Measuring Groundwater Irrigation Efficiency in Pakistan: A DEA Approach Using the Sub-vector and Slack-based Models

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Abstract

We estimate the efficiency of groundwater use in cotton production in the Punjab province of Pakistan. We use a survey data of 189 cotton producers comprising 98 tube-well owners and 91 water buyers in order to get the differential impact of tube-well ownership on groundwater use efficiency. We use data envelopment analysis to compute the technical, scale, cost and allocative efficiencies for tube-well owners and water buyers relative to a meta-frontier and groupfrontiers. The DEA sub-vector and slack-based models are used to compute groundwater use efficiency. The results indicate low levels of technical inefficiencies with water buyers being more inefficient relative to tube-well owners. However, groundwater use inefficiency is more pronounced than the respective technical efficiency. The sub-vector and slack-based estimates are highly correlated suggesting the robustness of the results. The results on returns to scale indicate that the majority of cotton growers are operating at increasing returns to scale, suggesting that efficiency can be improved by expanding the scale of operation.

We use a second-stage bootstrap truncated regression to investigate the factors that influence technical efficiency and groundwater use efficiency. We find that the level of education, seed quality and extension services have positive significant impacts on technical and groundwater use efficiency. We suggest that knowledge of crop water requirements and the use of improved crop varieties can play role in improving the efficiency of groundwater use.

JEL Classification: Q15, Q25, D24

AgEcon Search Categories: Production Economics, Productivity Analysis

Keywords: Pakistan, groundwater use efficiency, groundwater markets, technical efficiency, DEA, sub-vector, slack-based model, meta-frontier

1. Introduction

Pakistan is confronting one of the most striking challenges of water scarcity in the world. In a pre-dominant agrarian economy, the issue of water shortage has threatened the sustainability of agriculture which plays a prominent role in the country's economy. Due to the arid and semi-arid climate agriculture is highly dependent on irrigational water supplies from both canal and groundwater. However, surface water availability is not only deficient due to ecological constraints; it is also unevenly distributed within the Indus Basin of Pakistan (Bandaragoda and Rehman, 1995).

Due to deficient surface water supplies, agricultural development has been greatly influenced by the massive use of groundwater through private tube-well development. The number of tube-wells has increased from less than 30 thousand in 1965 to more than one million in 2010 (Chaudhry, 1990; Govt. of Pakistan, 2010). Resultantly, groundwater abstractions through these tube-wells have gone up to 60 km^3 each year, which exceed the annual recharge of 55 km^3 (FAO, 2009). The gap between replenishment and extractions is lowering the water tables significantly with more than 3 meters annually in some areas (Ahmad, 2007). Declining water tables are making groundwater supplies economically unviable for irrigation in many regions (Banerji et al., 2006) and are creating environmental problems (Kijne, 1999; Shah et al., 2000; Khan et al., 2008; Qureshi et al., 2009).

Over time, considerable efforts have been devoted to introduce several direct and indirect groundwater management strategies in Pakistan. The techno-institutional approaches, such as water-related property rights, direct or indirect water pricing and a permit system were found difficult to enforce (Qureshi et al., 2009). Therefore, much of the policy emphasis has been focused on adopting strategies such as on-farm water management. However, there is no restriction or governance regarding groundwater use. Access to groundwater resources is open and generally tied to land ownership (Jacoby et al., 2004). A tube-well owner has exclusive rights to groundwater use; he can extract and even can sell groundwater unimpeded (Meinzen-Dick, 1998; Qureshi et al., 2010). These groundwater transactions often occur through local informally developed groundwater markets (Meinzen-Dick, 1996; Thobani, 1998). In many parts of the country especially in deep water table regions, informal groundwater markets play an important role in irrigated agriculture through trading surplus pumping capacities between tube-well owners and non-owners. The groundwater markets offer economic benefits to tube-well owners and offer non-owners opportunities to improve their agricultural productivity (Shiferaw et al., 2008; Manjunatha et al., 2011). However, there is limited empirical evidence on groundwater use efficiency estimates under such a market structures.

In the previous literature, irrigation water use efficiency has been defined as the amount of water actually utilised by a crop compared to the amount of water supplied to the crop (McGucrin et al., 1992). This measure is physical in nature rather than economic, as it does not deal with the managerial capability of the farmers (Karagiannis al., 2003). However, recently, an alternative approach that is economic in nature is used to measure irrigation water use efficiency. A review of the current agro-economic literature shows that several studies have estimated the efficiency of water use in agriculture with economic intuition. For example, Karagiannis al., (2003) used a stochastic frontier production model to measure irrigation water use efficiency among out-of-season vegetable growers in Greece. Speelman et al., (2008) and Frija et al., (2009) used data envelopment analysis to estimate water use efficiency, respectively, among small-scale irrigators in South Africa and small-scale greenhouse vegetable farmers in Tunisia. These studies provide evidence on how much water could be saved at a farm level without altering the other inputs and output bundle and the technology used. However, we do not find significant evidence of irrigation water use efficiency in agro-economic literature which has focused at measuring water use efficiency in cotton production.

Pakistan is the 4th largest cotton producer in the world. Cotton is one of the major export commodities for Pakistan, accounting for 6.9% to the value added in agriculture and 1.4% to the gross domestic product. Pakistan's largest exports include cotton and cotton related goods and services, which account for about 60% of its global exports. In 2011, with 2.35 million tonnes of cotton production, Pakistan is ranked at number 4th in production and 3rd in consumption with a global share of 9.80 % in the global cotton market (GOP, 2011-12; FAO, 2012). Hence, any policy intervention improving cotton production would have serious implications for the national economy. Under such circumstances, if cotton productivity is one of the major policy goals on the one hand, improving irrigation efficiency is indispensable on the other hand. Figure 1 shows position of Pakistan in global cotton market.

<Insert Fig. 1>

Several studies on efficiency measurements of cotton production in Pakistan have focused on the technical efficiency of farms (Hussain et al., 1999; Shafiq and Rahman, 2000; Khan ad Iqbal, 2005; Abedullah et al., 2006). But, none of the studies has measured the irrigation efficiency of cotton farms in Pakistan. Therefore, the objective of this paper is to measure water use efficiency among cotton growers. The study uses the data envelopment analysis approach (DEA) to compute the technical, scale, cost, and allocative efficiencies relative to a meta-frontier and group frontiers. The sub-vector and slack-based DEA models are used to compute groundwater use efficiency. We hypothesise that tube-well ownership may cause efficiency differences among tube-well owners and water buyers. Informal water markets offer opportunities for non-owners to use groundwater, but this does not ensure equity of access in terms of time and space. Sometimes, water buyers need to be in queue for long time to get water. Therefore, tube-well owners and water buyers can be grouped into different categories operating under different states of technology; hence, estimating a separate frontier for each group would help to reveal the difference between technology and efficiency effects (Battese et al., 2004 and O'Donnell et al., 2008). The proposed methodology is applied to a randomly selected sample of 189 groundwater-irrigated cotton-growing farmers including 98 tube-well owners and 91 water buyers. In addition, a second-stage bootstrap truncated regression approach is used to identify the factors influencing technical efficiency and groundwater use efficiency.

This study contributes to the literature on groundwater economics in several ways. First, it is the first attempt to measure groundwater use efficiency among cotton-growing farmers under informal groundwater markets in Pakistan. Second, it uses the sub-vector and slack-based DEA models to compute groundwater use efficiency and compares the results of both methods. Moreover, this study also contributes to the national water policy in Pakistan by providing estimates on groundwater use efficiency in irrigation.

