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Technology adoption and assessment of eco-efficiency in water management

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ABSTRACT

This study focuses on the importance of water management in agriculture, considering both economic and environmental aspects. We aim to assess the eco-efficiency of farms by incorporating water-related indicators into performance evaluations. These eco-efficiency scores are further decomposed into water conservation efficiency (WCE) and water use efficiency (WUE). This paper uses a combination of Data Envelopment Analysis (DEA) and econometric analysis to calculate efficiency scores and identify the factors that influence efficiency for small-scale greenhouse farms in Crete (Greece) from 2009 to 2013. Findings reveal that: i) the average technical efficiency (TE) score for the sample is 0.891, indicating a relatively high level of efficiency; ii) the scores for WCE and WUE are 0.180 and 0.174 on average, respectively, suggesting room for improvement in managing water resources; iii) farmers who adopt alternative irrigation technology demonstrate higher technical efficiency compared to the overall sample, while non-adopters show even higher levels of efficiency. Moreover, non-adopters have been found to exhibit relatively better water conservation and use efficiency, indicating that adopters need to adjust their irrigation management practices and fine-tune the system's settings. Lastly, the findings suggest that utilizing more advanced irrigation technologies can enable farmers to effectively counteract the detrimental effects of aridity in managing water resources.

1. Introduction

Water resource protection is regarded as one of the most pressing issues confronting humanity (Vörösmarty et al., 2010). Water scarcity and deteriorated water quality impose a direct threat to the achievement of the objectives outlined in the European Water Framework Directive (Petersen et al., 2009) and the United Nations Sustainable Development Goals (SDGs) (Tsani et al., 2020). Low water security has ramifications for many SDGs, including food security, water shortages, climate change, biodiversity loss, health hazards, and water quality (Allan et al., 2013; Dopico et al., 2022; Grey and Sadoff, 2007; Varis et al., 2017). Moreover, the present annual losses attributed to drought are estimated to be approximately €9 billion for the European Union and the United Kingdom. Notably, between 39 and 60 % of these losses could be associated with the agricultural sector (Cammalleri et al., 2020).

A broad array of research has investigated water use efficiency from both engineering and agronomic perspectives (Oyonarte et al., 2022; Pereira et al., 2012). Other studies broaden the scope by considering water as an economic factor, allowing therefore the assessment of the economic dimension of water use efficiency (Gadanakis et al., 2015; Lilienfeld and Asmild, 2007; Varghese et al., 2013). The majority of these studies employ a sub-vector DEA model (Färe et al., 1994), to estimate excess water use and they model water use as an input a la par with other conventional inputs, such as land and labor. An important limitation of the sub-vector efficiency approach is that it relies on a modeling approach that fails to take into consideration trade-offs between the environmental and economic aspects of production by not placing equal emphasis on them. Indeed, while reducing water use is environmentally sustainable, there may be a trade-off with potential reductions in agricultural yield. It's essential to ensure that minimizing water use does not compromise the economic viability of the farm. In other studies, the concept of eco-efficiency is used to analyze water management systems (Beltrán-Esteve et al., 2017; Georgopoulou et al., 2016). These studies typically rely on life cycle analysis but only consider small samples of specific farm types and rarely examine their evolution over time.

This study contributes to the literature by empirically extending the eco-efficiency approach (Korhonen and Luptacik, 2004; Kuosmanen and

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Kortelainen, 2005) to include aspects of water conservation behavior. Furthermore, our approach considers the explicit relationship between economic outcomes and environmental issues within the same production technology. The core idea is that water loss can be minimized while maintaining constant production of the desired output. This focus is especially relevant in a semi-arid Mediterranean region, where water scarcity impacts both sustainability and farm productivity. Linking water issues to economic outcomes highlights the importance of balancing environmental concerns with farmers' income. Additionally, by analyzing a sample panel of vegetable greenhouse producers, both non-adopters and adopters of alternative irrigation technology, we aim to demonstrate whether eco-efficiency scores improve over time for those who adopt the new irrigation technology.

