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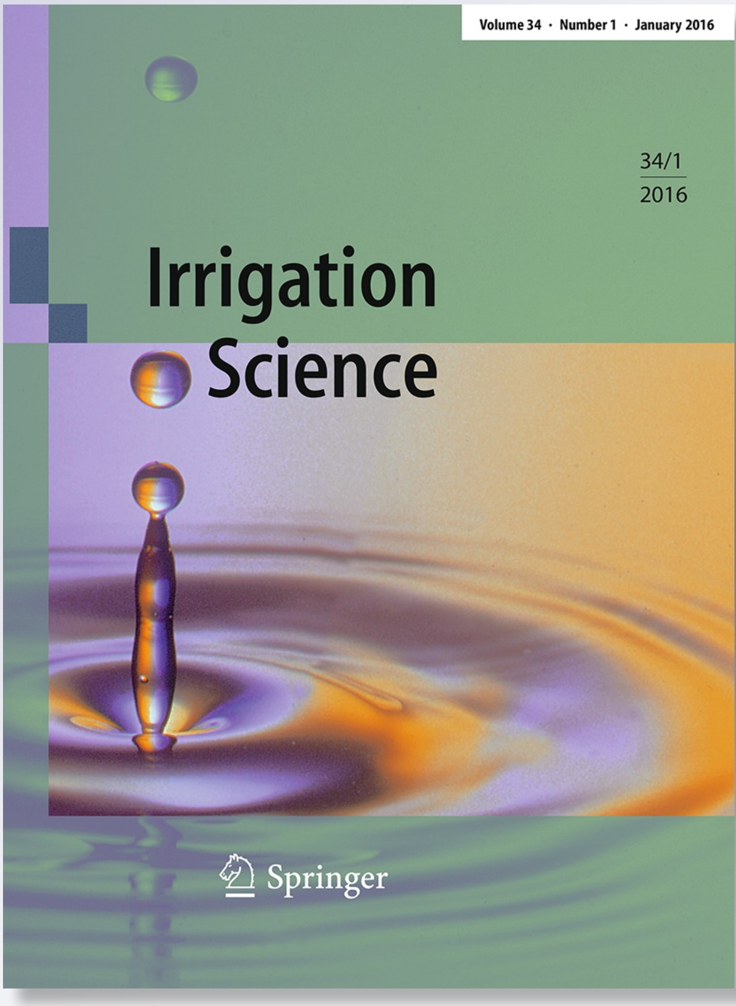

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ORIGINAL PAPER

Impact of informal groundwater markets on efficiency of irrigated farms in India: a bootstrap data envelopment analysis approach

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Abstract In recent years, the proliferation of private well irrigation systems in South Asia, especially in the hard rock areas of India, has stimulated the growth of informal groundwater markets. These markets allow water-buying farmers, who are unable to invest in wells, to benefit from irrigation while enhancing the economic benefits of water-selling farmers. In this way, they have a positive impact on farm income. On the other hand, they are believed to have contributed to the problem of over-exploitation of groundwater aquifers. This study examines the role of groundwater markets in determining the efficiency of irrigated farms. Technical, allocative and economic efficiency of groundwater-irrigated farms is determined, using a bootstrapped data envelopment analysis, and the determinants of the efficiency are explored using a bootstrapped truncated regression. For this purpose, data were collected from three different groups of groundwater-irrigated farmers: (i) a control group of 30 farmers who are neither selling nor buying groundwater; (ii) a group of 30 water-selling farmers; and (iii) a group of 30 water-buying farmers. The results demonstrate that there is substantial technical, allocative and economic inefficiency in the irrigated production due to overuse of inputs and that this inefficiency is higher among the control group farmers followed by water sellers and water buyers. Also in the second-stage regression, participation in the water markets is revealed as an important factor positively affecting efficiency scores. This shows that it is relevant for the government to make appropriate institutional policy interventions to capitalize on the benefits associated with the water markets, while at the same time, ensuring that the negative external effects are avoided.

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Introduction

Irrigation water is a vital resource in ensuring food and livelihood security. After 1950s, the expansion of irrigated agriculture in conjunction with the use of high-yielding varieties and increased use of inputs accomplished improved food production in developing countries. Currently, irrigated agriculture covers 275 million hectares (approximately 20 % of world's arable land) and accounts for 40 % of global food production (Molden et al. 2010). In case of India, irrigation played a crucial role in green revolution that transformed the country's agricultural scenario, while ensuring food security, especially in respect of food grains. Over the years, a dramatic shift from surface water to groundwater for irrigation (currently about 60 % of the total area) has resulted in groundwater being the key resource in sustaining livelihoods and ensuring food security in the country (World Bank 2010). However, effects of a consistent groundwater overdraft overtime have led to declining water tables, premature failures (wells failing to yield water) of wells and a decline in groundwater output, especially in hard rock areas of India, which constitute about two-third of the country's area. These hard rock areas remain characterized by an insufficient and uncertain rainfall, a limited groundwater recharge and a limited access to perennial rivers (Chandrakanth et al. 2004; Nagaraj et al. 2005; World Bank 2010). Under these unfavourable physical conditions, ever-increasing demand for agricultural production (driven by population and economic growth) and the policy environment favouring groundwater extraction (e.g. energy subsidies) (World Bank 2010) has lead to depletion of the resource. The increasing scarcity of groundwater due to over extraction of the resource is a challenge to the sustainability of farming in these areas.