The paper is organised as follows. The next section describes the theoretical background of DEA and main frameworks employed for the efficiency measurements. In the methodological section, we describe an input-oriented DEA model under variable returns to scale to compute technical and cost efficiencies, and we describe sub-vector and slack-based models to estimate groundwater use 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. Methodological Framework

2.1 Efficiency measures

Since the 1970s, the efficiency concept has been widely used in performance evaluation for individual decision making units (*DMUs*) such as manufacturing firms or public sector agencies. The efficiency and productivity of DMUs is measured either by a parametric method such as stochastic frontier analysis (SFA), or by a non-parametric measure, such as data envelopment analysis methods (DEA).

The parametric approach (SFA) estimates the efficiency and productivity measures statistically, while the non-parametric approach (DEA) constructs a linear piecewise frontier to describe the relationship between inputs and outputs. Several studies (e.g., Wadud and White, 2000; Thiam et al., 2001 and Alene and Zeller, 2005) found the comparative results of both approaches to be highly correlated. The choice of any particular approach, however, depends on the objective of the research, the type of production unit and the data available (Wadud and White, 2000). The major advantage of a non-parametric approach is that it does not assume any a priori functional relationship between the inputs and outputs.

2.2 Data envelopment analysis and efficiency measures

Data envelopment analysis was introduced by Charnes et al., (1978), who extended Farrell's (1957) idea of measuring technical efficiency relative to a production frontier to develop a multi-factor (multiple inputs and outputs) productivity analysis model. The DEA model proposed by Charnes et al., (1978) assumed constant returns to scale (CRS). Later, Banker et al., (1984) introduced a DEA model under variable returns to scale (VRS). The concept of CRS is not economically feasible in many situations, where by increasing inputs, we cannot increase the output proportionally; for example, in agricultural production we have diminishing returns in case of water or fertiliser use.

The evaluation of a *DMU* or a farm is usually based on economic efficiency, which is generally based on technical efficiency and cost or allocative efficiency. Technical efficiency is the ability of a firm to produce maximum possible output within an available set of inputs under the given technology. Allocative efficiency is defined as the ability of a firm to equate marginal value product and marginal cost. Technical efficiency can further be decomposed into pure technical efficiency and scale efficiency. Scale efficiency relates to the most efficient scale of operation in the sense of maximising average productivity. These measures of technical, cost, scale and allocative efficiencies can be derived using DEA under variable returns to scale and constant returns to scale (Banker et al., 1984). The DEA efficiency measurements can be either input oriented or output oriented[1]. As the objective of our study is to measure groundwater use efficiency, we chose input-oriented DEA approach.

2.2.1 Technical efficiency

Let us consider *n DMUs* that produce an output *Y* using input *X*. *X* is an $m \times n$ matrix of inputs (*m*=1, 2...6), and *Y* represents an $s \times n$ output row vector (*s*=1, i.e., cotton yield). For DMU_{j_o}, the input and output data are represented by column vector x_{j_o} and row vector y_{j_o}. Following Banker et al., (1984), to compute technical efficiency under VRS for DMU_{j_o}, we solve the following linear programming problem:

$$\text{Min}_{(\lambda,\theta)}\ \theta \tag{1}$$

Subject to:

$$\sum_{j=1}^{n}\lambda_j Y_j - y_{j_o} \geq 0,\ \sum_{j=1}^{n}\lambda_j X_j - \theta x_{j_o} \leq 0,\ \sum_{j=1}^{n}\lambda_j = 1,\ \lambda_j \geq 0$$

where θ is a scalar and λ is the $n\times 1$ vector of inputs and output weights. The equation $\sum_{j=1}^{n}\lambda_j = 1$ is a convexity constraint to compute technical efficiency under VRS specification. To compute scale efficiency, we further impose a restriction $\sum_{j=1}^{n}\lambda_j \leq 1$ in equation (1) to calculate technical efficiency under constant returns to scale (CRS). We use the following equation, as shown by Coelli et al., (2002), to compute scale efficiency:

$$SE = TE_{crs} / TE_{vrs} \tag{2}$$

Scale efficiency=1 implies that *DMU* is operating at an optimal scale, while scale efficiency<1 indicates a scale inefficiency that can be either due to decreasing (supra optimal) or increasing (sub optimal) returns to scale. To find whether a *DMU* is operating at decreasing or increasing returns to scale, a non-increasing returns to scale restriction $\sum_{j=1}^{n}\lambda_j \geq 1$ is imposed in equation (1). The relationships $TE_{NIRS} = TE_{VRS}$, $TE_{NIRS} = TE_{VRS}$ and $TE_{VRS} = TE_{CRS}$ indicates the existence of DRS, IRS and CRS, respectively (Coelli et al., 2005).

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[1] From an input-orientation perspective, we can determine how much the input use of a DMU can be reduced without altering the output level. However, using an output-orientation, we can determine the maximum achievable output given the input quantities.

2.2.2 Cost efficiency

To compute the cost efficiency for a DMU_{j_o}, we consider the following DEA linear program with cost minimization objective, where $x^*_{j_o}$ represents the cost minimization vector of inputs given the input prices w_{jo}.

$$\text{Min}_{(\lambda, x^*_{jo})} w'_{jo} x^*_{jo} \tag{3}$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j Y_j - y_{jo} \geq 0, \ \sum_{j=1}^{n} \lambda_j X_j - x^*_{jo} \geq 0, \ \sum_{j=1}^{n} \lambda_j = 1, \ \lambda_j \geq 0$$

The total cost efficiency for DMU_{j_o} is calculated as $CE = w'_{j_o} x^*_{j_o} / w'_{j_o} x_{j_o}$. That is, CE is the ratio of minimum cost to actual cost for DMU_{j_o}. The allocative efficiency is then calculated with the following equation:

$$AE = CE / TE \tag{4}$$

2.2.3 Meta-frontier, group frontier and technology gap ratios

To determine the impact of tube-well ownership on farm efficiency, we estimate efficiencies relative to a meta-frontier and group-specific frontiers for tube-well owners and water buyers. O'Donnell et al., (2008) explained that a meta-frontier model envelops various group-frontiers. The estimation of a meta-frontier offers to compare efficiencies from group frontiers that enable us to calculate the technology gaps between the meta-frontier technology and group-frontier technology. The meta-frontier concept was formally introduced by Battese and Rao, (2002) and Battese et al., (2004) for a stochastic frontier and was extended by O'Donnell et al., (2008) to DEA. In DEA, group frontiers are constructed by estimating a DEA model for each group, and the meta-frontier is then estimated by pooling all observations for all groups. The technology gap ratio (*TGR*), according to O'Donnell et al., (2008), can be estimated using the following equation:

$$TGR_i = TE_i^* / TE_i \tag{5}$$

where *TGR* is the technology gap ratio, TE_i^* is the technical efficiency with respect to the meta-frontier, and TE_i is the technical efficiency with respect to the group frontier. The technical efficiency relative to the meta-frontier is always less than the technical efficiency relative to the group frontier, thus bounding the *TGR* value between 0 and 1. If the *TGR* value is close to 1, this indicates that a group-specific production frontier is close to the meta-frontier, indicating a more advanced technology level. In contrast, the closer the TGR is to 0, the further the group frontier is from the meta-frontier, indicating a less developed production technology level (see O'Donnell et al., 2008, for details).