In addition to the influence of natural conditions such as climate, soil characteristics, and land slope, farmers' decisions related to natural resource use and management also play a key role in determining water use and conservation behaviors. More specifically, appropriate crop choice and water conservation practices are able to substantially improve water use efficiency (Agamile et al., 2021; Howard et al., 2023). Additionally, a number of CAP measures have been designed to influence farmers' water conservation strategies, either directly or indirectly. These measures include initiatives to prevent agricultural runoff from contaminating water bodies and authorisation procedures for irrigation as part of the cross-compliance rules. Green direct payments are one of the additional measures aimed at encouraging the adoption of policies aimed at crop diversification and improving soil quality and water retention (European Commission, 2023). Rural development programs, which explicitly incorporate measures supporting water conservation, include investments in water-saving technologies like drip irrigation, as well as participation in agri-environment-climate schemes (ENRD, 2018). Considering the significant water demands and the expansive nature of agricultural activities, there is a prevalent emphasis in public discussions on the imperative to improve irrigation water use efficiency and promote conservation efforts. This aspect will be the central focus of the present paper.

2. Methodology

Research that incorporates environmental considerations into traditional frontier-based performance measures can be divided into two groups (Tyteca, 1997; Tyteca, 1996). The first group treats environmental damage either as an unintended output or as an input. Studies following this approach have labeled this measure as "environmental efficiency" (Reinhard et al., 2000; Reinhard et al., 1999). In this "environmental efficiency" approach, conventional inputs are related to both desirable and undesirable outputs, and it can be modeled through a single-equation framework (Chambers et al., 1996; Färe et al., 2005) or through a multi-equation framework (Murty et al., 2012). The second modeling assumption links economic outcomes to environmental concerns rather than to traditional inputs, nowadays known as "frontier eco-efficiency models" (Korhonen and Luptacik, 2004; Kuosmanen and Kortelainen, 2005). Our methodology builds on this second ecological-economic approach, as it enables the examination of the trade-off between the production of desirable outputs and undesirable ouputs (e.g. water loss). We believe this is particularly relevant to the context we are studying. Specifically, we focus on water issues in a Mediterranean region as our ecological context. Water scarcity and efficient water management are critical concerns in this area, significantly affecting both environmental sustainability and agricultural productivity. Our aim is to link these environmental issues directly to economic outcomes, as farm income is also an essential factor that must remain on the agenda.

2.1. Measuring water eco-efficiency

Computing eco-efficiency measures to assess farms' performance in minimizing environmental damage while maintaining the existing level of economic performance requires the estimation of a production frontier. Following Kuosmanen and Kortelainen (2005), we use the non-parametric Data Envelopment Analysis (DEA) to estimate this production frontier. The eco-efficiency index employed in our study quantifies the relationship between the production of desirable outputs and the adverse impacts of water use. Specifically, the eco-efficiency is conceptualized as the ratio of the weighted sum of total agricultural revenues (y) to the weighted sum of irrigation water loss (b). In our study, we consider water loss as the undesirable output, which is measured in cubic meters (m^3). In order to estimate water loss, we draw on the work of Chatzimichael et al. (2019), who developed a theoretical framework that quantifies irrigation water effectiveness[1] (g). The value of g ranges between 0 and 1 and is influenced by environmental and soil conditions $g(q,d,s,k) \in [0,1]$. To estimate water losses (b) for each farm, we multiply the volume of water used in cubic meters (w_i) by the corresponding value of $1-g$.

$$b_i = w_i{}^*(1 - g_i(q,d,s,k) \tag{1}$$

The DEA representation of the eco-efficiency frontier is given by:

$$\min_{\theta_i^{EE},\mu^i} \left\{\text{Eco} - \text{efficiency}^i\right\}^{-1} = \theta_i^{EE}$$

s.t.

