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RESEARCH ARTICLE

Are participants in markets for water rights more efficient in the use of water than non-participants? A case study for Limarí Valley (Chile)

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Abstract The need to increase water productivity in agriculture has been stressed as one of the most important factors to achieve greater agricultural productivity and sustainability. The main aim of this paper is to investigate whether there are differences in water use efficiency (WUE) between farmers who participate in water markets and farmers who do not participate in them. Moreover, the use of a non-radial data envelopment analysis model allows to compute global efficiency (GE), WUE as well the efficiency in the use of other inputs such as fertilizers, pesticides, energy, and labor. In a second stage, external factors that may affect GE and WUE are explored. The empirical application focuses on a sample of farmers located in Limarí Valley (Chile) where regulated permanent water rights (WR) markets for surface water have a long tradition. Results illustrate that WR sellers are the most efficient in the use of water while non-traders are the farmers that present the lowest WUE. From a policy perspective, significant conclusions are drawn from the assessment of agricultural water productivity in the framework of water markets.

Keywords Russell measure · DEA · Water use efficiency · Irrigation · Permanent water rights market

Introduction

In Latin America and the Caribbean (LAC), as in other regions of the world, agriculture is the main user of freshwater accounting for about 75 % of human water use (Siebert et al. 2010). The need to increase water use efficiency (WUE) in agriculture has been stressed as one of the most important factors to achieve greater agricultural productivity and sustainability (Rosegrant et al. 2013; Donoso et al. 2014; Baležentis et al. 2014). WUE has several interpretations. Thus, in phys-

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ical terms, WUE is defined as the ratio of the amount of water used by a crop to the amount of water applied or as the ratio of crop yield to amount of water applied for crop cultivation (El-Wahed and Ali 2013). However, WUE can also be defined from an economic perspective as the economic return per unit of water used for crop production (Azad et al. 2015). In this study, we followed this latter approach and according to Azad and Ancev (2014) and Azad et al. (2015), WUE is understood as economic efficiency of water use.

Additionally, several factors such as population growth, rapid urbanization, water contamination and pollution, and increased water demands due to increased economic growth are putting considerable pressure on agriculture. As a result, marginal value of water for other uses has increased and in some areas is higher than that of agricultural uses (Donohew 2009; Saver et al. 2015). This increasing value differential of water between agriculture and other uses, such as municipal uses, increases the relevance of market-based reallocation so as to move water from low value agricultural uses to higher value uses (Fleifle et al. 2014).

Markets for water rights (WR) are known as permanent water markets since WR are permanently transferred between buyers and sellers. By contrast, in spot water markets, water allocations or water flows are traded for a period of time. Both types of water markets emerged more than 30 years ago as an important policy instrument to facilitate the reallocation of scarce and fully committed water resources between competing users (Bjornlund 2003a; Garrick et al. 2009; Garrick et al. 2013). Markets for water rights have formally been implemented in Australia, Chile, South Africa, the USA, and China (Ghimire and Griffin 2014; Grafton et al. 2011; Nieuwoudt and Armitage 2004; Haddad 2000). In the last 15 years, the number of informal groundwater markets in Asia has increased noticeably (Hadjigeorgalis 2009; Manjunatha et al. 2011). Formal permanent WR market and spot water markets are those that are supported by a legal and institutional water framework. Informal markets, on the other hand, are based on social ties rather than water regulation; for example, informal groundwater markets in India and Africa are enforced through users' cooperation (Manjunatha et al. 2011; Grafton et al. 2011).

WR markets are proving successful as countries gain more experience with this allocation mechanism (Donoso 2012a; Garrick et al. 2013; Hadjigeorgalis 2009). These cases have indicated that market mechanisms represent a good means to allocate water for two main reasons. First, it secures transfer of water from low value to higher value activities (Donoso 2006). Second, it puts the burden of information collection on water users and avoids problems of asymmetric information (Donoso 2012b). They also improve the ability of individual irrigators to manage risk and uncertainty associated with water supply (Bjornlund 2003b). Competitive permanent WR markets and spot water markets using changes in the price of water to signal changes in scarcity achieve allocative efficiency where water uses have private good properties of rival consumption and low costs of exclusion, and all social costs of water supply and consumption are also private costs (Freebairn 2005; Hung et al. 2014). In this context, in two pioneering studies, Cummings and Nercissiantz (1992) and Rosegrant and Binswanger (1994) explored the potential of WR markets to improve WUE.

Several papers have evaluated WUE in agriculture under different contexts and for different purposes. For example, Lilienfeld and Asmild (2007) estimated the excess of water in agricultural irrigation in Kansas and determined the impacts of irrigation system types as well as other variables on WUE. The aim of the Rodríguez Díaz et al. (2004) paper was to evaluate the comparability of extensive and intensive agriculture from a WUE point of view. Yilmaz et al. (2009) assessed the WUE of Turkish farmers taking into account the managerial preferences of the decision makers. Njiraini and Guthiga (2013) evaluated WUE of a sample of farmers and explored the main factors affecting efficiency scores. More recently, Wheeler et al. (2015) assessed the correlation between spot market trade and water use for different Australian farm types.

However, these studies have not analyzed whether there are differences in WUE between farmers who participate and do not participate in permanent WR markets or spot water markets. To the best of our knowledge, only the paper by Manjunatha et al. (2011) evaluated WUE of farmers grouping them into three categories, namely water sellers, water buyers, and non-participants in spot water markets. They concluded that water buyers are the most efficient farmers in the use of water.[1] This study was undertaken in Karnataka (India) where spot water markets are informal and based on groundwater. Hence, their findings cannot be extrapolated to regulated permanent WR markets or spot water markets based on surface water. Moreover, a restriction of this previous study was that it was limited to assess WUE but it did not investigate the potential factors affecting WUE.

