Research Article

The water use efficiency and its determinants in small horticultural farms in Algeria

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Abstract

The objectives of this study are to calculate the water use efficiency (WUE) and its determinants in small-scale horticultural farms in Jijel-Taher in the Northeast of Algeria. This paper is divided into two main parts. We first start by calculating the scores of technical and water use efficiencies using data envelopment analysis method of a sample of 93 horticultural farms. Secondly, a Tobit regression was used to identify the determinants of WUE. Results showed that average technical efficiency scores are 68% and 79%, respectively, for CRS and VRS assumptions, while average WUE scores obtained are only 51% and 61% under CRS and VRS assumptions, respectively. Tobit regression shows that the total number of cultivated crops and water sources, the percentage of greenhouses, the level of education and technical assistance, the form of commercialization, and the access of farmers to credit are significantly affecting WUE.

Keywords Water use efficiency · Irrigation · Tobit · DEA · Algeria

1 Introduction

The aridity of the climate and the irregular rainfall in most regions in Algeria makes the use of irrigation essential in order to ensure higher yields and guarantees more stable agricultural production. While irrigation has many positive impacts on agricultural and rural developments, it is, however, often accompanied by several negative changes including degradation of the physical, biological and human environments [19].

Algeria is considered among the poorest countries in terms of water availability per capita, which remain below the theoretical threshold of scarcity set by the World Bank at 1000 m^3/Capita/year. In 1962, the theoretical water availability in Algeria was about 1500 m^3/Capita/year, while in 2014, it is only about 292 m^3/Capita/year [16]. This is showing that water scarcity is getting worse in Algeria, mostly due to the growing demand for drinking, agricultural and industrial water.

Such water crisis flows more from inefficient use and poor management than of any physical limit on supply augmentation [36]. In this perspective, agricultural sector remains the heavier in terms of water use with around 60% of the annually mobilized water used for irrigation. Under such situation, it is important to assess water use inefficiencies in the irrigation sector in order to be able to generate more water savings and sustain the use of this resource [28].

Within this perspective, our work aims to contribute to this discussion by analyzing the determinants of water use efficiency in 93 irrigated farms in northeastern Algeria. For this purpose, we will use the classic two-stage data envelopment analysis (DEA) approach. The water efficiency scores are estimated in the first stage. In the second stage, these efficiency scores will be regressed to identify determinants. The literature describes several approaches to assessing the effect of exogenous factors on efficiency. The ordinary square method (MCO) has been widely used.

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However, it is subject to much criticism because it is inadequate when it comes to censored variables [2]. Fried et al. [20] recommend the use of the double-censored Tobit regression as an alternative approach to MCO because it addresses the characteristics of the distribution of efficiency scores.

In the literature, the majority of work on water use efficiency focus almost on engineering irrigation water efficiency [24]. In this situation, irrigation water efficiency is given by the ratio of the amount of water actually used by crop to the water applied to the crop. In such a context, farm management is not considered and thus does not correspond to the definition of technical efficiency given by Farrell [18] (adopted in this study), which is a measure of management capability. Moreover, these approaches (engineering and agronomic techniques) do not consider water as an economic good and therefore they do not allow the evaluation of the economic level of water use efficiency [45]. To do so, we will calculate efficiency scores based on the concept of input specific technical efficiency [25]. This measure has an economic rather than an engineering meaning, and it aims to assess farmers' managerial ability to implement technological processes [26].

Our basic assumption considers the irrigated agricultural activity as a production process transforming several inputs into outputs [35, 38, 39]. The volume of water consumed would therefore be considered among other inputs in order to calculate the efficiency with which the irrigators transform these inputs into production value. The principle of benchmarking (i.e., comparing the least performing to the most efficient) would be adopted through the use of the DEA method. A substantial literature on efficiency of agricultural production has been developed. Few of them focus on efficiency of a particular input, such as water. In order to calculate water use efficiency (WUE), the method developed by Färe et al. [17] will be used in our study. This method consists on a mathematical transformation of the DEA model. Efficiency calculation for only water use allows to estimate how much irrigation water can be proportionally reduced, without affecting the production levels [10].