In the context of increasing irrigation costs due to declining water tables and the frequent incidences of wells failure (indicate water scarcity), water markets have emerged, expanding to over 15 % of the irrigated area in India (Saleth 2004). Groundwater markets ensure a ready access to the resource for farmers who are unable to make the necessary investments (well deepening or drilling new wells) in wells to meet their irrigation water demand which in turn offer them an opportunity to benefit from improved agricultural productivity (Shiferaw et al. 2008). At the same time, the surplus pumping capacity of farmers who invest in drilling new and deeper wells (supply side) gets utilized, fetching financial benefits to the bore well/tube well owner. Hence, water markets appear to be improving the aggregate welfare of the society (Saleth 1996, 2004). Currently, groundwater markets in India are mostly a localized, village level informal arrangement, organized through farmers' own initiatives. Different kinds of informal arrangements that enable exchange of pumped water with crop share, labour or cash exist. Payments are enforced through users' cooperation as water rights in these markets are often not explicitly defined (Shah 1993; Mukherji 2004; Zekri and Easter 2007).

The hypothesis here is that groundwater markets induce the market participants (buyers and sellers) to use water more efficiently, given the price signals conveyed by the market. An uncertain or delayed water use might negatively affect crop growth or decrease the marginal productivity of other inputs (fertilizer, labour, chemicals). In this context, well ownership gives an assured and increased access to water (Jacoby et al. 2004) and hence provides more secured benefits. These conditions warrant an empirical study examining the impact of groundwater markets on efficiency of irrigated farmers. In the present study, we employ a two-stage analytical procedure to analyse the impact of groundwater markets on the efficiency of irrigated farmers. We first investigate whether groundwater markets lead to a significant improvement in the efficiency of farmers (buyers and sellers) when compared to the group of non-participant (in the groundwater market) farmers in the research location using bootstrapped data envelopment analysis (DEA). In the second step, the factors influencing the efficiency scores are analysed using a bootstrapped truncated regression model.

Primary data was collected from 90 farmers, 30 under each category [control group (who are neither selling nor buying groundwater), water sellers and water buyers], located in the Eastern Dry Zone (EDZ) of the Karnataka state. The EDZ of Karnataka, situated in the hard rock region of peninsular India, is characterized by an average annual rainfall of 784 mm with no access to perennial rivers (Government of Karnataka 2006). Consequently, about 90 % of agriculture in EDZ is groundwater based. Currently, the region is declared as a groundwater-overexploited zone by the Central Groundwater Board of India, indicating that the stage of groundwater development (use) has exceeded full potential (abstraction exceeding recharge rates) and that any future groundwater development has to be linked with water conservation measures (Saleth 1996; Nagaraj et al. 2005). The groundwater market activity is intense in EDZ, as this region caters to the demands of the neighbouring mega city of Bangalore.

Groundwater markets have been studied by several authors focusing on the functioning and associated benefits (Brooks and Harris 2008; Zekri and Easter 2005; Bjornlund 2003; Mukherji 2004; Shah 1993; Nagaraj et al. 2005; Deepak et al. 2005) or on the technical efficiency of groundwater use (Manjunatha et al. 2011). In our view, technical efficiency of groundwater by itself may not fully capture the impacts of water markets since the efficiency of farms depends also on the allocation and use of other inputs. In addition, given the market, groundwater has different prices for different categories of farmers that may impact the efficiency of its use in agriculture production. Hence, this article focuses on the technical, allocative and economic efficiency of water buyers, water sellers and control group farmers (self-users). It is to be noted that these aspects received little attention in the literature and were not adequately addressed in any of the past studies. Further, the study analyses the determinants of the efficiency scores as part of evaluating whether participation in water markets, along with other socio-economic and farm characteristics, influences these scores. Given the need to improve water use efficiency to ensure prudent use of this scarce resource, the study is expected to provide insights for policy makers.

The rest of the paper is organized in three sections: section two outlines the methodology related to data envelopment analysis (DEA) for estimation of efficiencies and truncated regression for analysing determinants of efficiency. In addition, data collection and variables used in the models are explicitly discussed. Section three presents

"Results and discussion" followed by "Conclusions" in the final section.

Methodology

Measuring efficiency using bootstrap data envelopment analysis (DEA)

The performance of a farm can be analysed based on technical, allocative and economic efficiency measures (Farrell 1957). Technical efficiency (TE) measures a farm's ability to use the available technology in the most effective way, while allocative efficiency (AE), which is dependent on prices, measures a farm's ability to make optimal decisions with respect to product mix and resource allocation. Combining measures of technical and allocative efficiency yields a measure of economic efficiency.

The efficiency analysis literature can be divided into two main branches namely, parametric and nonparametric methods. Data envelopment analysis (DEA) is the most popular nonparametric method. It is a linear programming method which constructs a nonparametric envelopment frontier over the data points. DEA estimates efficiency without factoring in statistical noise and is thus a deterministic method which is its main disadvantage. On the other hand, its main advantage is flexibility, due to its nonparametric nature. In contrast, parametric methods (such as stochastic frontier analysis) require an assumption about the functional form of the production function. The need to make a priori assumption about the functional form and distribution of one-sided error term is a drawback associated with stochastic frontier analysis (Forsund et al. 1980). Both methods estimate a firm's relative position to the efficiency frontier (Coelli et al. 2002). Recently, new methods such as stochastic DEA (Veettil et al. 2013), fuzzy DEA (Agarwal 2014) or the stochastic non-smooth envelopment of data (StoNED) (Kuosmanen and Kortelainen 2012) have been developed. In our analysis, another recent innovation, bootstrap DEA is used for estimating the efficiencies of farmers. The standard DEA models are deterministic and produce point estimates of efficiency. Simar and Wilson (2000) showed that these estimates are biased and moreover mostly their statistical properties stand ignored. To correct the bias in the estimators and to generate confidence intervals, this article employs the smoothed bootstrap procedure introduced by Simar and Wilson (1998).