2.3 Measuring groundwater use efficiency

Two approaches are used for measure efficiency for a particular input in data envelopment analysis: the sub-vector efficiency approach (SVM) and the slack-based method (SBM). The SVM was introduced by Färe et al., (1994) to measure input-specific efficiency, keeping other inputs and output constant. The SBM was introduced by Tone (2001) to measure the excessive use of any particular input. The major difference between the two methods is that the SVM is a non-radial efficiency measure that ignores possible non-zero slacks, while SBM calculates efficiency together with the slack values.

2.3.1 Sub-vector efficiency analysis

In the literature, the sub-vector efficiency concept has been widely used to measure input-specific technical efficiencies. Following the idea of Färe et al., (1994) Speelman et al., (2008), Frija et al., (2009) and Manjunatha et al., (2011) used the concept of the sub-vector efficiency to estimate a possible reduction in irrigation water use. This "possible reduction" can be referred as the "irrigation water use efficiency" (Frija et al., 2010). The irrigation water use efficiency θ^t for a given DMU_{j_o} can be calculated using the following linear programming problem:

$$\text{Min}_{(\lambda^t,\theta)}\ \theta^t \qquad (6)$$

Subject to:

$$\sum_{j=1}^{n}\lambda_j Y_j \geq y_{j_o}\ \text{(i)},\ \sum_{j=1}^{n}\lambda_j X_{m-t,n} \leq x_{mj_o}\ (ii),\ \sum_{j=1}^{n}\lambda_j X_{t,n} \leq \theta^t x_{tj_o}\ \text{(iii)},\ \sum_{j=1}^{n}\lambda_j = 1\ \text{(iv)},\ \lambda_j \geq 0\ \text{(v)}$$

where θ^t is the sub-vector technical efficiency of input "t" for a DMU_{j_o}. The constraints (i), (iv) and (v) are the same as in equation 1. In the second constraint the input "t" column is excluded, whereas the third constraint includes only the "t" input. Here, θ^t can have a score between 0 and 1, where a score of 1 indicates that a *DMU* is using groundwater efficiently. A value of less than 1 for a *DMU* indicates that water use inefficiency exists, meaning that there is some potential to save water use in irrigation.

2.3.2 Slack-based model

To get Koopmans[2] efficiency, Cooper et al., (2000) introduced slacks into the DEA model under VRS. The slacks represent the difference between the optimal values and the observed values of the inputs and outputs. The linear programme that represents the DEA model to calculate slacks under VRS is formulated as follows:

$$\text{Min}_{(\lambda,\theta,S^-,S^+)}\left[\theta-\varepsilon\left(\sum_{i=1}^{m}S_i^- + \sum_{r=1}^{s}S_r^+\right)\right], \tag{7}$$

Subject to:

$$\sum_{j=1}^{n}\lambda_j Y_{rj} - S_r^+ = y_{rj_o},\ (r=1,\ldots,s), \sum_{j=1}^{n}\lambda_i X_{ij} + S_i^- = \theta x_{ij_o},\ (i=1,\ldots,m), \sum_{j=1}^{n}\lambda_j = 1,$$

$\lambda_j \geq 0\,(j=1,\ldots,n), S_i^-, S_r^+ \geq 0\ \forall i$ and r.

where X is an $m \times n$ matrix of inputs, and Y represents an $s \times n$ output row vector, and S_i^-, S_i^+ represents the inputs and output slacks. The symbol ε is a non-Archimedean infinitesimal defined to be smaller than any positive real number. By solving this programme, we are able to interpret the results as follows:

(1) If $\theta^* = 1$ and all slacks $S_i^{-*} =, S_r^{+*} = 0$, the DMU_{j_o} is considered to be strongly efficient.

(2) If $\theta^* = 1$ and $S_i^{-*} \neq 0$ and/or $S_r^{+*} \neq 0$, the DMU_{j_o} is considered to be weakly efficient.

Following the idea of SBM, Chemak et al., (2010) measured the excessive use of water in irrigation. They measured irrigation water use efficiency with the following equation:

$$IWE = TE - \frac{Ve_i}{Vo_i} \tag{8}$$

where TE is the technical efficiency estimated using equation (1), Ve_i is the slack value of the input i, and Vo_i is the observed value of the input i.

<Insert Fig. 1>

To explain the difference between SVM and SBM, we use a graphical illustration in Fig 1. Let us consider six farms using two inputs (water and fertiliser) to produce a single output.

[2] According to Pareto-Koopmans (Pareto 1909 and Koopmans 1951) efficiency, it is not possible to improve any input or output without decreasing some other input or output (Ray 2004).

Based on the efficiency concept, farms B, C, D, E and F are the best performers because they are located on the frontier. A linear combination of their input use defines a production frontier that envelops all of the other observed farms. Farm A is inefficient because it is not located on the frontier. The radial contraction of inputs x_1 and x_2 (water and fertiliser) produces a projected point on the frontier A^o, which is a linear combination of all the observed data points. The technical efficiency of farm A with respect to farms B, C, D, E and F can be measured as $TE_A = OA^o / OA$. The technical efficiency concept involves radial contraction of all input sets. However, the SVM concept involves reduction of a particular input while keeping all other inputs and the output constant. The sub-vector efficiency of farm A for input x_1 (here water) could be measured by reducing x_1 to a point A' while keeping x_2 and the output constant. Hence, the sub-vector efficiency of input x_1 (water) for farm A can be given by the ratio $IE = O'A' / O'A$.

However, for SBM in the above case, both farms E and F are technically efficient, but farm E uses a lesser amount of input x_1 when compared to farm F. The measure of this excessive input use $(ox_1^F - ox_1^E)$ is called the slack value. This slack value helps us to compute input-specific technical efficiencies. For example, the technical efficiency of input x_1 which is water in this case, for the farm F relative to farm E can be measured by the equation $IE_F = Te_F - \frac{Ox_1^F - Ox_1^E}{Ox_1^F}$.

2.4 Truncated regression analysis

Application of a regression model in a second stage has been widely used to investigate determinants of DEA efficiency measures. In the literature, we find the Tobit regression as the most commonly used approach (e.g., Wadud and White, 2000; Dhungana et al., 2004; Speelman et al., 2008 and Frija et al., 2010). The use of Tobit regression in a second stage has been justified by the argument that because efficiency scores vary between zero and one, they are censored values. However, McDonald, (2008) argued that efficiency scores are not censored but are actually fractional values. Alternatively, McDonald, (2008) and Banker and Natarajan, (2008) proposed that Ordinary Least Squares (OLS) in a second stage yields more consistent results than the Tobit regression. However, the use of OLS is consistent only under very peculiar and unusual assumptions of the data-generating process (Simar and Wilson, 2011).

In an earlier paper, Simar and Wilson, (2007) noted that conventional approaches to inference in two-stage efficiency are invalid due to i) the complex and unknown serial correlation among estimated efficiencies and ii) the lack of description about the data-generating process. These authors proved that in a second stage, single bootstrap truncated regression performs better than OLS and the Tobit models. Therefore, we chose single bootstrap truncated regression to identify the determinants of groundwater use efficiency. The estimated specification for the regression model is as follows:

$$y_i = \alpha_i + \sum_{i=1}^{n} \beta_i z_i + \varepsilon_i \geq 0; \text{for } i = 1,....,N \quad \text{and } \varepsilon_i \rightarrow N(0,\sigma^2) \qquad (9)$$

where y_i is either technical, cost, allocative or water use efficiency, Z_i is the set of explanatory variables for $i = 1,....,12,$ and ε_i is the error term.