In order to contribute to the research on this matter, the primary aim of this paper is to assess farmer's WUE differentiating between farmers who participate as sellers or buyers in a regulated permanent surface WR markets or do not participate. In doing so, an empirical application is developed using a sample of farmers located at Limarí Valley (LV) (Chile). From a methodological point of view, we applied a non-oriented data envelopment analysis (DEA) model. The advantage of this type of model is it enables estimating an efficiency score for each input and a global efficiency (GE) score

[1] Efficient farmers are those who obtain maximum production with given resources (output oriented) or minimize input use to reach a give production level (input oriented), that is, farmers with higher water productivities.

considering all inputs involved in the productive process. Since its introduction, the non-radial DEA approach has been applied to assess the efficiency of a range of different types of organizations and services such as ports, wastewater treatment plants, airports, and banks, among others (De Witte and Marques 2010; Medal-Bartual et al. 2012; Lozano and Gutiérrez 2011; Molinos-Senante et al. 2015a). In spite of the great advantage of this approach, to the best of our knowledge, only Azad et al. (2015) applied a non-radial DEA model to estimate the economic efficiency of water use in agriculture. Nevertheless, their assessment focused on analyzing WUE for various types of irrigated enterprises, while our study focuses on assessing the WUE of farmers involved in permanent WR markets. Moreover, due to the low number of units evaluated for each group of irrigated enterprises, Azad et al. (2015) considered that the production process only needs two inputs, namely water and managerial costs. To overcome such limitation, our study integrated five inputs: (i) fertilizers, (ii) pesticides, (iii) energy, (iv) labor, and (v) water. Hence, our assessment provides more detailed and reliable results. The second objective of the paper is to explore additional factors other than participation in permanent WR markets that might affect GE and WUE.

The methodology and the results of our research are expected to be of great interest and use for policy makers, farmers, and researchers. As far as we know, our study is pioneering in producing an efficiency score for each input used for agricultural production at the farm level. It provides empirical evidence on GE and WUE differences between farmers participating in regulated permanent surface WR markets and farmers who do not participate in them. Moreover, the research verifies that non-radial DEA models are useful as benchmarking tools enabling the identification of the best farmers who should be considered as references.

The paper unfolds as follows. Section 2 presents the methodology employed in this study, followed by a description of the water rights market in the case study and a discussion of the sample data in Section 3. Section 4 presents the main findings, and the final section concludes the paper.

Methodology

The efficiency concept is used to describe the optimal use of all production factors in a productive process, in accordance with existing technology. To measure the efficiency of decision making units (DMUs) (farmers in our case study), there are two main approaches, namely parametric and non-parametric methods. Parametric methods are based on an econometric approach and therefore require specification of the functional form of the frontier. This requirement is likely to be restrictive in many cases (Azad et al. 2015). By contrast, non-parametric methods such as DEA allow for the estimation of production efficiencies without parameterizing the technology. Broadly, two types of DEA models can be distinguished, namely radial and non-radial models. The first ones allow for the measurement of the efficiency of units by estimating the maximum possible proportional reduction in inputs given an output level (input orientation). But the limitation of this approach is that this reduction must be the same for all inputs. In contrast, a non-radial approach allows us to reduce various inputs used in the production system in different proportion (Molinos-Senante et al. 2015b). Moreover, it has been illustrated that non-radial DEA models have a larger discriminating power in assessing the efficiencies of the units (Zhou et al. 2007). Hence, a non-radial DEA method was chosen for this study (Färe et al. 1994). Unlike the sub-vector approach, the non-radial DEA approach enables us to obtain an efficiency score for each input involved in the evaluated production process and not just for water use. Hence, it provides a more accurate and complete efficiency assessment than the sub-vector approach.

An important issue to take into account in the selection of the DEA model to be used is the returns to scale consideration. Increasing returns to scale in agricultural production systems has been found to exist in the USA and European Union (Hallam 1991; Chavas 2001; Mundlak 2005; Lilienfeld and Asmild 2007; OECD 2012). However, a given technology characterized by a fixed input mix, average cost tends to decrease with scale up to a certain size, beyond which average cost begins to increase (Sheng et al. 2015); thus, in the long run, agriculture may not necessarily experience increasing returns to scale; limitations in land availability and quality, labor availability, and missing markets for other inputs, among others, may limit the opportunities for increasing returns to scale in agriculture. This inverse relationship between farm size and productivity has almost become a “stylized fact” in the economic development literature. However, there is also evidence for constant returns to scale (CRS) (Bardhan 1973; Townsend et al. 1998).

Thus, to verify whether the DMUs analyzed in this study operate under CRS or variable returns to scale (VRS) technology, the methodological approach proposed by Molinos-Senante et al. (2015a) was applied. Accordingly, we tested whether efficiency scores under CRS are not statistically significant from efficiency scores under VRS; if this is the case, then the technology of the DMUs is CRS, on the contrary technology is characterized by VRS. Thus, efficiency scores under both CRS and VRS approaches were estimated. To validate whether the difference observed between CRS and VRS efficiency scores was statistically significant, the Mann-Whitney non-parametric test was selected due to the non-normal distribution of the efficiency scores. The null hypothesis (H_0) was that the k samples are from the same population. If a p value lower than or equal to 0.05 is obtained, the null hypothesis can be rejected at the 95 % level of statistical significance. In other words, if the p value is smaller than 0.05, then the DMUs operate under VRS technology. The p value of the Mann-Whitney tests was 0.04. Hence, the DMUs analyzed operate under VRS technology.

The non-radial DEA approach allows estimating GE and WUE. On the one hand, GE informs about the overall efficiency based on all outputs and inputs involved in the productive process. As it is shown in Eq. (1), GE is the average of the efficiency of each input. In this case study, GE is the average of the efficiency scores regarding the use of water, fertilizers, pesticides, energy, and labor. On the other hand, WUE is a measure of the efficiency in the use of water by farmers.

The non-radial DEA model to estimate the efficiency of farmers is as follows:

Given $K = 1, 2, \ldots, k, \ldots K$ DMUs, each utilizing a vector of inputs $x^k = (x_1^k, x_2^k, \ldots, x_N^k)$ to produce a vector of outputs $y^k = (y_1^k, y_2^k, \ldots, y_M^k)$, and with intensity vector λ for variables, the GE index is calculated with the following expression:

$$\mathrm{GE}(y, x) = \min \left\{ \sum_{n=1}^{N} \theta n / N : (\theta_1 x_1, \theta_2 x_2, \ldots, \theta_N x_N) \in L(y), 0 \leq \theta n \leq 1 \right\} \quad (1)$$

where θn is the efficiency index of each input, N is the number of inputs, and $L(y)$ is the possibility set. According to Eq. (1), the various inputs are minimized by different proportions, unlike radial measurements, where all inputs are minimized by the same proportion.