$$\mathrm{y}^{\mathrm{i}'} \le \sum_{\mathrm{i}=1}^{\mathrm{I}} \mu^{\mathrm{i}}\mathrm{y}^{\mathrm{i}}$$

$$\theta_{\mathrm{i}}^{\mathrm{EE}}\mathrm{b}^{\mathrm{i}'} \ge \sum_{\mathrm{i}=1}^{\mathrm{I}} \mu^{\mathrm{i}}\mathrm{b}^{\mathrm{i}'} \tag{2}$$

where μ is the vector of intensity variables; θ^{EE} is the eco-efficiency score with values ranging from zero to one. In terms of interpretation, the objective function in model (2) is to minimize the sum of undesirable outcomes (water loss (b)) while maintaining the existing level of desirable outcomes (total revenues (y)). The eco-efficiency model (2) aims to minimizing θ_i^{EE}, which represents the proportional reduction in water loss needed to reach the eco-efficiency frontier. By doing so, it identifies the smallest possible water loss while satisfying the constraints of maintaining the current level of desirable output.

For the sake of comparison, we also compute technical efficiency scores for each farm in the sample. Technical efficiency measurement only takes into consideration the interaction between conventional inputs (x_n) and desirable output (total revenues (y)), while ignoring the presence of undesirable output (b). The DEA representation of technical efficiency scores is given by:

$$\min_{\theta_i^{TE},\lambda^i} \left\{\text{Technical efficiency}^i\right\}^{-1} = \theta_i^{TE}$$

s.t.

$$\mathrm{y}^{\mathrm{i}'} \le \sum_{\mathrm{i}=1}^{\mathrm{I}} \lambda^{\mathrm{i}}\mathrm{y}^{\mathrm{i}}$$

$$\theta_{\mathrm{i}}^{\mathrm{TE}}\mathrm{x}_{\mathrm{n}}^{\mathrm{i}'} \ge \sum_{\mathrm{i}=1}^{\mathrm{I}} \lambda^{\mathrm{i}}\mathrm{x}_{\mathrm{n}}^{\mathrm{i}}, \mathrm{n} = 1, \ldots, \mathrm{N} \tag{3}$$

[1] The variable $g(q,d,s,k)$ represents a ratio ranging from 0 to 1, with a value of 1 indicating high effectiveness in terms of irrigation. Where $q \in R+$ denotes soil water holding capacity, $d \in R+$ is a general aridity index capturing microclimate changes and $s \in R+$ represents the slope of the plot. k indicates the state of irrigation technology.The undesirable output (water loss) of each farm is given by: $b = (1-g)^*$*Water use*

where θ^{TE} is the technical efficiency score with values ranging from zero to one.

Our models assume constant returns to scale due to the unique constraints faced by the sample farms. Specifically, land, a critical input for greenhouse farming, is increasingly scarce and degraded, limiting opportunities for farm expansion. As a result, scale differences are minimal, and efficiency improvements are assumed to arise primarily from better resource management and operational practices rather than changes in scale.

2.2. Decomposing eco-efficiency

While model (2) evaluates the overall potential of a farm to reduce its water loss given its production of desirable outputs, we follow Eder et al. (2021) to allow for a more nuanced analysis of inefficiency sources, as the eco-efficiency score can be decomposed into two parts: water use efficiency and water conservation efficiency.

For the case of water use efficiency, it is easy to show that model (2) can also be obtained by dividing the observed ratio of total revenues (y) to water loss (b) of farm under evaluation by the maximum value of the ratio of total revenues (y) to water loss (b) observed in the sample of N farms:

$$\theta_i^{EE} = \theta_i^{WUE} = \frac{y_i/b_i}{max\left\{\frac{y_i}{b_i}\right\}} \tag{4}$$

In Eq. (4), which serves as our measure for water use efficiency (WUE), the WUE of the farm under evaluation can be enhanced by either reducing irrigation water effectiveness (g) or minimizing water volume while maintaining a constant desirable output.