In order to ease interpretation of the results, it is useful to recall the classic DEA models with respect to technical and allocative efficiency. Characteristic of DEA is that a piecewise frontier surface is assembled by solving a sequence of linear programming problems, one for each farm and relating each farm to the frontier. The frontier created envelops the observed input and output data of each farm. Simultaneously with the creation of the frontier surface, the efficiency measures are obtained (Speelman et al. 2008; Coelli and Battese 1996).

Consider N farms, each using P inputs to produce Q outputs. For the ith farm, input and output data are represented by the column vectors x_i and y_i, respectively. The P by N input matrix, X, and the Q by N output matrix, Y, then represent the data for all N farms in the sample:

The DEA model for estimating technical efficiencies is presented in Eq. (1):

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

Subject to:

$$-yi + Y\lambda \geq 0,$$

$$\theta xi - X\lambda \geq 0,$$

$$N1'\lambda = 1,$$

$$\lambda \geq 0$$

where θ is a scalar, $N1$ is the vector of ones and λ is a vector of constants. The model is solved for each farm considering the highest radial contraction of the input vector x_i within the technology set. The θ value corresponding to this contraction is the technical efficiency score of ith farm. This index ranges between zero and one, one representing that the farm lies on the frontier and is efficient and a value less than one representing that input use can be reduced proportionally without any reduction in the output. The first constraint guarantees that the output produced by the ith farm is less than that on the frontier. The second constraint limits the relative decrease in input use, when the θ is minimized to the input use realized with the best observed technology. The third constraint is a convexity constraint that generates a variable returns to scale (VRS) assumption of the model. Without the convexity constraint, the constant returns to scale (CRS) model is obtained. Under CRS, a linear relationship between input and output is assumed. Agricultural production is, however, typically considered to contain scale effects. Therefore, the VRS assumption is also considered for estimating efficiencies (Speelman et al. 2008; Banker et al. 1989). The VRS assumption allows for calculation of technical efficiency and scale efficiency effects (Coelli et al. 2005). Allocative efficiency can be measured when the input prices are available. A technically efficient farm may not be allocative efficient, because it might not use an optimal mix of inputs, given their prices.

The allocative and economic efficiencies are obtained by solving equation for the minimum production cost (2):

$$\text{Min}_{\lambda,x_i^*} w_i' x_i^*, \tag{2}$$

Subject to:

$$-yi + Y\lambda \geq 0$$

$$x_i^* - X\lambda \geq 0$$

$$N1'\lambda = 1$$

$$\lambda \geq 0$$

where w_i is the vector of input prices for the ith farm and x_i^* is the cost-minimizing vector of input quantities for the ith farm, given the input prices w_i and the output levels y_i. The cost or economic efficiency (EE) is the ratio of minimum cost to observed cost for the ith farm (Eq. 3):

$$\mathrm{EE} = \frac{w_i^{\prime} x_i^*}{w_i^{\prime} x_i} \quad (3)$$

Following Farrell (1957), the allocative efficiency (AE) is calculated, using Eq. (4):

$$\mathrm{AE} = \frac{\mathrm{EE}}{\mathrm{TE}} \quad (4)$$

Both the CRS and VRS DEA models for technical efficiency and economic efficiency are estimated, using the smoothed bootstrap procedure for DEA estimators proposed by Simar and Wilson (1998, 2000) using 'R' statistical software. After calculation of efficiencies, it is tested whether average scores differ across the three groups. The statistical significance of the differences in technical, allocative and economic efficiency across different groups of farmers is tested using the adapted Li-test (Li 1996; Li et al. 2009). This test allows us to draw comparisons between two DEA distributions (Balaguer-Coll et al. 2013) and measure the distance between two density functions by the integrated squared error (Pagan and Ullah 1999).

Identifying determinants of efficiency using bootstrap truncated regression

In the second stage of our analysis, we regress the bias-corrected efficiency scores (bootstrapped) on a set of factors, using the following regression model (Eq. 5):

$$\overline{\overline{\theta}}_i = a + Z_i\delta + \varepsilon_i, \quad i = 1, \ldots, n \quad (5)$$

where $\overline{\overline{\theta}}_{i\ i}$ is bias-corrected estimates of DEA efficiency scores, $\varepsilon_i \sim N\left(0, \sigma_\varepsilon^2\right)$ with left truncation at $1 - Z_i\delta$; a is a constant term and Zi is a vector of specific variables. Please note that bootstrapping is applied to the truncated regression as well. Simar and Wilson (2007) detail the bootstrap truncated regression algorithm. We request the interested readers to refer to the article for details. The bootstrapped truncated regression model is estimated using 'R' statistical software. Based on the previous research, a number of explanatory variables are considered in the regression of efficiency scores (Alam et al. 2011; Coelli et al. 2002, 2003; Binam et al. 2004; Speelman et al. 2008; Manjunatha et al. 2013; Aravindakshan et al. 2015). These include the age and education levels of farmers, farm household size, their participation in water markets, their access to extension/information sources, involvement of family members in agriculture-related water management, and land fragmentation.