3. Principal Features of the Study Areas

The study is conducted within two districts, i.e., *Lodhran* from the cotton-wheat region[3] and *Jhang* from the mixed-cropping region of the Punjab province, Pakistan. In the study areas, rural households heavily rely on groundwater as their major source of irrigation because canal water supplies are limited to non-existent in parts of these districts. However, the area under study is solely groundwater irrigated in *Jhang,* while partly irrigated by canal water in the *Lodhran* district. In *Lodhran* canals supply water only during the *Kharif*[4] season. The canal water contribution during the *Kharif* season of 2010 was observed to range 20-44 percent of the total irrigation requirement (Author's survey, 2011). Therefore, the majority of the irrigation water comes through groundwater. The study areas in both districts have deep water tables that require high tube-well installation costs. The installation cost has been found to increase seven times to bore a tube-well at a depth of 24 metres compared to install a tube-well at a depth of 6 metres (Qureshi et al., 2003). The variation in the bore depth was observed to range between 60 metres and 99 metres in *Lodhran* and from 33 metres to 57 metres in *Jhang* (Author's survey, 2010-2011). We find that due to low water tables and the high installation cost, tube-well population is relatively less dense in *Lodhran* and parts of the

[3] Due to climatic variations and the nature of cropping patterns, the Punjab province has been classified into five cropping regions; barani region, mixed-cropping region, rice-wheat region, cotton-wheat region and pulses-wheat region.
[4] 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.

Jhang district. Therefore, groundwater markets are more active in *Lodhran* and *Jhang* compared to other districts having shallow water tables.

In the study areas, farm size plays an important role in informal groundwater markets. Large farms are often found to be involved in selling groundwater (Meinzen-Dick, 1996; Shah et al., 2008). However, under the given electricity shortage and growing cropping intensities, it has become difficult for large farms to have surplus water supplies. Only medium-size farms or large farms having more than one tube-well are involved in selling groundwater in the study districts.

3.1 Data and variable definitions

The data used in this study are based on a detailed survey conducted during the *Kharif* season 2010 in the *Lodhran* and *Jhang* districts of the Punjab province, Pakistan.
A multi-stage sampling technique was used in data collection. At the first stage, one *tehsil*[5] was selected purposively from each district. In the next stage, 10 villages were selected at random from each purposively selected *tehsil*. In the study areas, a village usually contains of 70-80 household farms. The information about tube-well owners and water buyers were collected with the help of the extension field staff and key informants for the selected villages. Finally, from each village, 10 groundwater users (5 tube-well owners and 5 water buyers) were selected randomly to obtain the differential impact of well ownership and to reveal the difference of amount of water applied and the production gains of tube-well owners and water buyers, thus making a total sample size of 189 groundwater users, i.e., 98 tub-well owners and 91 water buyers.

The data were collected using an interview schedule. During the interview, we collected information on various output and input quantities. The inputs are measured as (1) seed and fertiliser in kg/acre, (2) pesticide and farm operations as number of applications/acre, (3) total labour, consisting of hired (casual and permanent) and family labour in hours/acre, and (5) groundwater use in cubic metres/acre. Cotton yield (output) is measured in kg/acre as well. For different inputs and output quantities, information on their respective price was also

[5] *Tehsil is* an administrative unit. A district usually consists of 5-6 tehsils (sub-districts) in Pakistan.

collected in Pakistani Rupees[6]. The descriptive statistics of the variables used in the DEA model are presented in Table 1.

Information on groundwater utilisation at farm level is on one side, it even does not exist at the district level due to large number of non-registered small-scale and fragmented groundwater users (Qureshi et al., 2003). Therefore, we collected information about the number of irrigations for a particular crop, time of irrigation, bore depth, diameter of suction pipe, and power of the engine. Using this information in an approximate estimation model as used by Eyhorn et al., (2005) and Srivastava et al., (2009), we measured groundwater extraction in litres using the following formula and then converted into m^3.

$$Q = \frac{t \times 129574.1 \times BHP}{[d \ + \ (255.5998 \times BHP^2) / \ d^2 \times D^4)]} \qquad (10)$$

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.

<Insert Table 1>

Table 1 compares selected variables used in the DEA analysis. Descriptive statistics show considerable variations in the use of the inputs and output produced by tube-well owners and water buyers. The average farm size of the sample farms is 7.7 acres with average of 9.7 acres for the tube-well owners and 5.5 for the water buyers. All farms in the sample are characterised as farms with a large share of family labour, and we see considerable variation in the number of hours worked on farms. Overall, the average cotton yield is 831 kg/acre, with 836 kg/acre for the tube-well owners and 824 kg/acre for the water buyers. There is also a significant difference in the seed rate, with a mean of 8.3 kg/acre, ranging from 5 to 10 kg/acre. The amount of seed used generally varies because of conventional sowing methods, the time of sowing and the type of variety cultivated. Similarly, there is great variability across the farms in fertiliser and chemical application. In the case of groundwater irrigation, buyers on average use 7% less groundwater than tube-well owners, while they pay, on average 2 times more price to irrigate one acre of cotton crop. The respective prices of the different inputs also show significant variability. On average, the fertiliser, labour, and irrigation cost constitute 70% of the total production cost. The share of the irrigation cost to the total production cost is observed to be between 12% for the tube-well owners while 20% for the water buyers.

[6] Average exchange rate at the time of data collection (June-November 2010) was Rs.85.25/US$.

The explanatory variables used to explain the efficiency differentials in the second-stage regression include (1) the age of the farmer in years (age-squared was also included to examine the possibility of decreasing return of human capital), (2) farm size in acres, (3) a dummy variable indicating the cropping region, (4) a dummy variable indicating family status, (5) a dummy variable indicating the education level of the farmers, (6) a dummy variable indicating the farm's tenancy status, (7) a dummy variable for seed quality, (8) a dummy variable indicating tube-well ownership, (9) a dummy variable indicating access to canal water, (10) a dummy variable for off-farm income activities, (11) a dummy variable for credit or loans for the farm, and (12) a dummy variable indicating access to extension services. Table 2 presents the summary statistics of the explanatory variables.

<Insert Table 2>

The surveyed farms from the cotton-wheat region mainly grow cotton and wheat, while in the mixed-cropping region, wheat, cotton, sugarcane and rice are the major crops. The average farmer's age is 44 years, ranging from 25 to 65 years. The rural sociology of the study districts is dominated by the joint family system. Among the sampled farms, approximately 68% of the farming families are living as joint families. The statistics on education clearly reflects a lack of education. It has been observed that 45% of the surveyed farmers have no formal education. Only 21% of the farmers have an education level above matriculation. A significant part of the surveyed farmers cultivate their own land. Only 19.5% of the farmers are tenants. Similarly, only a small proportion of the farms have adopted some kind of agricultural innovations such improved seed varieties and seed treatments etc. Only 28% of the farmers are found to use improved seed for cotton crop. Because farming is a major livelihood activity among rural communities, only a small proportion (16.5%) of the farmers has off-farm income sources. The statistics indicate that region of extension services and agricultural credit is limited in the study areas. Only 24% of the farmers managed to get credit from private banks or public agencies, and 31% of the farmers participated in agricultural training programmes or received advice from the extension field staff.

4. Empirical Results and Discussion

4.1 Technical, scale, cost and allocative efficiencies

The results on the technical, scale, cost and allocative efficiencies under meta-frontier and group-frontier specifications are presented in Tables 3 and 4. The results indicate that the tube-well owners and water buyers are more technically efficient under group frontier than the met-frontier. The estimated mean technical efficiency under the meta-frontier is 87% and 86%, respectively, for the tube-well owners and water buyers, which means that a 13% and 14% increase in production is possible with the present state of technology. Thus, improving technical efficiency can help to improve farm productivity and ultimately farm income. Empirical results indicate a gradual improvement in technical efficiency, implying that over the time, technical efficiency among the cotton growers is improving in Pakistan. For example, Abedullah et al., (2006) reported similar 88% mean technical efficiency among large scale cotton growers in Pakistan. However, Hussain et al., (1999) reported 77% technical efficiency estimates among the cotton growers in Pakistan.