Previous works investigating WUE were conducted in the North African region including Dhehibi et al. [14], Frija et al. [23] and Chebil et al. [7] demonstrated low levels of WUE in this region. According to these authors, such low WUE levels are mostly due to low education and training levels of farmers, small size of the farm, higher availability of the water resource, inadequate scheduling, irrigation methods applied, and the type of cultivated crops. However, in our knowledge that have not been studied in the Algerian context, making this paper the first study of the Algerian agriculture to analyze the determinants of water use efficiency at the farm level using a nonparametric method. The findings of this study contribute to the enrichment of literature and provide policy implication and recommendations that allow enhancing irrigation water use efficiency.

The remainder of the paper is composed of four parts. The second part provides a presentation of the theoretical framework by defining the concept of technical efficiency as well as the different models currently available for its calculation. The third methodological part presents the mathematical formulation of the DEA and the Tobit models used in this study as well as a description of the study area and the used data. Results of the study are presented and discussed in the fourth section.

2 Theoretical background: efficiency concept and its calculation

Work on efficiency was initiated by Koopmans [27], Debreu [13] and Farrell [18]. Koopmans [27] was the first to propose a definition of technical efficiency. It considers that a production plan of a firm is technically effective "if it is technologically impossible to increase output and/or reduce an input without simultaneously reducing at least one other output and/or increasing at least one other input". Farrell [18] was also the first to divide economic efficiency into two components, namely technical efficiency (related to technical know-how and production technologies) and allocative (linked to the ability of the firm to allocate its inputs in a way which minimizes its production costs). Our study is limited to the calculation of technical efficiency that reflects the potential of farms to avoid wasteful use of resources [29]. The technical efficiency can be calculated by two orientations, respectively: (1) output-oriented efficiency (producing more without increasing the level of resources/inputs used) or (2) input-oriented efficiency (reducing the amount of resources/inputs used without changing the output level) [11, 21]. In this study, we used the input-oriented efficiency. Indeed, in the case of agricultural farms using natural resources (i.e., irrigation water), efficiency oriented toward minimizing inputs (in order to avoid wastage) is more suitable [11, 42].

In the literature, the multitude of frontier models developed on the basis of Farrell's work can be categorized into two, namely parametric and nonparametric approaches [5]. The most widely used methods are, respectively, the stochastic production function and the DEA method [38]. Parametric approaches are based on a specific functional form and must presuppose a frontier function giving the maximum output according to inputs [1] and suppose that any gap between the estimated function and the observations is explained by both the producer's inefficiency and some random elements which are not under the owner's control. On the other hand, nonparametric approaches do not impose a functional form. The production frontier of the DEA method is a convex isoquant constructed using linear programming techniques and must be estimated from the data sample. This frontier is represented by a linear isoquant which envelops the combinations of inputs-outputs observed in such a way that all the points are on or under the production boundary [10].[1] The DEA method is called deterministic by definition because it assumes the absence of random errors. In this case, it is assumed that the differences observed are due to productive inefficiencies [5, 40]. The degree of productive efficiency will therefore represent the gap between each observation and the production frontier.

In recent years, many authors have been interested in developing the DEA method to go beyond the limits of conventional approaches. Among them, we cite: the stochastic DEA developed to handle input and output uncertainty [31, 43], the semi-parametric form of the DEA method [12, 37] to avoid the correlation problem that affects efficiency scores, and the fuzzy-DEA approach to handle input and output uncertainty [47].

The DEA method has some advantages over the econometric approach to efficiency measurement. Firstly, because the DEA method does not require specific assumptions about the functional form of the production frontier, it is determined by the data. This boundary represents individuals with best practices. Then, technical efficiency is represented by the distance between that frontier (so-called effective frontier) and individuals below that frontier. There are also some limitations to this method. This includes the fact that by imposing less structure and constraints on the production boundary, DEA approaches also imply the absence of hazards or measurement errors. Where these actually exist, it can create confusion between measured efficiency and random deviations from the production frontier. Furthermore, several studies have compared the two methods. The results showed that results obtained through the two methods are highly correlated [3, 41, 44]. In this case, and for our study, the DEA method is preferred, especially because it allows to calculate sub-vector efficiencies [32].