For each farm k', we can obtain values for the previous GE by solving the following linear programming optimization (Eq. (2)):

$$\begin{aligned}
&\mathrm{GE}\left(y^{k'}, x^{k'}\right) = \frac{1}{N} \min \sum_{n=1}^{N} \theta n \\
&s.\ t. \\
&\sum_{k=1}^{K} \lambda_k y_{km} \geq y_{k'm} \qquad m = 1, \ldots, M \\
&\sum_{k=1}^{K} \lambda_k x_{kn} \leq \theta_n x_{k'n} \qquad n = 1, \ldots, N \\
&\sum_{k=1}^{K} \lambda_k = 1 \qquad k = 1, \ldots, K \\
&\lambda_k \geq 0 \qquad k = 1, \ldots, K
\end{aligned} \quad (2)$$

where GE is the global efficiency measure while each θ_n obtained provides an efficiency indicator for each of the inputs considered. The objective of this problem is to minimize the inputs needed to produce a given level of outputs. The first constraint in Eq. (2) establishes a best practice frontier. The second constraint states the condition of the input-oriented efficiency measure. The convexity constraint is imposed by the third constraint in order to ensure that an inefficient firm is only benchmarked against firms of similar size; this means that the projected point (for that DMU) on the DEA frontier is a convex combination of observed DMUs (Njiraini and Guthiga 2013). The fourth and fifth equations are simply non-negativity constraints.

Both the GE and the efficiency scores for each input θ_n are bounded between 0 and 1. A farmer is efficient in the use of all inputs only if GE = 1, i.e., if all θ_n are equal to 1. A value of 1 indicates that the observation is a best performer located on the production frontier and has no potential reduction of inputs. On the contrary, a farmer is inefficient if $0 \leq \mathrm{GE} < 1$. In other words, if one of the scores of inputs θ_n is different from the unit, it is then considered inefficient. In our case, we are specifically interested in the efficiency of water use and therefore WUE smaller than 1 implies that water saving can be achieved.

Once the GE and WUE were calculated for all evaluated farmers, we tested if average scores differed among the following three groups—WR sellers, WR sellers, and non-traders. Since efficiency scores are effectively censored between 0 and 1 and that is not possible to ensure that our sample meets the assumption of homoscedasticity and normalcy, we must apply a non-parametric test. In particular, the Kruskal-Wallis test was applied.

Factors influencing efficiency scores

One important issue in efficiency analysis is to detect how external environmental factors might influence the production process and the resulting efficiency of the DMUs (Benito et al. 2013). This procedure is known as a second stage of analysis, and it is aimed to determine which variables explain the efficiency scores obtained through DEA model.

In doing so, most studies, even recent ones, use either ordinary least squares (OLS) or tobit regressions. Nonetheless, this procedure suffers important shortcomings (Bădin et al. 2014). While it is not our intention to thoroughly analyze the limitations of such approach, the following ones should be cited: (i) the data generating process has not been described in all of these studies that follow such an approach (Simar and Wilson 2007); (ii) efficiency scores are censored, therefore OLS is not appropriate (Grosskopf 1996); (iii) if the variables selected for the second estimation step are expected to affect efficiency, they should have been included in the first modeling stage to obtain efficiency scores (Grosskopf 1996); (iv) if the variables used in specifying the original efficiency model are correlated with the explanatory variables used in the second stage, then the second stage estimates will be inconsistent and biased; and (v) erroneous results can be obtained mainly due to the serial correlation between the error term and the set of covariants in the second stage (Simar and Wilson 2007).

Daraio and Simar (2005) proposed an alternative approach to evaluate the influence of the operational environment on efficiency scores. The methodology consists in applying a non-parametric smoothed regression of the ratios between the order-m conditional efficiencies and the unconditional efficiencies (Carvalho and Marques 2011). Other alternative approaches are the semi-parametric bootstrap-based approach proposed by Simar and Wilson (2007) and the methodology developed by Bădin et al. (2014) in the framework of partial order frontiers. Since efficiency scores computed using DEA are based on a non-parametric method, it is natural to apply non-parametric statistics to provide a basis for statistical inference. Moreover, this approach does not require assumptions that the underlying distribution of efficiency scores is normal (Grosskopf 1996). The approach followed in this study was based on grouping the DMUs according to certain characteristics or factors that appear to be related to efficiency and verifying whether there are statistically significant differences between the group efficiency scores using the Kruskal-Wallis and Mann-Whitney non-parametric tests (Molinos-Senante et al. 2015a).

Sample description

Markets for water rights in Limarí Valley

The Limarí river basin is located between latitudes 30° 15′ and 31° 25′ and is bordered by the Elqui River watershed to the north and by the Choapa River watershed on the south, in the Coquimbo Region of Chile (see Fig. 1).

This 12,000-km^2 basin has a semi-arid climate whose hydrology is dominated by highly variable snowmelt. Precipitation in the valley, averaging almost 150 mm annually, primarily occurs during the winter months. Water in this basin, which is stored in the Andes Mountains, becomes available for irrigation use only during the spring and summer months (from October to March). Average annual inflows are more than 450 hm^3/year (14.3 m^3/s), the amount of annual inflow that is exceeded in 85 % of all years (a critical threshold of water supply security) is only 89 hm^3/year (Vicuña et al. 2014).

This basin has 466 water distribution channels, with 7398 water right holders. The irrigation water demand in the basin is 724.402.000 m^3/year. The total irrigated surface is 44.047 ha of which 23.345 ha is irrigated with gravitational methods and 20.702 has adopted efficient irrigation technology (650 has sprinkler and drip 21.352 drip irrigation).

There are 5180 farmers in the Limarí Basin (INE 2007). Agricultural production in the Paloma System is diverse, with land planted in traditional crops such as maize, beans, and potatoes, horticultural crops (artichokes, peppers, and tomatoes), grains, pasture as well as valuable perennial crops such as avocados, export grapes, and grapes used for pisco, a local liquor. The perennial crops are grown mainly in the area below the dams. The farmer base is also diverse and consists of orchard owners, medium-sized farms, and a few large multinational fruit exporters.

The Limarí's energy source is the Central Interconnected System (SIC) which extends from the Antofagasta Region in the north to the Big Island of Chiloe, in the Los Lagos Region, in the south. The SIC has an installed generation capacity of 9385.746 MW, of which 47.41 % are from hydroelectric plants, 51.86 % thermal plants, and 0.73 % wind farms (Ministerio de Energía 2015).

The Limarí's watershed hydrologic system is primarily niveous, since its waters proceed from spring and summer snowmelt. The watershed's average annual precipitation is only 140 mm. The irrigation infrastructure in the valley is known as the Paloma system. The complete regulated system consists of three water reservoirs: Recoleta, Cogotí, and Paloma subsystems (see Fig. 2).

