted models slightly differ in some cases. However,

[8] The estimated positive coefficients in the inefficiency effects model indicate that variables has negative effect on technical efficiency while in the second-stage positive sign indicates positive and negative sign indicates negative impact on irrigation efficiency.

Table 6
Explaining irrigation water efficiency differentials.

Parameter	Unrestricted		Final estimates (adjusted model)	
	Coefficient estimate	Std. Error	Coefficient estimate	Std. Error
δ_{AGE}	−0.001	(0.002)	−0.001	(0.002)
δ_{EDC}	0.021	(0.028)	0.016	(0.025)
δ_{OFIN}	−0.003	(0.043)	0.059	(0.039)
δ_{LTS}	−0.057	(0.037)	−0.035	(0.034)
δ_{SDQ}	0.083**	(0.042)	0.091**	(0.038)
δ_{TWO}	0.062**	(0.035)	−0.017	(0.031)
δ_{EXT}	0.057	(0.038)	0.074**	(0.034)
δ_{WTD}	0.093**	(0.041)	0.152***	(0.038)
δ_{SPER}	0.057	(0.035)	0.065**	(0.031)
δ_{GWSH}	0.125***	(0.037)	0.107***	(0.033)
Constant	0.454***	(0.090)	0.392***	(0.082)
R^2	0.388		0.468	

Note: *AGE*, farmer's age in years; *EDC*, dummy variable indicating farmer's education level; *OFIN*, dummy variable indicating farmer's off-farm business activities; *LTS*, dummy variable representing land tenure status; *SDQ*, dummy variable for seed quality; *TWO*, dummy variable indicating tube-well ownership; *EXT*, dummy variable representing access to extension services; *WTD*, dummy variable indicating farmer's perception about decline in groundwater table; *SPER*, dummy variable indicating farmer's perception about salinity perception.

** Significant at 5%.
*** Significant at 1%.

the difference is not statistically significant. We see that farmer's education, off-farm business activities and tube-well ownership do not significantly affect technical efficiency. As expected, old farmers and tenants have slightly lower technical efficiency levels than their counterparts. We find that improved seeds and extension services play a significant role in improving technical efficiency. The results on farmers perceptions indicate that farmers who perceive that over-extraction of groundwater resources may deteriorate its quality and availability are generally more efficient than those farmers who think otherwise.

Irrigation water-use efficiency differentials are presented in Table 6. The second-stage regression results suggest that seed quality, perception of declining groundwater table and effect of groundwater shortage on future cropping patterns are significant in improving irrigation water-use efficiency under both the unrestricted and restricted model estimates. Estimates for tube-well ownership and extension services, however, vary under the unrestricted and restricted models. The parameters of tube-well ownership are significant under the unrestricted model estimates while non-significant under the restricted model estimates whereas extension services show significant impact under the restricted model and non-significant under the unrestricted model.

Most of the estimated coefficients in the inefficiency model and second-stage irrigation water-use efficiency differentials confirm to *a priori* expectations about their impact on efficiency levels. Our estimates indicate that farmer's age significantly impact the level of technical efficiency while non-significant on irrigation water-use efficiency. Quite a number of other studies suggest that old farmers are more sceptical to adopting new farming techniques and technologies and hence lag in agricultural production, e.g., (Speelman et al., 2008; Villano and Fleming, 2006). The coefficient of land tenure status indicates that non-owners are technically more efficient than the land owners. These results contradict the common intuition that, *ceteris paribus*, land owners usually invest more in new production technologies and, consequently, increase their expected returns (Frija et al., 2009; Gebremedhin and Swinton, 2003; Speelman et al., 2008). However, some studies have also reported negative impact of land ownership on farm efficiency (Byiringiro and Reardon, 1996). Nonetheless, our results support the notion that farmers who rent in land will also devote extra effort in management oversight to generate returns above what they pay for rent, hence they are more efficient. Similarly, estimates for irrigation water-use efficiency suggest that land owners are less efficient compared to non-owners. As expected, education and extension services have positive impact (education positive but non-significant while extension positive and significant) on technical efficiency and irrigation water-use efficiency, supporting the premise that increases in human capital enables farmers to improve resource utilization and thus achieve higher efficiencies. In the literature, we find mixed results for the efficiency and education relationship, e.g., Karagiannis et al. (2003) and Solı's et al. (2009) found the impact of education significant while Haji (2007) and Speelman et al. (2008) found the impact of education non-significant. These mixed results indicate that using general years of schooling could not be the substitute of specialized education, e.g., agricultural education has different requirements compared to the social sciences education. The impact of extension services on technical and irrigation water-use efficiency are consistent with the commonly established assumption that the farmers who tend to seek more extension advice and get involved in training programmes are technically more efficient than those who have less or no contact with the agricultural extension staff (Frija et al., 2009; Parikh and Shah, 1994).