<Insert Table 3&4>

The mean scale efficiencies for tube-well owners and water buyers are 93% and 88% respectively, under the meta-frontier specification. The group-specific scale efficiency estimates indicate the same score for the water buyers and a 90% scale efficiency for the tube-well owners. These results imply that the scale of operation among the tube-well owners varied but did not differ for the water buyers under either setting. Based on the meta-frontier results on returns to scale (Table 5) we find that (1) more water buyers than tube-well owners are operating at sub optimal scale while (2) more tube-well owners than water buyers tend to operate at an optimal scale. Similarly, under the group-frontiers, more water buyers than tube-well owners are operating at an optimal scale while more tube-well owners than water buyers are operating at a sub-optimal scale. A vast majority of tube-well owners and water buyers under the meta-frontier and group-frontiers are found to be operating at increasing returns to scale, which means that most of the farms should be larger than they presently are to produce efficiently under the given state of technology and inputs combination.

<Insert Table 5>

The mean cost efficiency estimates are found 68% and 71%, respectively, among the tube-well owners respectively under the meta-frontier and group-frontiers. The mean cost efficiency estimates for water buyers are similar to the tube-well owners (71%) under group-frontier specification, however, water buyers are slightly more cost efficient than tub-well owners under the meta-frontier. The meta-frontier and group-frontier mean estimates of allocative efficiency are found 78% and 76% for the tube-well owners while water buyers with 79% mean allocative efficiency under the meta-frontier and group-frontier settings are slightly more allocative efficient than the tube-well owners. On average, higher cost and allocative efficiency among water buyers may be attributable to the fact that because they pay higher (more than two times) groundwater prices than the tube-well owners, they tend to use an optimal input mix. In addition this fact, both the tube-well owners and water buyers can reduce substantially their cost of production under either the meta-frontier or group frontier specifications. The mean cost efficiency estimates based on the meta-frontier approach indicate 32% and 31% reduction in cost of production respectively for the tube-well owners and water buyers, while group frontier estimates suggest a 29% reduction in cost of production for the both tube-well owners and water buyers.

4.2 Technology gap ratios

As observed from Table 6, the average technology gap ratio (*TGR*) for the water buyers shows that they are operating closer to the meta-frontier than are the tube-well owners. In others words, water buyers use technology more efficiently than the tube-well owners. A difference test[7] with a *p*-value of 0.000 indicates that the technology gap ratio among the tube-well owners and water buyers is statistically significant. On average, the tube-well owners exhibit a technology gap ratio of 0.94 compared to the water buyers 0.98 technology gap ratio. This ratio implies that given the technology potentially available, the tube-well owners at the fixed input endowment exploit, on average, 94% of their potential output, whereas the water buyers achieve 98% of their potential output. In a recent study, Rao et al., (2012) presented a view that in addition to the technological differences, the effect on total productivity might differ if different technological groups are operating at different levels of economies of scale and scope. In this case of groundwater irrigators for cotton in the Punjab, we observe both of the above- mentioned situations, i.e., the tube-well owners and water buyers not only differ technologically, but they are also operating at substantially different scales of operation.

<Insert Table 6>

The cost gap ratio (*CGR*) tells us a different story. The difference test with a *p*-value of 0.467 indicates that the cost gap ratios among the tube-well owners and water buyers are not statistically significant. We can see that the tube-well owners and water buyers exhibit 0.94 and 0.96 average cost gap ratios respectively. This ratio implies that under the given input prices, the tube-well owners achieve 94% of their potential output, while the water buyers attain 96% their potential output, indicating a greater cost efficiency level for water buyers than the tube-well owners.

[7] A paired t-test was applied to analyse the difference of the means of technology and cost gap ratios among the tub-well owners and water buyers.

4.3 Groundwater use efficiency

The sub-vector and slack-based groundwater use efficiency estimates are presented in Table 7. The results show large-scale inefficiency in groundwater use in irrigation among the tube-well owners and water buyers. The mean sub-vector estimates under the meta-frontier indicate 31% and 29% inefficiency in groundwater use, respectively, among the tube-well owners and water buyers. The slack-based results suggest, however, 21% and 18% inefficiency in groundwater use, respectively, among the tube-well owners and water buyers. The group-specific sub-vector and slack-based estimate indicates 9% and 8% less inefficiency in groundwater use for the tube-well owners, respectively, than the meta-frontier setting. However, the sub-vector and slack-based estimates for water buyers with just 1% less inefficiency is almost similar under the meta-frontier and the group frontier. The sub-vector and slack-based estimates imply a considerable scope for reducing groundwater use with the observed values of other inputs and maintaining the same output level. This result means that if efficiency improves, it should be possible to reallocate a proportion of the groundwater to the other water demands without compromising cotton production. We further note from the Table 8 that technical efficiency is highly correlated with groundwater use efficiency. This means that besides the impact on groundwater resource sustainability, improved irrigation water use efficiency will also have an impact on agricultural productivity.

<Insert Table 7>

As we see from Table 7, water buyers are more efficient in water use than the tube-well owners. Spearman's rank correlation coefficients of 0.781 and 0.812 indicate that water buyers produce more output per cubic meter of groundwater than the tube-well owners. This result may be because water buyers pay higher price[8] for groundwater than tube-well owners, which induces water buyers to use groundwater more efficiently. These results imply that water pricing can be a trigger to improve efficiency of groundwater use in irrigation as argued by some authors (Gómez-Limón and Riesgo, 2004; Johansson, 2002 and Sahibzada, 2002)[9].

Irrigation water use inefficiencies are not uncommon in other parts of the world. A large degree of irrigation water use inefficiencies was also reported by Karagiannis et al., (2003)

[8] Water buyers were found to pay Rs. 6.4 per m^3 of groundwater while tube-well owners paid Rs. 3.4.

[9] It has been argued that at least some pricing is necessary to make farmers aware of the water scarcity and to induce them to adopt water-saving technologies. Therefore, "getting prices right" is considered an important tool to improve water use efficiency and to encourage its conservation.

for out-of-season vegetable farming, Lilienfeld and Asmild, (2007) for irrigated agriculture in western Kansas, USA, Speelman et al., (2008) for small-scale irrigators in South Africa and Frija et al., (2009) for small-scale greenhouse farms in Tunisia.

<Insert Table 8>

The results presented in Table 8 indicate that the sub-vector efficiency captures relatively lower degrees of efficiency compared to the slack-based model. However, the correlation statistics indicate that the sub-vector and slack-based estimates are highly correlated. We applied the Kolmogorov-Smirnov (KS) test to examine the normality of the distribution for sub-vector and slack-based water use efficiency and technical efficiency. The empirical cumulative frequency function (ECDF) for the distribution of (sub-vector WUE and slack-based WUE, TE and sub-vector and slack-based WUE) is shown in Fig.3. The test results show that the CDF of the slack-based WUE significantly dominates over the sub-vector WUE. Furthermore, the CDF of TE significantly dominates over the sub-vector and slack-based WUE. The test results imply that the sub-vector and slack-based efficiency of groundwater use is significantly lower than the respective technical efficiency. A paired sample t-test further analysed the equality of means among technical efficiency and the sub-vector and slack-based water use efficiency. The t-statistics 16.424 with a *p*-value 0.000 show significant difference between the technical and the sub-vector groundwater use efficiency. Therefore, we reject H_o that the difference between the technical and the sub-vector efficiency means is equal to zero. Similarly, t-statistics 9.628 with a *p*-value of 0.000 indicate that the mean difference is also significant between technical and slack-based water use efficiency. This implies that in terms of groundwater use efficiency, tube-well owners and water buyers could not achieve the level of their technical efficiency.