Achieving a reduction in water use while holding the desirable output constant implies an increase in technical efficiency. Consequently, variations in θ_i^{WUE} can be attributed to differences in technical efficiency across farms. However, we aim to derive an eco-efficiency measure that excludes the effects of technical efficiency. To isolate eco-efficiency resulting from water conservation behavior (represented by irrigation water effectiveness(g)), we assume that all farms are technically efficient. This entails adjusting water use to its technically efficient level for all farms and solving model (2) individually. This process yields a measure known as “pure eco-efficiency,” which we refer to as water conservation efficiency (WCE):

$$\theta_i^{WCE} = \frac{\frac{y_i}{b_i\theta_i^{TE}}}{max\left\{\frac{y_i}{b_i\theta_i^{TE}}\right\}} \tag{5}$$

Fig. 1 depicts the general presentation of the water eco-efficiency concept when one desirable output (y) and one undesirable output (water losss (b)) are generated under the same production frontier (T). Observations above the production frontier are unfeasible, those lying on the frontier are considered to be eco-efficient, while units below are considered to be eco-inefficient. The Figure shows two farms (A and C) using identical input quantities. However, these two farms differ in their levels of desirable and undesirable outputs.

As farm A lies on the frontier, it is identified as a water-use efficient farm. Additionally, farm A is considered technically efficient since it generates the highest output $y_A > y_C$ (assuming both farms use the same input quantities). Consequently, it is also considered as the most water conservation efficient, as it exhibits the lowest water loss (b). When it comes to potential strategies to improve these eco-efficiency levels, one viable option that could be considered is for farm C to adopt a modern technology (e.g. overhead sprinklers). This technological adoption has the potential to improve irrigation effectiveness, thereby reducing water loss from b_C to b_{C^*} while maintaining economic output constant (y_C). This assumption aligns with existing literature emphasizing the significant role of adopting modern agricultural technologies in enhancing overall farm performance.

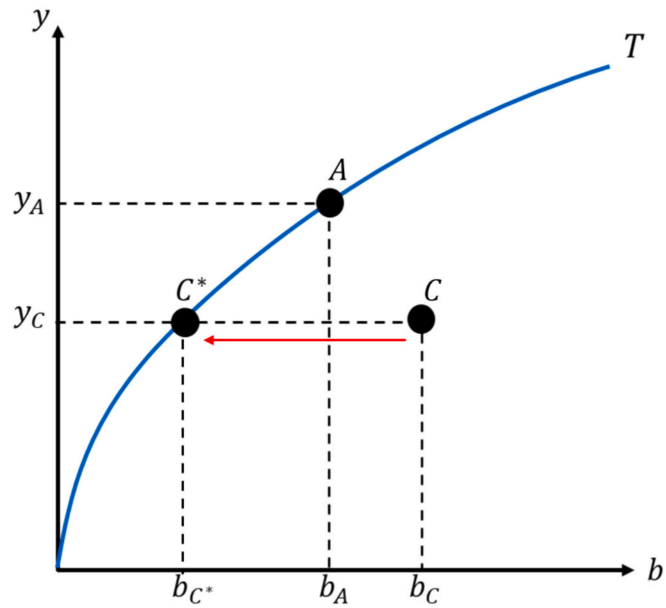

Fig. 1. Schematic representation of the concept of eco-efficiency in the context of water conservation.

2.3. Efficiency determinants

In order to further assess the impacts of a set of explanatory variables on the efficiency scores, a regression procedure is used to study the predictors of farm performance. We measure this effect through Simar and Wilson (2007) bootstrap truncated regression model. Such a semi-parametric approach allows to overcome the serial correlation problems of DEA efficiency estimates occurring when employing standard approaches such as censored regression models. The regression is expressed by the following model:

$$Eff_{it} = \alpha_0 + \alpha_1 X_{it} + \epsilon_{it} \tag{6}$$

where Eff_{it} are the estimates of efficiency scores resulting from the models in (2) and (3), and Eq. (5). X_{it} is the matrix of regressors expected to affect farm efficiency scores. This analysis is particularly relevant from a policy perspective as it provides actionable insights into the specific factors that drive or hinder agricultural efficiency (Czyżewski et al., 2020; Gémar et al., 2018; Pérez Urdiales et al., 2016). The selected determinants include the Aridity Index, which reflects the climatic conditions and water scarcity in the region. We also examined as a determinant the Water Holding Capacity of the soil, which affects the availability and retention of water for agricultural use. Other variables considered here were age, education level of the farmers, the extent of extension services utilized, the size of the farm, and the total amount of subsidies received in monetary terms. Unlike inputs and outputs, which directly reflect production activities and outcomes, the determinants analyzed in this study represent external and underlying factors that influence efficiency indirectly. Understanding these determinants enables policymakers to design targeted interventions, such as improving access to extension services, offering education and training programs for farmers, or optimizing subsidy allocation. Furthermore, addressing environmental constraints like aridity and soil water retention capacity through policy measures such as infrastructure investment in irrigation or soil management programs can significantly enhance agricultural sustainability. By aligning policies with the identified drivers of efficiency, governments can support farmers in achieving both economic viability and resource conservation.

3. Data

The study utilized a dataset comprising 56 vegetable greenhouse producers located in the Ierapetra Valley in Southern Crete, Greece. The data used in this study are the same as in the study of Chatzimichael et al. (2019) and were obtained directly from the authors' shared resources[2].[3] This dataset covered a period of four cropping years,[4] from 2009 to 2013, for 56 greenhouse producers resulting in a total of 224 observations. The selection of these greenhouse producers was randomized as a part of a larger survey that aimed to examine the impact of modern irrigation technology on the efficiency of water usage in the Ierapetra Valley. The survey was funded by the Agricultural Department of the Regional Directorate in Crete, with the objective of addressing water limitations in the semi-arid Mediterranean basin region in recent years.

The Agricultural Department of the Regional Directorate enlisted extension agents to collect the data for this study. These agents conducted interviews with the selected greenhouse producers using a standardized questionnaire. The interviews were conducted in early June of the final cropping year, which was 2012–2013. During the interviews, producers were asked to provide details about when they adopted the new irrigation technology, along with information on output, labor, land usage, and water usage in their greenhouse operations. They provided data for the last four cropping years. In Crete, the vegetable greenhouse cropping year typically starts between mid-August and early September and continues until the end of May.

Around 80 % of the farms in this valley depend on water from the local public irrigation system, which is connected to the Bramianos dam in central Crete. For this survey, farms using their own wells for irrigation were excluded. Before 2005, most greenhouses in the area used drip irrigation systems, where multiple tubes were connected to a central water supply line, with each tube providing water to a row of vegetable plants. However, starting in 2005, greenhouse producers had the option to adopt an alternative irrigation technology, known as overhead sprinklers. In this system, a series of overhead water pipes in the greenhouse release mist through several sprinkler heads. These overhead sprinkler systems are usually automated, controlled by moisture sensors and timers. They are deemed more efficient in water usage and minimizing evapotranspiration (ET) compared to traditional drip irrigation systems. Consequently, adopting overhead sprinkler systems in the greenhouses of this semi-arid Mediterranean basin area could significantly reduce water stress in greenhouse production.

Table 1 provides descriptive statistics of the variables utilized in this study. The inputs considered include labor, both family and hired, measured in hours. Seeds are measured in euros, and land is measured in stremmas, with 1 stremma equivalent to 0.1 ha. Water is measured in cubic meters (m^3). Additionally, there is a weighted intermediate input index, measured in euros, that combines various goods and materials used during the cropping year, such as pesticides, fertilizers, and electricity. The desired output variable for each farm is the total revenue from farm output, measured in euros. This represents a weighted output index that combines the production of four different vegetables grown in the greenhouses: tomatoes, cucumbers, peppers, and eggplants. Finally, the undesirable output is quantified as water loss, measured in cubic meters (m^3). This is calculated by multiplying the volume of water used by the inverse of the irrigation effectiveness, denoted as (1-g). In addition to assessing efficiency measures, our study also investigated the potential factors influencing farmers' efficiency. We considered a range of variables that capture both socioeconomic and environmental aspects. Summary statistics of the selected determinants are given in Table 1.