The results for seed quality show a statistically significant positive association between seed quality and technical and irrigation water-use efficiency. We find that off-farm income is positively associated with technical efficiency, suggesting that with alternative income resources, farmers may have a better edge to purchase and use an optimal input mix which in turn results in better efficiency gains (Karagiannis et al., 2003). However, off-farm income, leads to different results for irrigation water-use efficiency, being negative under the unrestricted model and positive under the restricted model. The impact of tube-well ownership on technical efficiency implies that tube-well owners have better assurance and control over irrigation in terms of spatio-temporal crop water requirements and hence their expected returns are higher than the water buyers. However, statistically significant different parameter estimates for the impact of tube-well-ownership on irrigation water-use efficiency obtained under the unrestricted and restricted models suggest careful interpretation of efficiency explaining variables in the second-stage regression model.

Amongst the explanatory variables representing farmer's perceptions about groundwater resource, perception about salinity and the potential impact on future cropping patterns are positively associated with technical efficiency while perception about decline in groundwater tables is negatively associated with technical efficiency. However, irrigation water-use efficiency estimates suggest that farmers seriously consider the declining groundwater tables, salinity level and the groundwater availability while irrigating cotton fields.

6. Conclusion

The main objective of this study was to estimate the level of, and factors affecting, technical and irrigation water-use efficiency among groundwater-fed cotton farms in Pakistan. The results obtained from a cross-sectional dataset of 172 cotton growers, including 92 tube-well owners and 80 water buyers, indicate considerable technical and irrigation water application inefficiencies. We find that, on average, tube-well owners are technically more efficient than water buyers. Our results indicate that tube-well owners and water buyers can potentially increase cotton production by 19% and 28%, respectively without increasing the existing input level. Despite the severe water shortage in Punjab, the IWE estimates reflect poor irrigation water management practices at the farm level among the sample farms in study districts. Although, the study findings point out considerable technical inefficiencies in cotton production, irrigation water-use inefficiencies are more pronounced than technical inefficiencies. The mean irrigation water-use efficiency estimates suggest that a 46% and 54% reduction in the current water applications is feasible for tube-well owners and water buyers, respectively. The mean IWE estimates suggest considerable gains in terms of groundwater conservation by improving IWE across all farms. Based on the unrestricted model estimates, we calculated that by achieving 100% IWE 172 cotton cultivation farms can save a total of 0.57 million m^3 of groundwater, with 0.35 million m^3 savings for tube-well owners and 0.22 million m^3 for water buyers. The restricted model estimate suggest a total saving of 0.53 million m^3 for both tube-well owners and water buyers. In monetary terms, based on the unrestricted model estimates the surveyed cotton farms can save a sum of Rs. 2.3 million with Rs. 1.04 million for tube-well owners and Rs. 1.29 million for water buyers form total groundwater irrigation costs during one season of cotton cultivation. The restricted model estimates suggest a sum of Rs. 2.22 million savings across all farms.

Whilst the study results suggest implications for improving technical efficiency in cotton farming, one of the key underlying policy objectives is to suggest measures to improve irrigation water-use efficiency in cotton production. Based on TE estimates the study findings suggest that access to technology is not a major constraint in cotton production. The low IWE estimates suggest that substantial decreases in groundwater use can be achieved. By achieving higher irrigation water efficiency, there will be a significant room for lifting part of the increasing pressure on water resources. The only bottlenecks to improving irrigation water-use efficiency arise from lack of information about the existence of groundwater resources, their future availability, the consumptive crop water requirements and the conventional irrigation application practices. The relationship between irrigation water-use efficiency estimates and farmer's characteristics guide policy makers and extension workers on how to better aim efforts to improve irrigation water-use efficiency. We suggest that educating farmers about the actual crop water requirements and groundwater resource availability may help to achieve higher irrigation water-use efficiencies. Moreover, water buyers are generally down the water supply chain and they face more water uncertainties that lead to inefficient use of irrigation water. Therefore, we suggest that additional policies are required that improves allocation security and equity of access for water buyers whilst also providing information of the state and quality of groundwater resources.

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