3 Materials and methods

The basic principle of the data envelopment analysis (DEA) method is to compare the performances of all farms with the best among them. In this study, we will calculate both: (1) the technical efficiency of all inputs and (2) the technical efficiency of a single input, which is water. To do this, sub-vector efficiency concept is introduced in order to generate technical efficiency measures for a subset of inputs rather than for the entire vector of inputs. The concept looks at the possible reduction in a subset of inputs, holding all other inputs and outputs constant [17, 32–34]. A second step of the study consists of analyzing the determinants of the efficiency measures, particularly the water-saving technologies. Tobit model is estimated as a function of various attributes of the farmers and farms within the sample. This model allows to deduce which aspects of the farms' human and physical resources might be targeted by public investment to improve efficiency [4, 6].

3.1 Calculation of technical efficiency and water sub-vector efficiency

The model below shows the case where there are *N* input and *M* output for each firm *I*. For the *i*-th firm, these are represented by the vectors x_i and q_i columns, respectively. *X* is the input matrix *NxI* and *Q* the output matrix *MxI*; they represent the data of the firms *I*.

The technical efficiency can be calculated by solving Eq. (1):

$$\mathrm{Min}_{\theta,\lambda}\theta$$

With:

$$\begin{aligned} &-\boldsymbol{q_i} + \boldsymbol{Q}\lambda \geq \mathbf{0}, \\ &\theta \boldsymbol{x_i} - \boldsymbol{X}\lambda \geq \mathbf{0}, \\ &\boldsymbol{N}\mathbf{1}'\lambda = \mathbf{1} \\ &\lambda \geq \mathbf{0} \end{aligned} \tag{1}$$

where $\boldsymbol{\theta}$ is a scalar and λ is a *Ix1* vector of constants. The model is solved once for each farm and therefore gets a $\boldsymbol{\theta}$ value for each firm. The value of $\boldsymbol{\theta}$ obtained corresponds to the score of the technical efficiency of the first *i*-th firm. It is between 0 and 1; the value 1 indicates a point on the frontier; it thus represents a technically efficient firm [18].

The sub-vector technical efficiency for the variable *k* is calculated for each firm *i* by solving Eq. (2):

$$\mathrm{Min}_{\theta,\lambda}\theta^k$$

With:

$$\begin{aligned} &-\boldsymbol{q_i} + \boldsymbol{Q}\lambda \geq \mathbf{0},\ \boldsymbol{X_i^{n-k}} \\ &\theta^k \boldsymbol{x_i^k} - \boldsymbol{X^k}\lambda \geq \ \mathbf{0}, \\ &\boldsymbol{x_i^{n-k}} - \boldsymbol{X^{n-k}}\lambda \geq \ \mathbf{0}, \end{aligned} \tag{2}$$

[1] See [10] for more details.

Fig. 1 Study area, irrigated perimeter Jijel-Taher in Northeast of Algeria. *Source*: Google Earth

$$N1'\lambda = 1$$

$$\lambda \geq 0,$$

where θ^k is the score of sub-vector technical efficiency related to the input k for the firm i, in which k is reduced while maintaining the other inputs and output constant. The terms x_i^{n-k} and X^{n-k} refer to x_i^v and X^v without introducing the input k. x_i^k and X^k include only the input k.

We note that, to take account of the return scale, we introduce the constraint $N1'\lambda = 1$ to the constant return to scale model [8, 23, 32].

3.2 Tobit model

For determining the factors which affect WUE of irrigators in our sample, a Tobit model was chosen because efficiency is a bounded quantitative variable (bounded between zero and one) [46].