<Insert Fig. 3>

4.4 Explaining efficiency differentials

The empirical findings concerning the sources of the efficiency differentials among the farms are presented in Table 9. The results indicate that when we move from the cotton-wheat region to the mixed-cropping region cost efficiency and efficiency of groundwater use among the farms decreases. However, the technical efficiency does not change significantly with changing cropping region. The farmers in the mixed-cropping region must not only strive to be more cost efficient in cotton production, but also to be more responsive to declining water tables in the region.

<Insert Table 10>

The results indicate that the farmer's age is found to be negatively associated with the level of technical and cost efficiency. However, there is a positive relationship between age and groundwater efficiency. It has been argued in the literature that aged farmers are less inclined to due to less risk aversion and are more sceptical of the extension advice (Speelman et al., 2008). According to them old farmers are more experienced about the traditional farming practices, but less willing to adopt new ideas. Sometimes one of the two impacts dominates, resulting in mixed results for the effect of age on efficiency measures. For example, Karagiannis et al., (2003) found the impact of age to be statistically significant on the extent of technical efficiency, while Frija et al., (2010) found the impact of age non-significant on technical efficiency.

The positive farm size coefficient indicates that larger farms are more technical and cost efficient than small farms. However, we find that with increasing farm size, the efficiency of groundwater use decreases. Much empirical evidences show a positive relationship between the farm size and efficiency measures. For example, Wadud and White, (2000) and Balcombe et al., (2008) also found a positive relationship between farm size and efficiency. In the case of groundwater use efficiency, Spleeman et al. (2008) also found that with increasing cultivated area irrigation water use efficiency decreases significantly. However, Frija et al., (2009) found no significant relationship between the farm size and groundwater use efficiency among greenhouse vegetable growers.

The relationship between family size and technical, cost and groundwater use efficiency indicates that joint families are less efficient than single families. Haji, (2006) also found a negative relationship between the family size and farm efficiency. He pointed out that the large family size and the less attractive off-farm labour wages can contribute towards excessive use of labour on the farm.

The level of education has a positive significant impact on technical, cost and groundwater use efficiency meaning that education attainment significantly improves the level of farm efficiency. In the literature, however, we find mix results about the efficiency and education relationship, e.g., Karagiannis et al., (2003) found that degree of technical and water use efficiency is positively affected by the level of education. However, Haji, (2006) and Speelman et al., (2008) found that education does not affect technical and groundwater use efficiency. The mixed results of the impact of education in the literature can reveal that the level of education does not necessarily improve irrigation water use efficiency unless the farmers have knowledge about crop water requirements.

The positive relationship between land ownership and efficiency is intuitive (Speelman et al., 2008; Frija et al., 2009), land owners are more technical and cost efficient than tenants. Similarly, land ownership status also tends to contribute to improving groundwater use efficiency. The results for quality show statistically significant positive association between seed quality and technical, cost and groundwater use efficiency. This indicates that use of good quality seed of improved varieties improves the efficiency of farms.

We see that tube-well ownership is positively associated with the technical efficiency. This may be attributable to the fact that the tube-well owners have better assurance that they have sufficient irrigation water over time and space than water buyers, hence they are more technical efficient. However, tube-well ownership has a negative but non-significant impact on cost efficiency and groundwater efficiency.

We find that off-farm income is negatively associated with the technical, cost and groundwater use efficiency. This can be attributed due to the reason that farmers, who are engaged in off-farm income activities, usually pay less attention to farming activities. Hence, they seem less efficient. Similar is the case with credit, i.e., those farmers who opted to get credit are more technically efficient than who did not. The findings of Karagiannis et al., (2003) and Haji, (2006) also confirm the impact of off-farm income and credit positive in improving technical efficiency of the farms.

Finally, the positive significant impact of extension advice on the technical efficiency and groundwater use efficiency confirms the belief that the farmers who tend to seek more extension advice are technically more efficient than those who have less or no contact with extension staff (Parikh et al., 1995). The significant impact of extension advice in improving technical efficiency and groundwater use efficiency suggests that it could have significant impact on rationalizing groundwater use in irrigation sector.

5. Conclusion

The rapid declining of groundwater tables in Pakistan has raised many environmental and economic concerns in this region and consequently Pakistan must use its decreasing water resources more efficiently. To date, water policies have been dedicated towards on-farm water management through water conservation technology and optimisation of cropping patterns.

In this paper, we used data envelopment analysis to compute technical, scale, cost and allocative efficiencies for tube-well owners and water buyers relative to a meta-frontier and group frontiers in the Punjab province of Pakistan. The groundwater use efficiency is estimated using the sub-vector and slack-based efficiency models to make estimates of excessive groundwater use at the crop level, which is more useful for improving efficiency at the farm level.

The empirical results indicate that cotton farmers in the *Lodhran* and *Jhang* districts in the Punjab use nearly optimal quantities of inputs. However, the mean groundwater use efficiency in irrigation is much lower than the technical efficiency, implying that a significant reduction in groundwater use could be achieved. It seems that groundwater users have little incentive to use groundwater efficiently due to open access to groundwater resources. We find that water buyers are relatively more groundwater use efficient than tube-well owners implying that water buyers produce more output per m^3 of groundwater than tube-well owners. This can imply that water pricing induces water buyers to use groundwater more efficiently. Therefore, any policy intervention towards groundwater markets in terms of price regulation and water allocation could encourage farmers to use groundwater efficiently.

We concluded that the sub-vector and slack-based approaches are found highly correlated, hence inferring that they capture almost similar degree of input use efficiency.

From a policy perspective, we suggest that to improve the efficiency of production among cotton growers, efforts and development strategies should be directed towards educating farmers and encouraging farmers to use good quality seed and providing them better agricultural advisory services. The concordance between technical and groundwater use efficiency suggests that any improvement in groundwater use efficiency, apart from its impact on sustainability of groundwater resources, will also have impact on technical efficiency and ultimately on farm productivity. In this regard, a high role of the extension advice in improving technical and groundwater use efficiency, suggests extending the region of extension advice from crop management to groundwater management or either to create a separate water extension wing. The diffusion of appropriate technology, knowledge about crop water requirements and sustainable groundwater use and management practices can help in bridging gaps in the efficiency.