The Paloma System has a storage capacity of one billion cubic meters and a flexible water distribution infrastructure that connects the different irrigation districts. The system provides water for 65,000 irrigated hectares that receive water from the three subsystems. Around 57 % of surveyed farmers receive water from the Paloma subsystem, 32 % from the Recoleta subsystem, and 11 % from the Cogotí subsystem (Alevy et al. 2011). Regarding irrigation methods, 58 % of the total irrigated area has adopted water conservation technologies, mainly drip irrigation (57 %) and sprinkler method (1 %). The remaining land (42 %) is irrigated by flooding (Alevy et al. 2011).

Agricultural production in the Paloma System is diverse, with land planted with traditional crops, horticultural crops, pasture as well as valuable perennial fruit crops for export, such as table grapes, avocados, olive trees, almond trees, and citrus trees. Annual crops are quite diverse and involve maize, cucumbers, beans, peppers, and courgettes, among others, and represent 31 % of the land cultivated. On the other hand, perennial crops are 69 % of the land being table grapes the main product since 51 % of the land is devoted to cultivate this fruit (Alevy et al. 2011). The basin's farmers are diverse, ranging from small to a few large multinational fruit exporters.

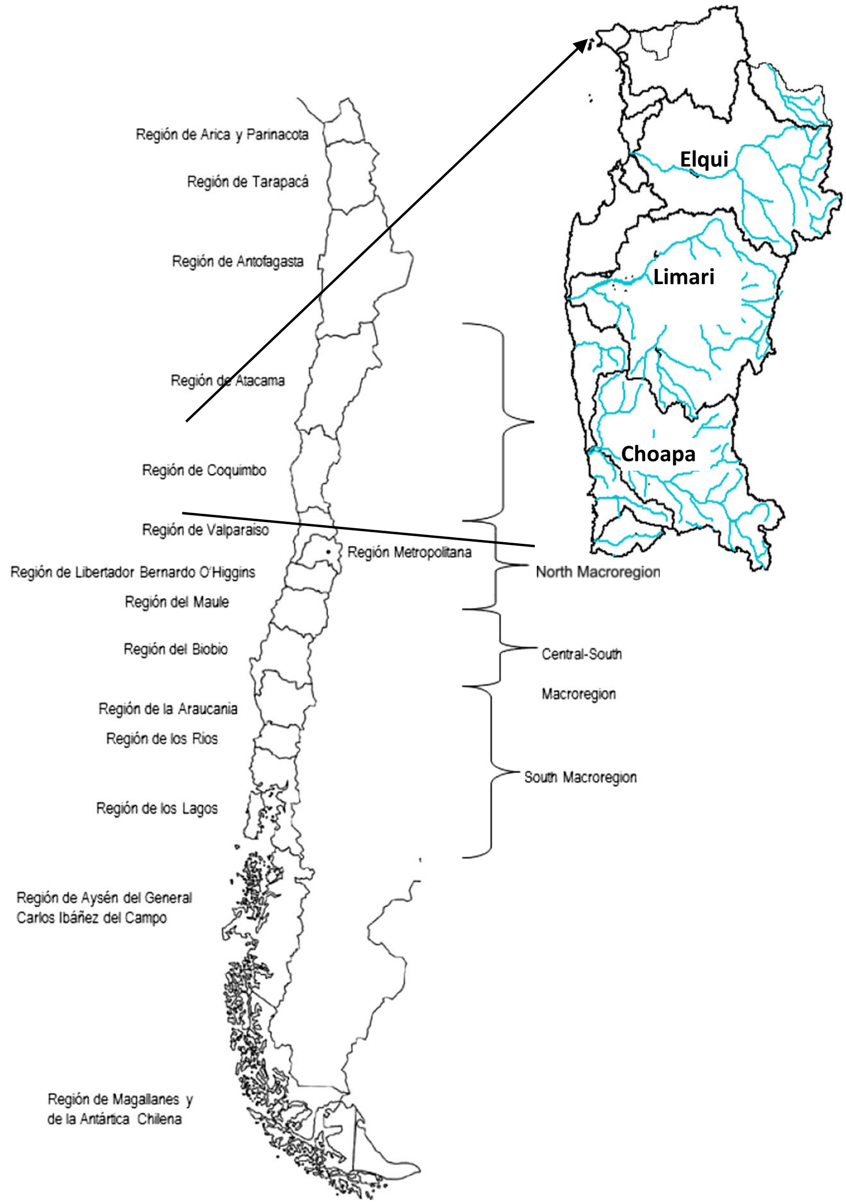
The main participants in the Limarí water market are farmers; over 90 % of water right transactions are between farmers (Alevy et al. 2011). Hadjigeorgalis (2008a) shows that markets for WR and spot water markets in the Limarí Basin have been successful in moving water and WR from low- to high-valued uses. The spot market has varied in size from 3.5 to 9.1 % of the allocated water supply (Cristi et al. 2002).

Data

Data were collected though a survey process performed in 2010[2] in the LV in Chile and the information pertained the period 2009–2010. The survey was conducted with the

[2] 2010 is the last survey available in this area. The survey was performed in the framework of the project: "Innova—Desarrollo de un mercado electrónico para el agua en Chile" (Innova—Development of an electronic market for water in Chile).

Fig. 1 Location of the Limarí Valley. Source: CCG (2009)



support of the Vigilance Committee of Río Grande Limarí and of the Canal Camarico, Embalse Cogotí, and Embalse Recoleta water user associations (Alevy et al. 2011).

The total number of farmers is 5180, and the sample size was determined using Cochran's technique (1963) assuming maximum variance for the attribute "water market participation," a confidence level of 95 %, and a sampling error of 5 %. Hence, the sample size was 385 farmers. A stratified sampling was employed distributing sample size between the nine irrigation districts of the LV. Within each district, farmers were randomly selected from each user association's registry; each selected farmer was chosen by randomly selecting their registration number from the user association's registry.