This method involves estimating a linear regression that expresses efficiency according to a set of socioeconomic variables. The Tobit model to estimate is defined as follows (check Eq. 3)

$$\theta^{k*} = \sum_{r=1}^{R} \beta_r z_r + e$$

$$\theta^k = \theta^{k*} \text{if } 0 < \theta^{k*} < 1 \tag{3}$$

$$0 \text{ if } \theta^{k*} < 0$$

$$1 \text{ if } \theta^{k*} > 1$$

where θ^k is the sub-vector technical efficiency related to the input k, it represents the variable to be explained. Z is a vector of explanatory variables related to the characteristics of the farm and the farmers, β is the vector of unknown parameter associated with the explanatory variables, and e the error term that is supposed to have a normal distribution with a mean equal to zero and a constant variance, σ^2.

3.3 Study area and sources of data

The study area occupies a central place in the north of the wilaya of Jijel (Northeast of Algeria) (Fig. 1), it is characterized by small horticultural farms, and the total agricultural area is around 4885 ha. The irrigated area is about 2011 ha, representing 36% of the agricultural area, and accumulates almost 60% of the total vegetable production in the region. This area is distinguished by a large number of irrigated vegetable farms. The area is divided with the same proportion between the open field crop (53.5% of the area) and greenhouses (46.5%). The two major irrigation techniques used are the gravity and drip irrigation systems.

Our data were collected on the basis of surveys from 93 contracted irrigators with the ONID during the agricultural campaign 2012–2013. Since the population is finite, with 600 farms, the sample size of 93 farms gives a survey rate of 15.5 which is considered acceptable. Hence, this representative sample gives a 9.3% margin of error (for a confidence range of 95%). This indicates that the results are accurate at 90.7%. The survey was conducted between January and June, 2014. We note that since there have been no institutional changes through reform programs

Table 1 Descriptive statistics of the variables used in efficiency measures

	Output (value)	Cultivated land (ha)	Water (m^3)	Labor (day/year)	Fertilizers (value)	Seeds (value)
Mean	403	1.91	5267	825	20.5	11
Standard deviation	36	2.06	465	67	19.4	1.7
Coefficient of variation	8.9	87.8	8.8	8.1	94.6	15.5
Minimum	54	0.2	600	189	2	0.9
Maximum	2064	14.5	26,800	4148	104	113

All variables given in value are in * 10^4 DZD = 87.3 USD

Table 2 Summary statistics for variables included in the Tobit regressions

	Variables continues				Variables dummy	
	Mean	SD	Min	Max	Nbr of farmers with dummy = 0	Nbr of farmers with dummy = 1
Farm size	2.55	2.24	0.5	14.5		
Age	40	9.7	24	69		
N. crops	2.3	1.2	1	6		
% greenhouses	66.4	40.7	0	100		
N. well users	2.44	1.69	1	6		
Well					41	52
Propriety					50	43
Education					32	61
Technical assistance					68	25
Financing					25	68
Commercialization					49	44

during this period, the data collected are, in our view, still relevant today. Indeed, these institutional changes (formal or informal) take long time to occur.

3.4 Variables used

Table 1 shows the different inputs (from 1 to 5) and output (6) used for the calculation of WUE scores: (1) cultivated land (ha), (2) applied irrigation water (m^3/farm), (3) labor (days), (4) fertilizers and pesticides (in DZD), (5) seeds (in DZD) and (6) total income of the farm from vegetable production activities (in DZD).

The independent variables regressed using the Tobit model are the following: (1) farmer's age (years), (2) arable agricultural land (farm size) (ha), (3) educational level of the farmer (1 = primary level and more; 0 = otherwise), (4) technical assistance and extension received (1 = if yes; 0 = if no), (5) existence of a well at the farm (1 = presence of well in farm; 0 = if not), (6) Number of well users, (7) type of land property (1 = if the farmer is the owner; 0 = if not), (8) Number of cultivated crops during the whole year, (9) percentage of greenhouses = percentage of the total area equipped with greenhouses, (10) commercialization channel (1 = at the farm; 0 = at the wholesale market), and (11) Access of farmers to credit (1 = if yes; 0 = if not) (Table 2).