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Table 1

Descriptive statistics of the variables used in DEA analysis

Variable Definition (unit)	Mean	SD	Min.	Max.
Inputs				
Seed/*Acre* (*kilograms*)	8.307	1.313	5	10
Seed cost/ *Acre* (*PKR.*)	2321.286	561.663	1400	4000
Total labour hours/ *Acre*	327.562	53.627	168	465
Total labour cost/ *Acre*	13619.277	2167.651	7000	19375
Fertilizer / *Acre* (*kilograms*)	208.175	60.303	50	450
Fertilizer cost/ *Acre* (*PKR.*)	5261.971	1785.904	1680	14025
Number of chemical applications	6.571	1.365	3	9
Chemical cost/ *Acre* (*PKR.*)	4355.153	1262.935	1600	7200
Number of farm operations	12.481	4.292	3	21
Machinery cost/ *Acre* (*PKR.*)	4004.853	827.633	2200	8000
Irrigation cost/ *Acre* (*PKR.*)	5811.677	2670.937	2232	17587.1429
Groundwater volume/ *Acre* (m^3)	2206.705	401.740	1421.75	3210.2
Cropped area in acres	7.683	6.042	1	25
Output				
Cotton yield/acre (kilograms)	831	178.87	480	1400

Table 2

Summary statistics of the variables included in the truncated regression

	Continuous variables				Proportion of farmers with dummy variables		
	Mean	SD	Min.	Max.	0	1	2
Farmers' age (Years)	44	9	25	65			
Farm size (Acres)	11.50	7.60	2	35			
Family status (0= *Single family,* 1=*Joint family*)					31.50	68.50	
Education (0=*Illiterate,* 1=*Up to*					45	33.50	21.50

metric, 2=*Above metric*)		
Off-farm income (*0=No,* 1=*Yes*)	83.50	16.50
Land tenure status (0=*Tenants,* 1=*Owners*)	19.50	80.50
Seed type (0= *Farmer seed,* 1=*Purchased seed*)	75.50	24.50
Seed quality (0=*Un-improved,* 1=*Improved*)	72	28
Tube well ownership (0= *Non-owners,* 1=*Owners*)	52	48
Access to canal water (0=*No,* 1=*Yes*)		
Credit access (0=*No,* 1=*Yes*)	76	24
Extension services (0=*No,* 1=*Yes*)	69	31

Table 3
Frequency distribution of technical, cost, scale and allocative efficiencies under meta-frontier specifications

	Tube-well owners				Water buyers			
Frequency (%)	TE	CE	SE	AE	TE	CE	SE	AE
<40	0	2	0	1	0	0	0	0
40-50	0	4	0	3	0	10	1	1
50-60	0	27	2	2	0	22	4	7
60-70	5	25	1	17	7	17	4	14
70-80	21	18	6	31	20	23	15	22
80-90	23	13	16	25	29	6	20	25
90-99	30	5	58	15	19	11	40	20
100	18	4	15	4	16	2	7	2
Mean	0.869	0.683	0.925	0.784	0.864	0.686	0.876	0.791
Std. Dev.	0.104	0.156	0.095	0.132	0.103	0.154	0.125	0.131
Minimum	0.646	0.330	0.500	0.335	0.637	0.401	0.468	0.401
Maximum	1	1	1	1	1	1	1	1

Table 4
Frequency distribution of technical, cost, scale and allocative efficiencies under group frontier specification

	Tube-well owners				Water buyers			
Frequency (%)	TE	CE	SE	AE	TE	CE	SE	AE
<40	0	1	0	2	0	0	0	0
40-50	0	4	1	1	0	8	1	1
50-60	0	21	1	3	0	19	4	7
60-70	0	29	5	26	4	20	4	14
70-80	10	15	8	28	15	20	11	21
80-90	26	11	22	18	29	10	22	27
90-99	24	12	43	15	21	9	38	16
100	38	5	18	5	22	5	11	5
Mean	0.922	0.707	0.902	0.764	0.883	0.707	0.880	0.798

Std. Dev.	0.087	0.160	0.112	0.140	0.099	0.158	0.125	0.135
Minimum	0.709	0.332	0.478	0.332	0.638	0.413	0.469	0.413
Maximum	1	1	1	1	1	1	1	1

Table 5
Returns to scale under meta-frontier and group frontier specifications

Returns to scale	Meta-frontier		Group frontier	
	Tube-well owners	Water buyers	Tube-well owners	Water buyers
IRS (%)	82	90	81	82
DRS (%)	3	2	1	5
CRS (%)	15	8	18	12

Table 6
Average technical efficiency for group frontier and meat-frontiers and technology gap ratio

	GTE	MTE	TGR	CGR
Tube-well owners	0.92	0.87	0.94	0.94
Water buyers	0.88	0.86	0.98	0.96

Note: GTE, MTE and TGR are group specific technical efficiency, meta-technical efficiency and technology gap ratio

Table 7
Frequency distribution of the sub-vector and slack-based water use efficiency under meta-frontier and group frontier specification

	Meta-frontier				Group frontier			
Frequency (%)	Sub-vector WUE		Slack based WUE		Sub-vector WUE		Slack based WUE	
	Owners	Buyers	Owners	Buyers	Owners	Buyers	Owners	Buyers
<30	2	0	0	0	0	0	0	0
30-40	18	1	0	0	1	1	0	0
40-50	21	8	3	0	6	8	2	1
50-60	15	23	8	6	20	19	1	6
60-70	15	17	24	13	15	19	9	15
70-80	5	18	15	18	9	19	19	18
80-90	5	3	21	26	6	2	15	23
90-99	17	5	10	12	4	3	15	8
100	2	16	17	16	37	20	37	20
Mean	0.689	0.709	0.788	0.822	0.783	0.721	0.873	0.812
Std. Dev.	0.198	0.182	0.154	0.131	0.206	0.187	0.137	0.143
Minimum	0.312	0.366	0.431	0.559	0.368	0.366	0.452	0.499
Maximum	1	1	1	1	1	1	1	1

Table 8

Spearman's rank correlation among technical efficiency and sub-vector and slack-based water use efficiencies

	TE	SV-WUE	SB-WUE
TE	1.000		
SV- WUE	0.775*	1.000	
SB-WUE	0.799*	0.911*	1.000

Table 9

Paired samples t-test demonstrating the difference between technical efficiency and water use efficiencies

	Mean difference	Std. Deviation	t-statistics
Sub-vector WUE –Te	-.253	.2180	-16.424***
Slack-based WUE-Te	-.109	.1614	-9.628***

Ho: mean (diff) = 0 *Ha*: mean (diff) ≠0 Pr (|T| > |t|) =0.000
Note: *** indicates a 1% significance level

Table 10
Truncated regression results of the factors affecting technical and water use efficiencies

Explanatory Variables	Technical efficiency		Cost efficiency		Water use efficiency	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Cropping region (0= *Cotton-wheat,* 1=*Mixed-cropping region*)	.0089	.0179	-.1295**	.0438	-.0681	.0446
Farmer's age (*Years*)						
Age	-.0072	.0048	-.0053	.0091	.0014	.0100
Age^2	.0000*	.0001	.0000	.0001	-.0000	.0001
Cropped area (*Acres*)	.0004	.0009	.0024	.0018	-.0005	.0018
Family status (0= *Single,* 1= *Joint family*)	-.0112	.0122	-.0089	.0229	-.0274	.0233
Education dummy (0= *Illiterate,* 1= *Up to Matriculation,* 2=*Above Matriculation*)						
Up to matriculation	.0148	.0120	.0039	.0234	.0139	.0241
Above matriculation	.0683***	.0187	.0768*	.0395	.1441***	.0417
Land tenure status dummy (0= *Tenants,* 1=*Owners*)	.0072	.0146	.0159	.0296	.0453	.0309
Seed quality (0= *Un-improved,* 1= *Improved*)	.1318***	.0114	.1510***	.0238	.1977***	.0255
Tube well ownership dummy (0=*Non-owners,* 1=*Well owners*)	.0069	.0141	-.0245	.0267	-.0186	.0296
Off-farm income (0=*No*, 1=*Yes*)	-.0093	.0144	-.0161	.0273	-.0408	.0284
Access to canal water (0=*No*, 1=*Yes*)	.0106	.0186	.1710***	.0455	.1018**	.0459
Credit dummy (0=*No*, 1=*Yes*)	-.0021	.0125	-.0151	.0242	-.0131	.0257
Extension services dummy (0=*No*, 1=*Yes*)	.0376***	.0117	.0082	.0265	.0641**	.0268
Constant	.9049***	.1085	.7123***	.2019	.5338**	.2232
Log likelihood	248.55		121.48		106.17	