However, a wide range of farmers were discarded for the final use in the DEA assessment due to data gaps. Thus, after discarding farmers with incomplete information, the data sample reduced to 108 farmers. Detailed information was elicited from the respondents using structured questionnaires covering mainly the following aspects: (i) general information about the farm family, including size of the family, education level of the family members, years of experience in agriculture, and additional sources of income of the family; (ii) information regarding the property of the land; (iii) information regarding production and commercialization of the crops; (iv) information regarding of the consumption and price of inputs for agriculture productions; and (v) information regarding water

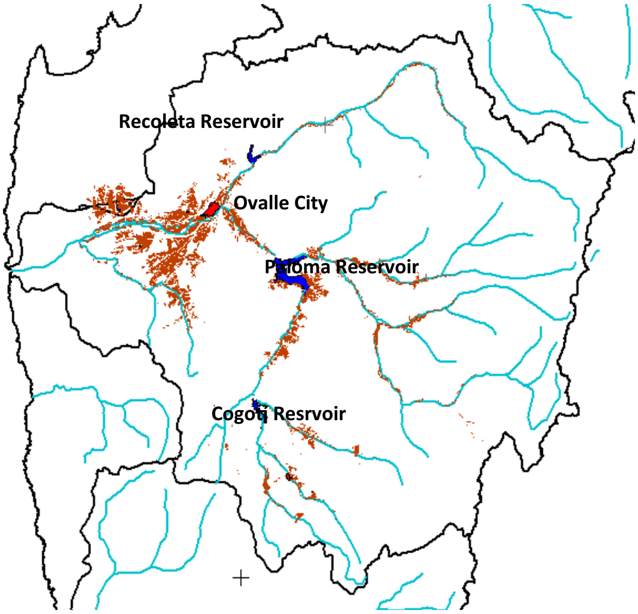


Fig. 2 Limarí Basin. Source CCG (2009)

use including purchases and sales of WR, reasons for buying and selling WR, and price of each WR transaction.

The first step to apply the non-radial DEA model (Eqs. (1) and (2)) is the definition of the inputs and outputs of the analyzed units (farms in our case). In this context, we want to note that previous works assessing the efficiency of water use in agriculture differ in the variables selected for the analysis since it is impossible in agriculture to evaluate all the inputs and outputs that are used and obtained during a given season (Yilmaz et al. 2009). Hence, following Rodríguez Díaz et al. (2004), Manjunatha et al. (2011), Njiraini and Guthiga (2013), and Azad et al. (2015), we characterized the process in an approximate way by considering output to be the total value of agricultural production in Chilean pesos (CLP). Five inputs were involved in the efficiency assessment: (i) total kilograms of fertilizers, (ii) total kilograms of pesticides, (iii) energy consumed expressed in CLP, (iv) labor in hours, and (v) total volume of water consumed in cubic meter. Table 1 summarizes the descriptive data.

A necessary assumption to apply DEA methodology is the "Cooper rule" meaning that the number of DMUs analyzed must be $n \geq \max\{m \cdot s, 3(m+s)\}$, where m is the number of inputs and s is the number of outputs (Cooper et al. 2007). Taking into account that the number of farms is 108 and the number of inputs and outputs considered are 5 and 1, respectively, in our study, the "Cooper rule" is met.

Following Manjunatha et al. (2011), three groups of farmers were identified: (i) WR sellers who sell a proportion or all of their WR, (ii) WR buyers who use their own WR and additionally buy WR, and (iii) non-traders who are farmers not involved in either selling or buying WR, i.e., they do not participate in the WR market. Only 18 % of surveyed farmers have participated in the permanent WR market,[3] trading WR independently from land.

Regarding the size of the landholding, Table 1 shows that on average terms, farmers selling WR are the largest. This result is consistent with the findings by Manjunatha et al. (2011) for groundwater markets in India. In this context, for the Australian spot water market, Wheeler et al. (2009) found that larger famers are more likely to be buyers of temporary water than smaller farmers. In our case study, non-traders in markets for WR are the farmers with the smallest size of land. Transaction costs probably explain this fact. Transaction costs act as a fixed cost that limits the minimum volume of each transaction, i.e., small transactions will not occur (Gómez-Lobo and Paredes 2001). However, performing the non-parametric test of Kruskal-Wallis on the distribution of land size for the three groups of farmers, we verified that the distributions of land size are not statistically significantly different (p value is 0.252) between WR sellers, buyers, and non-market participants. The paired comparison of land size distribution using Mann-Whitney test also verified that differences are not statistically significant (p values are 0.169, 0.122, and 0.936 when WR sellers vs. WR buyers, WR sellers vs. non-traders, and WR buyers vs. non-traders are, respectively, compared). These results confirm the finding by Hadjigeorgalis (2008b) that in the LV there were no significant differences between WR buyers and sellers in terms of farm size.

The average gross returns per hectare (ha) of WR sellers is approximately 2.4 and 1.3 times higher than for non-traders and WR buyers, respectively. Regarding water use, WR sellers consumed 0.9 and 0.7 times less water per ha than non-traders and WR buyers. Nevertheless, since agricultural production involves other inputs, a non-radial DEA model such as GE is needed to evaluate efficiency at farm level.

Results

Efficiency assessment

The efficiency of individual inputs and GE were calculated in General Algebraic and Modeling System (GAMS) software. Table 2 shows the mean of efficiency scores for each input and the GE for the 108 farms comprising our sample and grouped according to the three groups of farmers defined.[4]

[3] The Chilean Water Code of 1981 granted transferable water rights to individual water users to reach an efficient allocation of the resource through market transactions of water rights. In the permanent water market, water users trade water rights. On the other hand, water allocations are traded in the spot water market.

[4] Efficiency scores at individual level can be consulted as supplementary material.

Table 1 Sample description (mean values)

	Farmer category	All samples	Water sellers	Water buyers	Non-traders
	Number of DMUs	108	29	35	44
	Irrigated area (ha)	61.5	120.7	56.7	26.4
Output	Gross returns (CLP/year)	141,717,257	335,865,242	121,122,916	30,137,948
Inputs	Fertilizers (kg/year)	28,416	9181	5945	2703
	Pesticides (kg/year)	793	330	699	272
	Energy (CLP/year)	6,649,216	7,344,962	5,252,443	2,528,999
	Water (m^3/year)	143,092	229,815	152,121	78,750
	Labor (hours/year)	84,013	199,800	143,057	79,251

Source: Elaborated with survey data

CLP Chilean Pesos

For the complete sample, it is shown that the efficiency levels for each input and therefore the GE for the whole group are low. The average GE score is 0.412, indicating that there is substantial improvement potential for the 108 farmers evaluated as a whole. In addition, the high variability in GE scores (coefficient of variation = 58%) indicates inconsistency in terms of GE among farms. While some have relatively high GE scores, the majority have very low scores, which overall translates in a relatively poor GE performance. Thus, the average GE score is misleading since 50 % of the farmers' GE score are below 0.364, indicating that there is substantial improvement potential for the 108 farmers evaluated as a whole.