4 Results and discussion

4.1 Characteristics of the sample

The study area is dominated by small-size farms. Their average size is 2.6 ha. Around 60% of farmers have a land size equal to or less than 2 ha. Surveyed farms were relatively diversified in terms of the number of cultivated crops, with about 2.3 crops, in average, by farm. Horticultural production under greenhouses is frequent in the region. They are practiced in more than 85% of the surveyed farms, with tomato and pepper as the most dominant. Open field crops are also present in 48% of the surveyed farms with cauliflower in winter and watermelon and tomato as summer crops. There are two irrigation techniques: the gravity irrigation is used in 31% of the irrigated area, while the drip irrigation system covers 69% of the area. There is also a wide variability of water applications across farmers in

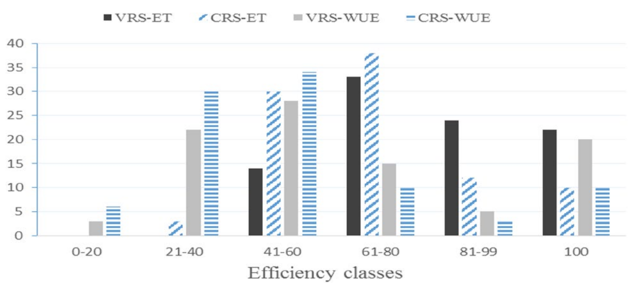

Fig. 2 Frequency distribution of technical and water sub-vector efficiencies under VRS and CRS specifications

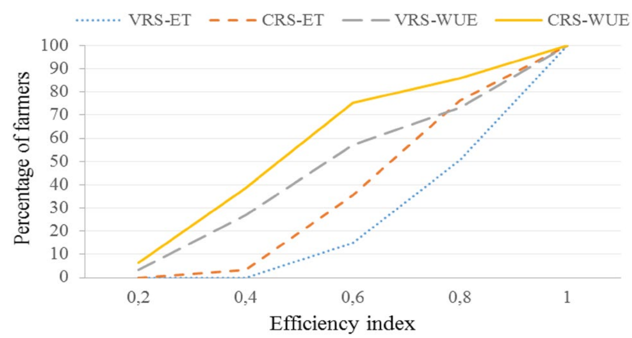

Fig. 3 Cumulative efficiency distribution for technical and water sub-vector efficiency under VRS and CRS specification

Table 3 Scores of technical and water sub-vector efficiencies under constant and variable returns to scale specifications

Efficiency classes (%)	Technical efficiency (% of farms)		WUE (% of farms)	
	CRS	VRS	CRS	VRS
Average efficiency	68	79	51	61
Efficiency min.	37	42	8	13
Scale efficiency	86		83	

the sample. It varies between 2000 and 6500 m^3/ha. Average age of surveyed farmers is about 40 years, with 84% of farmers older than 30 years and 34% of them not exceed the primary education level. Only 14% of farmers were receiving a technical training.

4.2 Measures of efficiency scores

The frequency distribution of the technical and water use efficiency estimates is illustrated in Fig. 2. We note that the calculations have been made using General Algebraic Modeling System (GAMS) program.

Average technical efficiency scores are 68% and 79%, respectively, under CRS and VRS assumptions (Table 3). These results show that, considering a VRS assumption, farmers can save an average of 21% of the inputs used while producing the same amount currently observed. The results also show a discrepancy between the technical efficiency values calculated under the CRS and VRS assumptions, resulting in a 14% scale inefficiency. This indicates that the technical efficiency of these holdings can be improved if this scale inefficiency can be eliminated.

The sub-vector efficiencies for water demonstrated large inefficiencies. The average WUE scores obtained are only 51% and 61% under CRS and VRS assumptions, respectively (Table 3). These results show that farms can get the same level of output with 39% less water (under the VRS) and using the same amount for the other inputs when compared to their peers on the frontier. This provides information on the ability to save a large quantity of water if we use irrigation water in a more rational way.