Study area and data collection

The data collection for the present study was undertaken in one of the taluks (a taluk is a lower administrative unit in India) of the Eastern Dry Zone (EDZ) of Karnataka state, located in the hard rock areas of south India. The total geographical area of Malur taluk is 645 sq. kms with a population of 0.207 million, with their mainstay of income being agriculture and wage employment (Government of Karnataka 2006). In addition, the region has no access to rivers, while local irrigation tanks (large-sized water harvesting ponds) have dried up due to reduced rainfall and limited desilting efforts (indicates general lack of efforts to maintain these common structures). Groundwater is the major source of irrigation, accounting to around 90 % (44,370 acres) of the irrigated area (Government of Karnataka 2006). Flood irrigation is the major irrigation method used. This inefficient irrigation method contributes, to a large extent, to the declining water tables, given a high level of evapotranspiration and low recharge capacity of groundwater aquifers. In the recent years, drip irrigation has emerged as an effective alternative irrigation method in terms of addressing physical and economic scarcity of water and is gradually becoming popular. This region supplies agricultural commodities, such as fruits, vegetables and flowers to the mega city of Bangalore. Several previous studies point to continuing groundwater overexploitation and the resulting lowering of water tables and frequent incidences of well failures (Chandrakanth et al. 2004; Nagaraj et al. 2005; Manjunatha et al. 2011, 2013) in the region. However, the physical and economic scarcity of groundwater has also resulted in the gradual expansion of water markets (Manjunatha et al. 2011). Currently, the region is characterized by high groundwater market activities.

Three categories of farmers were purposively sampled: (i) control group: this subsample includes 30 farmers who own and use bore wells for irrigation, but are not involved in either selling or buying of groundwater for irrigation; (ii) water sellers: this subsample includes 30 farmers who own bore wells and who do not only use part of their water for irrigation of the land, but also sell part of the groundwater to neighbouring farmers. They receive a rent for groundwater supplied to others in terms of on crop share, labour

Table 1 Descriptive statistics related to inputs and output used in DEA (per farm)

Variables	Farmer category					
	Control group		Water sellers		Water buyers	
	Mean	SD	Mean	SD	Mean	SD
Input variables in technical efficiency model						
Net irrigated land (acres)	2.00	1.28	2.37	1.05	1.33	1.07
Water (m^3)	8613.8	4471.4	11,008.8	4759.2	6722.5	4862
Labour (days)	253.4	133.1	345.2	160.1	193.3	128.4
Manure (tons)	22.6	15.9	31.1	15.7	15.8	12.1
Fertilizers (kgs)	1060	690	1500	765	750	630
Input variables in economic efficiency model						
Net irrigated land (acres)[a]	2.00	1.28	2.37	1.05	1.33	1.07
Irrigation cost (INR)	22,207.04	11,331.04	20,786.90	8830.92	13,708.73	11,612.82
Labour cost (INR)	19,370.67	10,236.66	26,763.33	12,453.03	15,134.67	9864.64
Manure cost (INR)	4526.67	3131.98	6220.00	3092.94	3153.33	2379.74
Chemical fertilizer cost (INR)	9668.33	6191.90	13,666.67	6736.10	6833.33	5597.77
Output variable in both the above models						
Net returns on irrigated land (INR)	138,602	80,850	196,975	92,748	100,300	66,054

[a] Land value details were unavailable from the study area. During the data collection period, one Indian Rupee (INR) = 0.02481 US$ = 0.01602 €

or cash; and (iii) water buyers: this subsample includes 30 farmers who buy irrigation water from neighbours. It must be noted, however, that some water buyers may also own wells. But these wells are not yielding sufficient groundwater for their irrigation activities. The farmers from each subsample were randomly selected. The survey data elicited from the respondents pertains to the year 2007–2008.

Using structured and pre-tested questionnaires, detailed information was elicited from the respondents. The following aspects were covered: general information about the farm family, including family size, educational level of the farmer, size of the land holdings, cropping pattern, details on wells, investment in wells, crop-wise input use and output, costs and crop returns, existence of water markets and their types, functioning and pricing systems, particulars of water purchases and sales, reasons for buying and selling of water. The expert knowledge of the local village institution was used while collecting information on water use and prices of output.

The inputs and output used for bootstrap DEA model are presented in Table 1. The input and output variables are estimated per farm. The net return per farm is considered as the output variable and is estimated by multiplying the crop yield with the output price. The output in terms of quantities can give misleading results because farmers grow diversified crops measured in different units and hence cannot be used in this study. The input variables used in the model include net irrigated land (acres), water (m^3), labour (days), organic manure (tons) and chemical fertilizers (Kgs). Input variables such as seed or seedlings and plant protection chemicals were not used as they individually were measured in different units. There was also not much difference in the seed and plant protection chemicals usage across and within groups. Water sellers and control group farmers use relatively more groundwater than water buyers. They consume more groundwater because they have their own water source, which provides them with an easier access to groundwater. Furthermore, it should be noted that water buyers pay more than the extraction costs for groundwater. Both water sellers and water buyers know the value of groundwater because one is paying for the resource use and the other is receiving income from selling it. In the use of inputs such as labour, manure and fertilizers, again water sellers accounted for the highest average usage followed by the control group.