When comparing GE among the different groups in our study, the average GE is highest among WR sellers (0.517), followed by the WR buyers (0.412). The non-trader group has the lowest GE (0.343). The higher GE of WR sellers is mainly due to their superior efficiency in water use since the efficiency in the use of such input is considerably larger than for other inputs involved in the assessment. For WR buyers, the input with the largest efficiency is also water use although in this case, differences between inputs efficiency are not as remarkable as in the case of WR sellers. On the other hand, for non-trader farmers, the efficiency in the use of the five inputs analyzed is quite similar. In fact, the score of WUE is the lowest one of all inputs. To verify from a statistical point of view whether global and input efficiency differences among the farmers' groups are statistically significant, the non-parametric test of Kruskal-Wallis was performed. The *p* values shown in Table 2 indicate that the differences in the GE among WR sellers, WR buyers, and non-traders are statistically significant. Regarding the efficiency of the individual inputs, for water use and pesticide use, the null hypothesis can be rejected, i.e., efficiency scores between farmers' groups for these inputs are statistically different. On the other hand, for the other three inputs—fertilizer, energy, and labor—the differences in the efficiency scores between farmers' groups are not statistically significant. Given the economic and environmental importance of energy consumption, there is a growing interest is improving energy use efficiency. In this context, Table 2 illustrates that farmers have a significant room to reduce energy use in Limarí Valley. Potential energy savings are quite similar for all farmers, i.e., participants and non-participants in WR markets.

Focusing on the discussion on the results of WUE, Fig. 3 shows that only 10 out of the 108 farmers evaluated (9.3 %) are efficient in the use of water. They comprise the best practice benchmark since efficient farmers cannot reduce their consumption of water keeping constant produced output levels. This finding involves that there is considerable possibility of reducing water consumption in the LV for agriculture irrigation since the 90.7 % of the farms evaluated are inefficient in the use of this input. It should be highlighted that increasing WUE does not involve a reduction in the total amount of water consumed at river basin level (Adamson and Loch 2014). Increased efficiency can result in rebound effects (Loch and Adamson 2015). The low efficiency in the use of water (0.450 for the whole sample) is consistent with previous WUE studies such as Rodríguez Díaz et al. (2004), Lilienfeld and Asmild (2007), Speelman et al. (2008), Yilmaz et al. (2009), Njiraini and Guthiga (2013), and Azad et al. (2015). Nevertheless, it should be noted that only Azad et al. (2015) applied a non-radial DEA model to compute efficiency scores of water use.

Since the main aim of this study is to evaluate if there are differences in the WUE between farmers who participate in the WR market and farmers who do not participate, Table 3 summarizes results of WUE by farmers' groups.

Table 3 shows that 21 % (6 out of the 29) of WR seller farmers are efficient in the use of water, while in the case of WR buyers, the percentage drops to 9 % (3 out of 35 farmers). The situation is even worse in the case of non-traders since only 1 of 44 farmers evaluated (2 %) is efficient in the use of water. As has been pointed out previously (Table 2), farmers selling WR are the most efficient in the use of this input. This finding contrasts with the conclusion of Manjunatha et al. (2011) who reported that farmers buying water are the most efficient in the use of water in the Eastern Dry Zone of Karnataka (India). However, there are two aspects that distinguish the case study evaluated by Manjunatha et al. (2011) and our case study: (i) they assessed an informal spot water

Table 2 Mean efficiency scores for each input type and global efficiency index for farmers' category and p value of the Kruskal-Wallis test for efficiency score differences between farmers' groups

	Fertilizers	Pesticides	Energy	Water	Labor	Global efficiency
Complete sample	0.380	0.418	0.431	0.450	0.381	0.412
Water sellers	0.486	0.538	0.494	0.615	0.452	0.517
Water buyers	0.344	0.419	0.448	0.469	0.380	0.412
Non-traders	0.338	0.338	0.377	0.326	0.336	0.343
P value	0.127	0.027	0.363	0.000	0.849	0.001

market while the LV water market is a formal permanent WR market and (ii) their water market's focus is on groundwater while in our case study it involves surface water. In the LV case study, permanent WR sellers are the most efficient in the use of water since each drop of water saved by farmers is susceptible to be sold obtaining extra income.

Further analysis of the results shows that although WR sellers are the farmers with the highest efficiency in the use of water, they are also the group with the largest standard deviation. This means that the most heterogeneous group is WR sellers. On the contrary, farmers who do not participate in the market are quite inefficient but homogeneous in their WUE. This finding is shown in Fig. 4, which indicates the distribution frequency of WUE for each farmers' group. It is illustrated that in the case of WR sellers, the proportion of farmers in each group of efficiency is similar. In fact, the group that exhibits the lowest inefficiency (score between 0.9 and 1.0) has a larger percentage of farmers. Within the group of non-traders, farmers who are efficient in the use of water are an exception since more than 93 % of them present an efficiency score between 0.1 and 0.5. These low efficiency values illustrate that participation in the permanent WR market represents a driver to increase WUE in agriculture. The distribution of farmers who buy WR in the market is similar to that of non-traders, since 85 % of WR buyers have efficiency scores between 0.2 and 0.6. It should be noted that no WR buyers and non-traders present an efficiency score between 0.7 and 0.9. This means that within these groups, farmers have low or high efficiency in the use of water but not moderate scores.

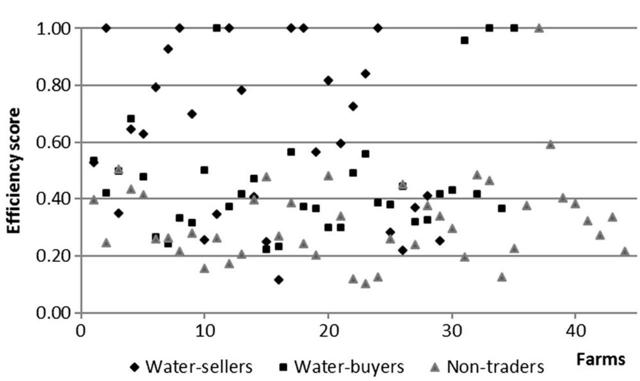


Fig. 3 Water use efficiency score by farm

Figure 4 also shows that none of the farmers evaluated have WUE scores lying between 0.0 and 0.1. The minimum score of efficiency for the entire sample is 0.102 which is a very low value. However, it is consistent with previous studies. For example, Rodríguez Díaz et al. (2004) reported a minimum value of WUE of 0.183. More recently, Njiraini and Guthiga (2013) verified that 45 % of their sampled farmers have WUE scores lower than 0.1 and Azad et al. (2015) evidenced that 50 % of all evaluated enterprises have a WUE index of less than 0.20. The findings of Manjunatha et al. (2011) are slightly divergent since in their empirical application, the minimum value of efficiency in the use of water was around 0.4. Nevertheless, it should be noted that their study focused on the use of groundwater while our sample involves farmers using surface water, with a more variable water supply.