Note: *, **, *** indicate significance at 10%, 5% and 1% respectively. Number of bootstraps=4000

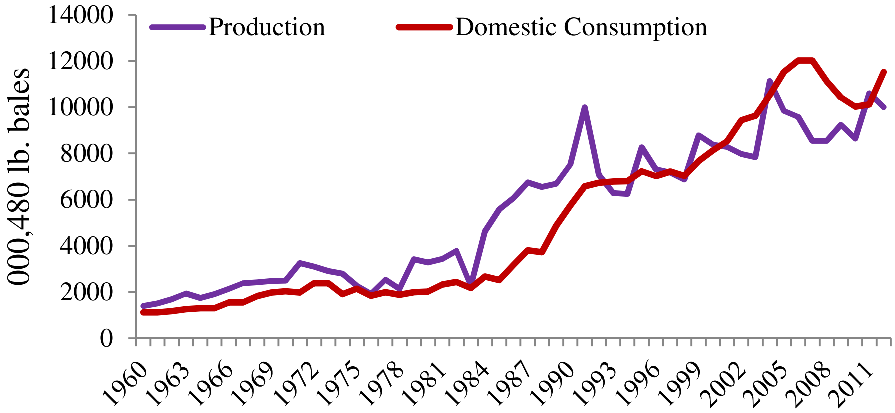

Figure 1. Cotton production and consumption gap in Pakistan

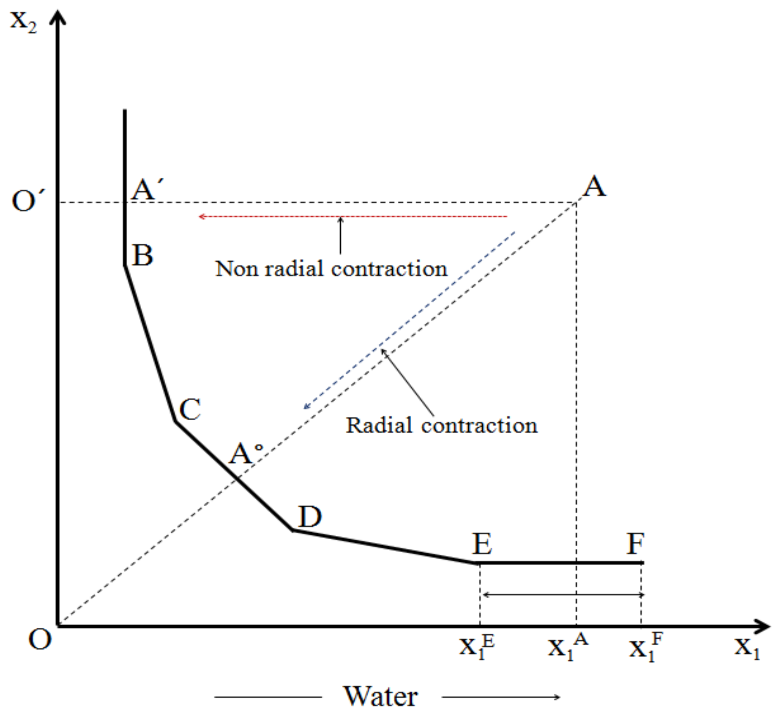

Fig. 2 Graphical representation of sub-vector and slack-based input-oriented efficiency

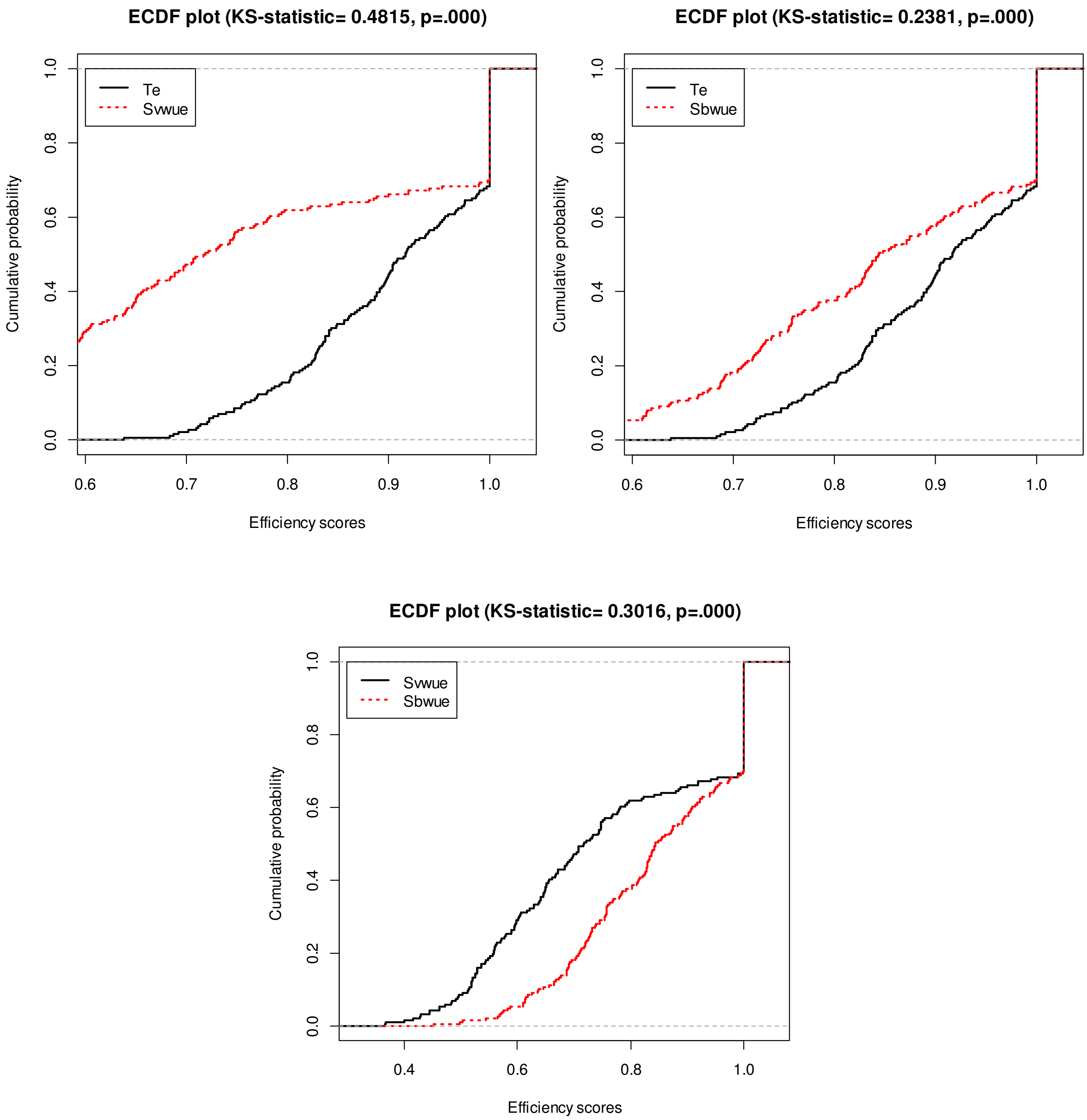

Fig. 3 Cumulative distribution for technical efficiency and sub-vector and slack-based water use efficiency