In the truncated regression models, various farmer-specific characteristics were regressed on the technical, allocative and economic efficiency. The independent variables used include the educational level of the farmer (years), farm household size (numbers), age of the farmer (years), family member directly involved in agriculture-related water management (number), access to extension/information sources (numbers), land fragmentation (1 if farmers land is fragmented; otherwise 0) and participation in the water markets (a dummy for water sellers (1 if farmer is a water seller; otherwise 0) and water buyers (1 if farmer is a water buyer; otherwise 0) is used). Technical efficiency refers to the use of a minimum amount of inputs to produce a given output. For variables such as the education level and access to extension/information sources, a positive

Table 2 Descriptive statistics related to variables used in the bootstrapped truncated regression

Variables	Continuous variables		Dummy variables	
	Mean	SD	No. of farmers with dummy = 1	No. of farmers with dummy = 0
Age of the farmer (years)	42.37	7.79		
Household size (numbers)	7.09	3.13		
Education of the farmer (schooling years)	6.79	4.49		
Access to extension/information sources (numbers)	1.33	0.67		
Family labour involved in agriculture-related water management (numbers)	4.39	1.85		
Fragmented land (fragmented land = 1)			33	57
Water sellers (water selling farmer = 1)			30	60
Water buyers (water-buying farmer = 1)			30	60

The fragmented land dummy refers to the situation where the farmers' land is spread. This constrains them from drilling bore wells, and hence they resort to either water buying or selling; sources of extension services to the farmers include agriculture department, private companies and input dealers

effect on TE could potentially be expected, because they are believed to improve the skills of the farmers. Also family agricultural labour could have a positive effect.

For age the effect could be either positive or negative. Older farmers are more experienced, but at the other hand might be reluctant to innovate. Both effects are sometimes found in literature (Speelman et al. 2008; Manjunatha et al. 2013). Also access to water might play a role. As stated in the introduction, water buyers have the least secured access to water and due to temporal water shortages might be less technical efficient. Finally, land fragmentation is expected to have a negative effect because it complicates the use of inputs.

Similar reasoning can be made for allocative efficiency. AE is concerned with the ability of farmers to use the correct input and output mix given the existing prices. This is linked to their ability to receive and interpret price signals. In this perspective, it is expected that the participation in the water markets will positively affect AE. Also age (interpreted as a proxy for experience), education and access to extension might improve the capacity to interpret prices and are thus expected to have a positive effect. For the rest of the variables, no significant effect on AE is expected (Table 2).

Results and discussion

Socio-economic characteristics of water sellers, water buyers and control group farmers

In rural agrarian regions of India, family size (reflects labour availability) is one of the indicators of socio-economic status in addition to size of the land holdings. The average family size is, respectively, 16 and 37 % lower for water sellers (7.2) and water buyers (5.4) as compared to control group farmers (8.6). The number of persons dependent on agriculture out of the total family size (family labour) is higher in the group of water sellers (4.8) and lower in the group of water buyers (3.7) as compared to the control group farmers (4.6). The remaining family members in each group are either children or old or work in off-farm activities. Water buyers' dependency on agriculture might be lower due to the lack of an own water supply source for farming and their small and fragmented land holdings. But work force available per unit area is still high, which often makes them to buy water. The average irrigated land size is 2, 2.4 and 1.3 acres for the control group, water sellers and water buyers, respectively. Considering landholdings of the farmers selling groundwater, 83 % of them are large farmers (landholdings more than 5 acres). From the farmers buying groundwater, 61 % are small and marginal farmers (landholdings up to 2.5 acres). This shows that groundwater sale for irrigation is dominated by large farmers, while small and marginal farmers are the predominant buyers of groundwater for agriculture. It should, however, be noted that small and marginal farmers also participate in groundwater sales. The above findings are similar to the results of Fujita and Hossain (1995) in respect of Bangladesh, Meinzen-Dick (1997) in respect of Punjab province of Pakistan and to those of Deepak et al. (2005) and Sharma and Sharma (2006) in the context of India. The latter also have reported a skewed distribution of land and water ownership. According to them, well owners are mostly resource-rich farmers who are involved in selling water and small farmers act as water buyers because they are often unable to make large investments needed for drilling bore wells (Nagaraj et al. 2005).

Bore wells are the only source of irrigation in the study area. There is a considerable variation in the number of bore wells owned by each group of farmers. The number of functioning and non-functioning wells is 32 and 38 for the control group, 41 and 24 for water sellers and 4 and 8 for water buyers. Thus, water buyers relatively own less number of wells and suffer more from well failures due to cumulative well interference, and hence they depend partially or completely on water sellers for getting water. Similar results were reported by Deepak et al. (2005) in that water buyers had the highest rate of well failure and the lowest number of functioning wells as compared to water sellers and self-users.

The cropping pattern of the farmers is a function of the availability of irrigation water during different seasons of the year. Tomatoes, potatoes, carrots and mulberries (host plant of silk worms, a perennial crop) are the major irrigated crops grown under all categories of sample farmers. One significant difference is that water sellers and control group farmers accounted for more cropping area as compared to water buyers, reflecting resource availability and use. This is contrary to the groundwater markets in the Ganga–Meghna–Brahmaputra basin; farmers in these regions also grow water-intensive crops such as paddy and sugarcane in addition to other high-value crops (Mukherji 2004). Unlike farmers in EDZ of India, farmers in the Ganga–Meghna–Brahmaputra basin have a ready access to perennial rivers in addition to shallow/deep tube wells enabling cultivation of water exhaustive cereals.