The Kruskal-Wallis test confirmed that the difference in the WUE among the three groups of farmers is statistically significant (Table 2). Subsequently, pairwise comparisons using Mann-Whitney test have been performed. Results show that non-traders, i.e., farmers who do not participate in WR markets, differ significantly from WR sellers and WR buyers in terms of their water use efficiency. The p values between non-traders and WR sellers and WR buyers were 0.000 and 0.001, respectively. Therefore, water use efficiencies between participants and non-participants in markets for WR are significantly different at 1 % level. The results of the Mann-Whitney test for the difference in WUE between WR sellers and WR buyers does not lead us to reject the null hypothesis at 5 % level, but at 7 %, there are significant differences since the p value is 0.069. Similar finding was reported by Manjunatha et al. (2011) who concluded that the differences in the water use efficiency between buyers and sellers are significant at 10 % level.

In summary, the empirical application developed for the LV illustrates that markets for WR tend to increase efficiency in the use of water since the efficiency scores of farmers participating in markets for WR are significantly higher than the WUE of farmers who do not participate in them. However, there are a number of other differences between participants and non-participants that also affect participation decisions, such as WR prices, climatic conditions, crop water requirements (Wheeler et al. 2009), farmer's age, education,

Table 3 Summary results of water use efficiency for farmers' groups

	% efficient units	Mean	Standard deviation	Minimum	Maximum
Water sellers	21	0.615	0.291	0.115	1.000
Water buyers	9	0.469	0.215	0.223	1.000
Non-traders	2	0.326	0.157	0.102	1.000

agricultural productivity, debt level, credit constraints, irrigated surface, and WR quantity (Bjornlund 2003a, 2006; Brooks and Harris 2008; Kuehne et al. 2010; Loch et al. 2012; Wheeler et al. 2009; Wheeler et al. 2010; Wheeler et al. 2012).

Explanatory factors of water use efficiency

The previous section verified that the participation in the water market is an explanatory factor of both GE and WUE. To go further in the investigation of additional factors affecting efficiency scores, a second step analysis was performed. The aim of this is to test for differences between efficiency scores (GE and WUE) for farms categorized by different representative variables. In doing so, the Mann-Whitney and Kruskal-Wallis non-parametric tests were applied. Intuitively, the Mann-Whitney and Kruskal-Wallis tests are similar to the traditional one-way analysis of variance (ANOVA). However, they do not assume a normal distribution unlike ANOVA. Hence, in this case study, Mann-Whitney and Kruskal-Wallis tests are more suitable since Kolmogorov-Smirnov test evidenced that efficiency scores are not distributed as a normal distribution. Based on previous studies (Lilienfeld and Asmild 2007; Olson and Vu 2009; Njiraini and Guthiga 2013) and our observations and taking into account the available information, we assumed that GE and WUE may be affected by the following factors: (i) size of the farm, (ii) type of crop grown, (iii) farmers' experience in agriculture, and (iv) irrigation system.

First, we used farm size as reference. To determine how this variable affects GE and WUE, we classified the farms into two groups based on mean cultivated area (61.5 ha). Table 4 shows that farmers that cultivate large areas are on average more efficient either from a global or water use perspective. The same trend is observed with respect to the percentage of efficient farmers, since 24 % of the large farms are efficient while this percentage drops to 6 % for small farmers. However, the Mann-Whitney test did not lead us to reject the equality of means hypothesis neither for GE nor for WUE. In other words, in our case study, the cultivated area is not an explanatory factor for efficiency. This result is consistent with the finding by Njiraini and Guthiga (2013). However, Lilienfeld and Asmild (2007) reached the contrary conclusion since they observed a negative relationship between water excess and the size of the farm. Hence, further investigation on this factor is recommendable.

The following explanatory variable considered was the type of irrigated crop grown. The large variability of crops in the LV did not allow us to evaluate each of them individually. Hence, farms were classified into three groups: (i) with permanent crops, (ii) with annual crops, and (iii) with a mix of permanent and annual crops. Farmers who cultivate permanent crops are slightly more efficient in terms of GE as well as WUE than farmers who grow annual or mixed crops. The percentage of efficient farmers is also the highest for this group. Nevertheless, the Kruskal-Wallis test results indicated that differences in the mean of the GE and the WUE for the three groups of farms evaluated are not statistically significant.

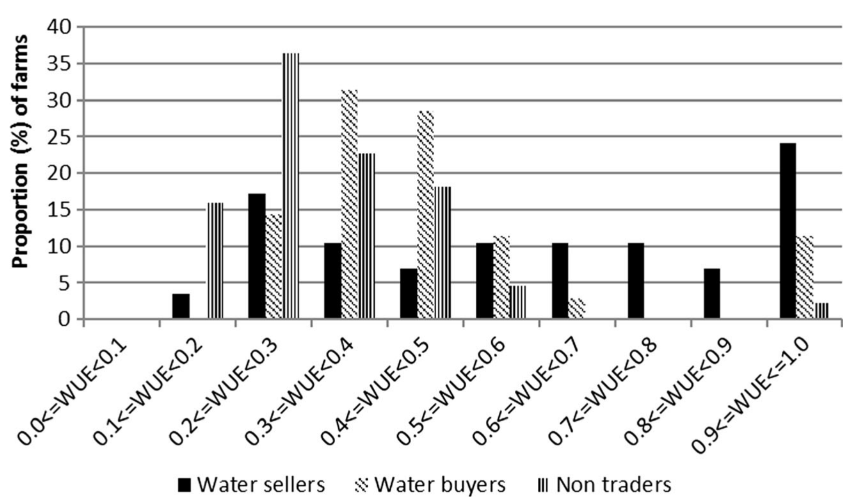


Fig. 4 Farmers grouped by water use efficiency (WUE) score

Table 4 Assessment of the factors affecting global efficiency (GE) and water use efficiency (WUE)