Figure 3 gives a graphical representation of the cumulative efficiency distributions for the efficiency scores. It is clear that under both returns to scale specifications the inefficiency of water use is higher than the overall technical efficiency.

Average scale efficiency, which can be calculated as the ratio between CRS and VRS efficiencies, is estimated at 83%. This measure indicates that many farms are not operating at an efficient scale and that adjusting the scale of the operation could improve the efficiency.

4.3 Determinants of the water use efficiency

The results of the Tobit model estimated using Gretl[2] software are illustrated in Table 4. The model is statistically valid. The Chi-square of the model is equal to 46.83, and it is statistically significant at 1% level.

According to Table 4, the variable number of crops has a negative coefficient and is statistically significant at 1%. This means that the sub-vector efficiency for water is lower when the number of crops increases. In other words, this shows that the specialized farms are the most efficient.

The variable commercialization shows a negative coefficient at 5%; this is explained by the superiority of the gain achieved by farmers integrated into the wholesale market compared to those who sell their products at the farm level. Economically, this can be explained by the difference in the sales price.

On the other hand, the relationship between WUE and the number of available water sources in the farms is statistically significant at 5%. This can be explained by the fact that, unlike farmers with only one source (public), farmer who has two sources of water (private and public) makes

[2] Gretl is a software package for econometric analysis.

Table 4 Tobit estimates of determinants of water use efficiency

	Coefficient	SE	*z*	*p* value	
Const	0.6717	0.1812	3.7066	0.0002	***
Propriety	−0.132	0.0971	−1.361	0.1735	
Farm size	0.0108	0.0119	0.9006	0.3678	
Well	0.1454	0.0636	2.2873	0.0222	**
N. well users	0.0175	0.0140	1.2534	0.2101	
N. crops	−0.1132	0.0260	−4.3572	0.0000	***
Age	0.0057	0.0025	1.4999	0.1336	
Education	0.1007	0.0582	1.7295	0.0837	*
Technical assistance	0.0768	0.0512	2.2611	0.0237	**
Commercialization	−0.1128	0.0486	−2.3189	0.0204	**
Access to credit	0.0941	0.0540	1.7415	0.0816	*
Percentage of greenhouses	0.0025	0.0013	1.9322	0.0533	*
Chi-deux (11)	46.8271		*p* value 2.31E−06		
Log likelihood	13.7502				

*significant at 10%, **significant at 5%, ***significant at 1%

irrigation at the right time, especially in critical periods. Indeed, in the field, we have noticed that farmers who have only one water source (public) tend to use gravity irrigation more than those with multiple water sources. According to their declarations, filling the space between furrows with water allows a supply for the plant over a longer period of time compared to irrigation using the drip system. This extends the duration between irrigations and thereby reduces the risk in relation to public water cuts.

It was also clear that the variables technical assistance and education effect positively and statistically significant at 5% and 10%, respectively, the WUE. This indicates that farmers who received an education and/or technical training are more efficient.

Access to credit has a positive and statistically significant effect on the WUE. This can be explained by the fact that the access of credit allows the investment and replacement of equipment which leading to reduce water consumption. Indeed, based on declarations made by farmers. One of the most important determinants of farmers' non-investment in drip irrigation system is its high cost. Finally, it is logical that the percentage of the area equipped with greenhouses effect significantly the WUE because this technique allows a better valorization of irrigation water.

4.4 Discussion

Results for estimates WUE show an average score of 61%. This indicates that irrigators use water in an inefficient way, and that it would be possible to reduce water consumption by 39% while having the same level of output (Gross Margin) with the present state of technology and unchanged input use, if the farmers use water more efficiently. The assessment of WUE in Tunisia, for example, also shows a low value of this indicator. Dhehibi et al. [14] have calculated scores of efficiency of the citrus producing farms in the Cap Bon region northeast of Tunisia and have identified a WUE score of 53%. Similarly, Frija et al. [23] have estimated the WUE at 42% in horticultural greenhouses in the eastern central area of Tunisia. Chebil et al. [7] have calculated an average score of WUE of 62% for wheat production in Kairouan in central Tunisia.