Technical, allocative and economic efficiency of water sellers, water buyers and control group farmers

Table 3 gives the frequency distribution of the efficiency estimates obtained using bootstrap DEA. The efficiency scores were estimated based on CRS and VRS bootstrap DEA specifications. We used 2000 bootstrap iterations for both the specifications, which is sufficient to be confident about the results produced. Results in Table 3 show a large variation in the estimated efficiency scores across and within groups, and these scores were clustered into nine groups: 5–20, 21–30, 31–40, 41–50, 51–60, 61–70, 71–80, 81–90 and 91–100 %, in order to explain the relative position of the farm with respect to the efficiency frontier. The average technical efficiency for the CRS and VRS DEA assumption is 0.58 and 0.73 for water buyers, while it is 0.64 and 0.69 for the water sellers and 0.50 and 0.60 for the control group. The estimated allocative efficiency mean values for the CRS and VRS are both 0.94 for water buyers, while it is 0.96 and 0.95 for water sellers and 0.85 and 0.90 for the control group farmers. The computed economic efficiency mean values for the CRS and VRS are 0.55 and 0.68 for water buyers, while it is 0.61 and 0.65 for water sellers and 0.43 and 0.54 for farmers in the control group. Water buyers account for the highest average technical and economic efficiencies, followed by water sellers and self-users, while water sellers record highest allocative efficiency. Farmers across all the groups overuse inputs leading to technical, allocative and cost inefficiency. The inefficiency is higher among the control group farmers, followed by water sellers and water buyers. Moreover, the degree of inefficiency is higher for the use of water than for other inputs in general. The analysis makes it clear that all groups have the potential to reduce the input use. It is found that the control group has the largest scope for reducing input use in general and water in particular, followed by water sellers and water buyers. This clearly points out the economic significance of groundwater markets in promoting input use efficiency. The results of this study are in line with Deepak et al. (2005) and Nagaraj et al. (2005) in water scarce regions of Karnataka, India. Both studies report a lower water use, higher productivities and net incomes for water-buying farmers, followed by water buyers and control farmers. The average point and interval estimates of TE, AE and EE under both CRS and VRS specifications are also presented in 'Appendix' Table 6.

The statistical significance of the differences in technical, allocative and economic efficiency among groups was estimated using the adapted Li-test (Li 1996; Li et al. 2009). This test accommodates for the fact that efficiency scores have an unknown distribution. The results presented in Table 4 show that all efficiency measures differ significantly across the three groups both under CRS and VRS assumptions.

Determinants of technical, allocative and economic efficiency

In order to explain the variations in efficiency scores across different groups, the bias-adjusted efficiency scores were regressed on a number of farm characteristics, using a bootstrapped truncated regression. The determinants of TE, AE and EE scores are reported in Table 5. It is to be noted that the family size has no significant influence on TE, AE or EE. This contrasts the result reported by Alam et al. (2011); who, for rice farms in Bangladesh, found a significant positive effect. According to them, a larger family size could substitute hired labour and affect positively the efficiency measures. Also the educational level of the farmers did not have any significant effect on the efficiency measures. In the literature, results of the effect of education are also inconclusive: Wadud and White (2000) and Coelli et al. (2003) also found no effects. In the case studies of Coelli and Battese (1996), Binam et al. (2004) and Alam et al. (2011), however, a positive and significant influence of a higher average educational level of sample households on efficiency measures was reported.

Although provision of extension services was hypothesized to have a positive effect on efficiency, access to extension/information sources was found to be insignificant. This is in line with the findings of Alam et al. (2011), Coelli et al.

Table 3 Frequency distribution of bias-adjusted efficiency scores under CRS and VRS assumptions

Efficiency index (%)	Number of farms across farm categories					
	Control group		Water sellers		Water buyers	
	CRS	VRS	CRS	VRS	CRS	VRS
Technical efficiency(TE)						
5–20	2	0	0	0	2	0
21–30	2	0	0	0	2	0
31–40	3	3	4	0	2	3
41–50	8	7	3	5	2	1
51–60	7	5	6	5	5	2
61–70	6	7	4	3	7	4
71–80	0	4	6	8	8	10
81–90	2	4	7	9	2	9
91–100	0	0	0	0	0	1
Average score	0.50	0.60	0.64	0.69	0.58	0.73
Allocative efficiency(AE)						
5–20	0	0	0	0	0	0
21–30	0	0	0	0	0	0
31–40	0	0	0	0	0	0
41–50	0	0	0	0	0	0
51–60	0	0	0	0	0	0
61–70	3	0	0	0	0	0
71–80	6	1	0	0	1	0
81–90	14	14	3	0	5	3
91–100	7	15	27	30	24	27
Average score	0.85	0.90	0.96	0.95	0.94	0.94
Economic efficiency(EE)						
5–20	3	0	0	0	2	0
21–30	4	0	1	0	2	0
31–40	6	5	5	2	3	3
41–50	9	8	4	6	4	1
51–60	4	6	3	2	6	3
61–70	2	7	5	6	4	5
71–80	2	2	7	12	7	12
81–90	0	2	5	2	2	6
91–100	0	0	0	0	0	0
Average score	0.43	0.54	0.61	0.65	0.55	0.68

(2002). The fragmentation of land parcels was hypothesized to have a negative impact on TE. It, however, has a varying effect on efficiency. Under CRS assumption, land fragmentation has no significant effect on AE and EE scores, but is found to cause a reduction in TE. Under VRS, it, however, also negatively affects AE, indicating that fragmented farms exhibit significantly lower efficiencies. Here, the causal mechanism linking land fragmentation to efficiency may be associated with problems farmers face in allocating irrigation. This reaffirms the findings of Speelman et al. (2008) and Bardhan (1973) that un-fragmented farms could manage resources more efficiently by availing themselves of economies of scale than the fragmented farms. The dummy variable for water sellers is found to be positive and significant in EE-CRS and AE-CRS ($p < 0.05$ and $p < 0.01$, respectively) as well as AE-VRS ($p < 0.001$), whereas the dummy variable for water buyers is positive and significant for TE-CRS ($p < 0.05$), AE-CRS ($p < 0.001$), and for TE-VRS($p < 0.05$), AE-VRS ($p < 0.001$) and EE-VRS ($p < 0.001$). The coefficient estimate (0.196) indicates that when a farmer producing under constant returns to scale sells water, his/her technical efficiency could be approximately 20 % higher than the average TE of the studied farmers and the economic efficiency could be approximately 16 % (coeff. est. = 0.164) higher than the average EE. At the same time, water sellers allocate inputs 7 % better than