	Number of farms	Mean global efficiency	% global efficient farms	Kruskal-Wallis for global efficiency	Mean water use efficiency	% water use efficient farms	Kruskal-Wallis water use efficiency
Cultivated area (ha)[a]							
<61.5	91	0.395	7	0.309	0.432	7	0.253
≥61.5	17	0.505	24		0.547	24	
Type of crop							
Permanent	43	0.453	14	0.205	0.501	14	0.173
Annual	29	0.407	10		0.425	10	
Mixed	36	0.367	3		0.408	3	
Experience (years)[a]							
<17	43	0.420	9	0.740	0.477	9	0.313
>17	65	0.427	9		0.456	9	
Irrigation system							
Flood	7	0.341	0	0.257	0.444	0	0.837
Sprinkler	22	0.426	9		0.461	9	
Drip	79	0.487	10		0.527	10	

[a] For these variables, the test of Mann-Whitney was used instead of Kruskal-Wallis as the sample was divided only into two groups

Njiraini and Guthiga (2013) reported that farmers' characteristics (gender, age, education, household size) do not influence their WUE. In order to further investigate on this matter, we evaluated whether farmer experience in agriculture affects their efficiency. Taking into account that the mean experience of farmers assessed was 16.6 years, farmers were categorized into two groups: (i) lower than 17 years of experience and (ii) more than 17 years of experience. Table 4 shows that most of farmers (65 %) are experienced farmers. Both groups of farmers (experienced and non-experienced) are similar from an efficiency point of view. In fact, the percentage of efficient farmers is the same in both groups. However, the Mann-Whitney test results indicate that the mean GE and WUE differences for experienced and non-experienced farmers are not statistically significant.

Finally, we analyzed if the type of irrigation system influenced the GE and WUE of farmers. Previous studies on this issue are inconclusive. On one hand, Lilienfeld and Asmild (2007) concluded that irrigation system types did not influence levels of WUE. On the other hand, Njiraini and Guthiga (2013) pointed out that the choice for the irrigation method is of prime importance in determining farmer water use efficiency. In order to deepen such analysis, our sample data was categorized into three groups based on the irrigation systems: (i) flood irrigation through furrows, (ii) sprinkler, and (iii) drip irrigation. It should be noted that only 7 out of the 108 evaluated farmers used flood irrigation method. This is the group with the lowest WUE. Additionally, consistent with Njiraini and Guthiga's (2013) results, we find that farmers using drip irrigation technology exhibited a higher average WUE. In spite of this, the Kruskal-Wallis test values indicated that both GE and WUE differences are not statistically significant. This finding is similar to Lilienfeld and Asmild's (2007) results. To further analyze this variable, a pairwise comparison (drip irrigation and sprinkler) was performed. The p value of the Mann-Whitney was 0.135 confirming that in our empirical application, irrigation technique is not a statistically significantly explanatory factor of WUE.

The fact that farmers who participate in WR markets have greater WUE has marked policy repercussions. It is valuable information for decision makers to enhance efforts to promote and develop strategic plans aimed to increase the participation of farmers in consolidated WR markets. Awareness of farmers about the potential benefits associated to their participation in the markets for WR could play an essential role in improving the sustainability of water management.

Conclusions

Previous studies on this topic have evaluated the efficiency in the use of water in agriculture, but only a few analyze the effect of a formal and informal spot water market. This is the first analysis of agricultural water use efficiency that studies whether there are differences in farmer water use efficiency in the case that they have participated in a regulated permanent surface WR market. To overcome this drawback, we assess water use efficiency classifying farmers as permanent WR sellers, permanent WR buyers, and non-traders. In doing so, the non-radial Russell DEA model was applied. The advantage of this model is that it provides an efficiency score for each input as well as a GE score.

The empirical application developed using a sample of farmers located in the Limarí Valley (Chile) shows that mean WUE is moderate-low. Hence, there are possibilities to improve water use efficiency in irrigated agriculture in the

Limarí Basin. This is consistent with results obtained in Australia and India, among others. It is important to mention that the variation in water application rate per hectare among the various irrigated farms does not necessarily have impact on water application efficiency level. This is because the efficient performance is measured from an economic point of view—monetary value-added from agricultural output in relation to water used for crop production.

Additionally, when comparing GE among the different groups in our study, the average GE is highest among WR sellers (0.517), followed by the WR buyers (0.412). The non-trader group has the lowest GE (0.343). The higher GE of WR sellers and WR buyers is mainly due to their superior efficiency in water use since the efficiency in the use of such input is considerably larger than for other inputs involved in the assessment. On the other hand, for non-trader farmers, the efficiency in the use of the five inputs analyzed is quite similar; in fact, the score of WUE is the lowest one of all inputs.

The assessment by groups illustrated that farmers participating in markets for permanent WR are more efficient from a water use point of view than farmers who do not participate in water trading. In particular, permanent WR sellers are the most efficient in the use of water, followed by permanent WR buyers. On the other hand, non-traders are farmers that present the lowest WUE.

In a second stage, non-parametric tests were applied to analyze the relationship of external factors with differences in global and water efficiency scores. The analysis evidenced that none of the evaluated variables—cultivated area, type of crop, farmers' experience in agriculture, and irrigation technology—significantly affect GE and WUE.

From a policy perspective, some important implications can be drawn from this research. First, given that farmers participating in markets for WR are more efficient than farmers who do not participate in them, promotion of WR markets by water authorities and policy makers would lead to increases in water use efficiency. On the one hand, in countries such as Australia, Chile, Spain, and USA where water property rights and the legal framework already exist, the main issue is the promotion of this economic policy instrument. In doing so, water authorities face several challenges such as to reduce transaction costs and to minimize negative third party and environmental externalities. On the other hand, there are many countries where markets for WR are not regulated. In this context, governments should promote institutional and legal modifications in order to enhance the implementation and development of water markets.

Secondly, as mean WUE is moderate-low (0.450), our sampled farmers have the potential to improve water use efficiency in irrigated agriculture while maintaining profits. Thus, the findings of this study point to the need for improvement of efficiency in using water, which is critical for the long-term sustainability of agriculture in this arid region which faces high water scarcity.

Third, as WUE was estimated at farm level, this information should be transferred to farmers with a benchmark analysis. This will provide realistic targets and relevant benchmarks helping farmers to implement best practices from an irrigation perspective.

An area for further study is to analyze the detailed contribution of each input to the GE and WUE and the drivers of the efficiency results for each group of farmers, using single and double bootstrap procedures which permit valid inference.

Finally, the variation of water use efficiency scores across farmers provides important information for policy design and future efforts to improve water use efficiency as well as to ensure sustainable irrigation. These analyses contribute significantly to policies and initiatives that incentivize farmer participation in irrigation improvement programs.

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