The results show a large difference between the scores of effectiveness under the two assumptions VRS and CRS with an average efficiency of scale of 83%. This indicates that farms can be more effective by operating at an optimal size and using the same combination of factors of production. Wide-scale inefficiencies were also reported by Speelman et al. [38] in an irrigation schemes in northwest province in South Africa, and Mahdi et al. [30] in a private irrigated scheme in southeastern Tunisia.

Through this study, we show that the number of crops has shown a negative and significant effect on the efficient use of the resource which means that the water use inefficiency is lower in specialized farms. Other authors such as Wadud and White [44] in rice farms in Bangladesh, and Speelman et al. [38] have reported that fragmentation has a negative effect on WUE. This is due to the fact that irrigation can be managed more efficiently on larger plots.

The results also showed that education, technical assistance and training have a significant and positive impact on WUE. This means that agricultural extension programs and education of farmers are the main instruments of policy for the government to improve the WUE. In contrast, Dhungana et al. [15] in Nepalese rice farms, Binam et al. [4] in smallholder farmers of Cameroon, and Dhehibi et al. [14] and Frija et al. [23] in Tunisia, reported a significant positive effect of education on efficiency for some of the regressions they performed.

Finally, this study showed that farms with more than one source of water (public and private) are the most effective. This could be explained by the availability of water for crop irrigation at the appropriate time. In fact, water supply cuts are frequent in our study area and sometimes farmers have to wait several days; therefore, they do not irrigate at the right time. This directly affects the efficiency of water use. The problem of water distribution in irrigated perimeters must therefore be addressed in order to ensure a better use of this resource. Similar finds are reported by Chebil et al. [8] for wheat farms in Tunisia. In this context, Frija [22] and Chemak et al. [9] showed that the source of water from public distribution networks positively affects WUE at the farm level.

However, the farmer's age does not contribute to a higher level of efficiency. In the literature, the effect of age is positive in the study of Dhungana et al. [15], but negative in the study of Wadud and White [44] and Binam et al. [4]. Considering theirs founds, one possible explanation is that two effects neutralize each other. Older farmers, for example, are more experienced and have more knowledge about their land and traditional practices, but are less willing to adopt new ideas.

5 Conclusion

The development and implementation of effective water demand management strategy is a major challenge which decision makers in Algeria must face in the coming years. Improving water use efficiency is a highly relevant solution to face the increasing growth of water demand and reduce losses. In this perspective, our work was interested in the study of the determinants that affect the efficient use of water by irrigators in an irrigated scheme in Northeast Algeria.

The results reveal a low water use efficiency score, suggesting that large amounts of water can be saved if this resource will be managed in a more effective manner. This result implies that improvement of WUE should be the first logical step for considerably increasing availability of water for agriculture. In a second step, the examination of the factors affecting WUE, using a Tobit regression, shows that in addition to the structural variables such as the number of crops, and the percentage of the surface covered by greenhouses, some farmer-specific variables as the level of education, technical assistance, and the type of financing have a significant effect on water use efficiency.

From the results, it is clear that a set of measures of assistance and training to farmers are necessary to promote better use of the resource and to aware farmers to the shortage of water. We also recommend the encouragement of the greenhouses crop production by facilitating access to credit and subsidies. Indeed, the conversion to these modern production techniques contributes to increase the country's food security while improving the profitability of farmers. Another key point is the positive relationship between the specialization of farms and the WUE. This result suggests that agricultural advisors should encourage farmers to grow high value-added crops.

Our study has some limitations because it interested in the study of a few socioeconomic determinants on the improvement of the water use at the farm level. More in-depth studies should be considered given the magnitude of the situation of the water sector in Algeria. This work can be completed by the study of water institutions and the influence of certain incentive and restrictive instruments as pricing and water quotas policies on water use efficiency.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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