Table 4 Test of equality of distributional densities in efficiency measures (Li-test)

Efficiency measure	Hypothesis	CRS		VRS	
		Test statistic (Tn)	*P* value	Test statistic (Tn)	*P* value
TE	$H_0: \theta_{te}^1 = \theta_{te}^2 = \theta_{te}^3$ $H_1: \theta_{te}^1 \neq \theta_{te}^2 \neq \theta_{te}^3$	2.204	0.013*	2.214	0.026*
AE	$H_0: \theta_{ae}^1 = \theta_{ae}^2 = \theta_{ae}^3$ $H_1: \theta_{ae}^1 \neq \theta_{ae}^2 \neq \theta_{ae}^3$	17.764	<2.22e−16***	5.666	0.002**
EE	$H_0: \theta_{ee}^1 = \theta_{ee}^2 = \theta_{ee}^3$ $H_1: \theta_{ee}^1 \neq \theta_{ee}^2 \neq \theta_{ee}^3$	3.845	0.003**	2.824	0.004**

1 = Control group farmers, 2 = water sellers and 3 = water buyers, θ_{te} = technical efficiency, θ_{ae} = allocative efficiency and θ_{ee} = economic efficiency

*, **, *** Null of equality is rejected at 5, 1 and 0.1 % levels, respectively. Test statistic from 1000 bootstrap replications

Table 5 Bootstrapped truncated regression results for the bias-adjusted efficiency measures

Variables	CRS			VRS		
	TE	AE	EE	TE	AE	EE
(Model intercept)	0.342* (−0.038, 0.723)	0.795*** (0.612, 0.978)	0.213 (−0.179, 0.606)	0.501** (0.198, 0.805)	0.880*** (0.803, 0.958)	0.411** (0.133, 0.689)
Age of the farmer (years)	0.003 (−0.005, 0.010)	0.000 (−0.004, 0.005)	0.002 (−0.006, 0.010)	0.001 (−0.005, 0.007)	−0.001 (−0.002, 0.000)	0.002 (−0.004, 0.007)
Household size (numbers)	−0.001 (−0.029, 0.026)	−0.007 (−0.024, 0.010)	0.000 (−0.029, 0.030)	0.000 (−0.031, 0.032)	0.004 (−0.006, 0.013)	0.019 (−0.008, 0.045)
Education of the farmer (years)	−0.007 (−0.029, 0.014)	0.002 (−0.009, 0.013)	0.001 (−0.021, 0.022)	−0.009 (−0.029, 0.010)	0.002 (−0.001, 0.005)	−0.010 (−0.027 0.007)
Fragmented land (fragmented land = 1)	−0.168** (−0.333, −0.003)	0.013 (−0.061, 0.088)	−0.124 (−0.290, 0.043)	−0.105 (−0.249, 0.038)	0.010* (−0.012, 0.031)	−0.075 (−0.195, 0.046)
Water sellers (water selling farmer = 1)	0.102 (−0.076, 0.280)	0.196*** (0.097, 0.296)	0.164* (−0.007, 0.334)	0.074 (−0.083, 0.231)	0.070*** (0.038, 0.103)	0.069 (−0.068, 0.205)
Water buyers (water-buying farmer = 1)	0.153* (−0.023, 0.330)	0.153*** (0.069, 0.237)	0.111 (−0.063, 0.286)	0.227** (0.065, 0.389)	0.058*** (0.026, 0.090)	0.271*** (0.117, 0.425)
Access to extension/information sources (numbers)	0.096 (−0.041, 0.232)	−0.045 (−0.107, 0.016)	0.096 (−0.032, 0.224)	0.050 (−0.067, 0.168)	−0.012 (−0.033, 0.009)	0.033 (−0.073, 0.139)
Family members directly involved in agricultural water management (numbers)	−0.016 (−0.074, 0.043)	0.020 (−0.015, 0.055)	−0.013 (−0.075, 0.049)	−0.001 (−0.063, 0.061)	0.002 (−0.011, 0.015)	−0.027 (−0.081 0.026)

The first entry in each cell is the coefficient estimate. Values in parentheses are the 95 % confidence band (lower and upper) derived from 2000 bootstrap replications

*, **, *** Indicate significance at 10, 5 and 1 % levels, respectively

their counterparts as indicated by the coefficient estimate in the truncated regression (0.070).

Although water buying by a farmer is not found affecting the economic efficiency under CRS, the coefficient estimates for AE and TE (both 0.153) indicated at approximately 15 % gains in both TE and AE as against the average TE and AE of the studied farmers. The corresponding efficiency gains under VRS for water buyers could be approximately 23, 6 and 27 % in TE, AE and EE, respectively, than the average efficiency measures of all samples (Table 5).

The positive influence of proxies for water sellers and water buyers across all models confirms that farmers participating in water markets realize relatively higher efficiencies. The finding shows that the price signals generated by the water markets encourage farmers to use resources more efficiently through, for example, reallocation of water to higher value uses. Furthermore, the water buyers, who typically are more resource constrained, are apparently forced to use their scarce resources more efficiently, generating a higher TE. Water access of this group thus seems certain enough to avoid negative effects that can result from uncertainty associated with water access. Although the effects on efficiencies seem to be largely positive, one has to be careful with the stimulation of water markets because, as several authors have shown, these markets can also impose negative externalities in terms of overexploitation of groundwater resources (Easter et al. 1999; Diwakara and Nagaraj 2003; Meinzen-Dick and Rosegrant 2001; Nirmal and Shreekant 2002). Therefore, the introduction of water markets in a particular location should consider socio-economics, cultural and hydrological factors, and transaction costs of its establishment and third-party effects (Meinzen-Dick and Rosegrant 2001; Easter et al. 1999).

Conclusions

The study estimated technical, allocative and economic efficiencies, using primary data collected from water sellers, water buyers and control group farmers in a hard rock region of India. A bootstrap DEA approach is utilized towards this end. Our results show larger efficiency gains both under the CRS and VRS assumption for those who participate in water markets as compared to the control group farmers. Also in the second-stage bootstrapped truncated regression, participation in the water markets came out as an important factor positively affecting efficiency measures. This is an indication of the positive role of water markets in inducing higher efficiency levels. Therefore, it is important for the government to make appropriate institutional policy interventions (e.g. framing policies for regulation and management of groundwater markets, formation of water users association for creating awareness regarding water use and problems of groundwater overdraft, effective agricultural water pricing) which allow reaping the full benefits of water markets without causing the negative external effects reported in literature.

The efficiency levels of farmers across all categories could be improved by reducing the amount of input use, and this reduction potential is highest for the control group farmers, followed by water sellers and water buyers. The major observations finding that water buyers are more efficient in using groundwater relative to water sellers and the control group can be explained as a response to higher price of groundwater paid by the water buyers. When comparing water sellers and the control group, water sellers are more efficient in using their resources than the control group farmers. The differences between water sellers and control group originate from the opportunity cost of water selling which promotes efficient use of resource. Hence, the groundwater markets appear to promote efficiency among those participating in water markets. It should be noted that the efficiency gains cannot be generalized to the entire population of irrigators in the Eastern Dry Zone (EDZ) of Karnataka, because the sampling procedure targeted the comparison of the three groups rather than having a representative sample. The study is nevertheless highly relevant because the comparison between the three groups gives the government valuable information to make appropriate institutional policy interventions to capitalize on the benefits associated with water markets, while at the same time, taking measures to prevent overexploitation of groundwater aquifers in the immediate future.

Appendix

See Table 6.

Table 6 Summary measures of TE, AE and EE

Groups	Efficiency measures		CRS			VRS		
			Mean	95 % Confidence interval (Lower)	95 % Confidence interval (Upper)	Mean	95 % Confidence interval (Lower)	95 % Confidence interval (Upper)
Control farmers	TE	Mean	0.50	0.54	0.45	0.60	0.66	0.55
		SD	0.18	0.20	0.17	0.15	0.18	0.13
		Minimum	0.10	0.11	0.09	0.34	0.38	0.31
		Maximum	0.87	0.97	0.80	0.89	0.99	0.81
Water sellers	TE	Mean	0.64	0.70	0.59	0.69	0.76	0.62
		SD	0.18	0.20	0.17	0.15	0.18	0.13
		Minimum	0.32	0.34	0.29	0.41	0.45	0.38
		Maximum	0.89	0.97	0.82	0.87	0.99	0.80
Water buyers	TE	Mean	0.58	0.64	0.52	0.73	0.80	0.65
		SD	0.19	0.22	0.17	0.15	0.18	0.14
		Minimum	0.17	0.19	0.15	0.36	0.40	0.31
		Maximum	0.87	0.97	0.81	0.91	0.99	0.84

Table 6 Continued

Groups	Efficiency measures		CRS			VRS		
			Mean	95 % Confidence interval (Lower)	95 % Confidence interval (Upper)	Mean	95 % Confidence interval (Lower)	95 % Confidence interval (Upper)
Control farmers	AE	Mean	0.85	0.36	0.44	0.90	0.45	0.55
		SD	0.08	0.12	0.16	0.05	0.11	0.15
		Minimum	0.63	0.08	0.10	0.80	0.31	0.37
		Maximum	0.92	0.92	0.91	0.96	0.93	0.92
Water sellers	AE	Mean	0.96	0.55	0.65	0.95	0.59	0.73
		SD	0.04	0.15	0.18	0.01	0.12	0.18
		Minimum	0.82	0.26	0.31	0.91	0.35	0.42
		Maximum	0.99	0.98	0.93	0.98	0.92	0.91
Water buyers	AE	Mean	0.94	0.47	0.54	0.94	0.65	0.77
		SD	0.04	0.16	0.18	0.02	0.16	0.19
		Minimum	0.79	0.10	0.11	0.88	0.27	0.35
		Maximum	0.99	0.95	0.88	0.99	0.98	0.90
Control farmers	EE	Mean	0.43	0.52	0.43	0.54	0.62	0.51
		SD	0.17	0.20	0.17	0.14	0.17	0.13
		Minimum	0.06	0.10	0.08	0.32	0.40	0.33
		Maximum	0.76	0.97	0.82	0.82	0.99	0.84
Water sellers	EE	Mean	0.61	0.71	0.60	0.65	0.77	0.63
		SD	0.18	0.20	0.17	0.14	0.18	0.14
		Minimum	0.26	0.31	0.26	0.39	0.43	0.36
		Maximum	0.84	0.97	0.84	0.85	0.99	0.83
Water buyers	EE	Mean	0.55	0.65	0.53	0.68	0.84	0.69
		SD	0.19	0.23	0.18	0.15	0.19	0.16
		Minimum	0.17	0.21	0.18	0.32	0.35	0.28
		Maximum	0.84	0.98	0.83	0.89	0.99	0.86

Bias-corrected efficiency scores were estimated with 2000 bootstrap iterations using an input-oriented DEA model

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