4. Results and discussion

4.1. Efficiency results

Table 2 shows the main statistics for the estimated technical, water-use, and water-conservation efficiency measures. The kernel density functions of these efficiency scores are depicted in Figs. 2 and 3. In the pooled sample, the average technical efficiency score from 2009 to 2013 is 0.891. This finding is consistent with previous research on Greek small-scale greenhouse farms. Vrachioli et al. (2021), for example, found relatively similar efficiency levels (0.841) when assessing technical efficiency of the same sample farms using stochastic frontier analysis. The left-skewed distribution of technical efficiency scores (Fig. 2) indicates that the majority of the farms are highly efficient, with only a few having a technical efficiency score less than 0.70. Additionally, upon analyzing the distribution of TE scores, we observe a distinct bimodal shape. This indicates the presence of two prominent groups within the dataset. The first small group is centered around a TE score of approximately 0.8, suggesting a relatively moderate level of efficiency. The second group, however, stands out with TE scores that approach a value of 1.0, indicating an exceptionally high level of efficiency. The presence of these two groups may highlight the heterogeneity in performance and suggests the existence of different factors or practices that contribute to the observed efficiency levels. When focusing on adopters, their average TE score rises to 0.923, reflecting a higher level of technical efficiency in comparison to the pooled sample. Conversely, non-adopters display an average TE score of 0.945, indicating an even higher level of technical efficiency when compared to both the pooled sample and adopters.

The pooled sample has an average WCE score of 0.180 and an average WUE score of 0.174, with a strong right skewness in the efficiency distribution (Fig. 2), indicating that there is room to improve water use and conservation efficiency. Compared to technical efficiency, the WCE and WUE have a greater standard deviation, meaning that there is more variation in how farms conserve and use water than in how they produce output. This could be due to different factors, such as climate, crop types, or management practices. Overall, these results suggest a considerable level of inefficiency in water use and conservation, highlighting the need for improvement in irrigation practices. These findings are consistent with the understanding that irrigation efficiency in Crete can vary based on the type of irrigation technology used, but overall, it tends to fall below its potential (Chartzoulakis et al., 2001). Given this context, the relatively low values observed in the study may reflect the existing challenges and opportunities faced by small-scale greenhouse farms in Crete regarding water use and conservation. The average WCE and WUE score among adopters rises to 0.220 and 0.211, respectively, indicating a relatively higher level of water conservation efficiency than the pooled sample. Non-adopters, on the other hand, have the highest average WCE (0.300) and WUE (0.295) scores of the three groups. This suggests that non-adopters, on average, conserve and use water more efficiently than both the pooled sample and adopters. This finding may seem counterintuitive at first because adopting a new irrigation technology would be expected to result in increased water use and conservation efficiency. However, during the initial stages of adopting a new technology, there may be a learning curve and a period of trial and error as farmers become familiar with the technology's requirements, operation, and potential benefits (Marra et al., 2003). This adjustment period can result in temporary inefficiencies as farmers refine their skills and make necessary adaptations to fully harness the benefits of the new technology. In the context of water use and conservation, the adoption of new irrigation systems or techniques, for example, may require farmers to learn optimal water scheduling, adjust irrigation management practices, and fine-tune the system's settings. During this

[2] https://academic.oup.com/erae/article/47/2/467/5498613#supplementary-data

[3] Vrachioli et al. (2021) also used the same dataset.

[4] The dataset spans four cropping years, specifically 2009–2010, 2010–2011, 2011–2012, and 2012–2013. Each cropping year extends across two calendar years, covering the period from 2009 to 2013.

Table 1
Descriptive statistics of sample data for the period 2009–2013.

		Units	All farms		Adopters		Non-adopters	
			Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Outputs	Total revenue	Euros	78,528.04	56,632.92	91,149.03	63,698.72	60,419.67	38,157.41
	Water loss	M^3	259.31	267.59	303.03	279.88	196.58	236.54
Inputs	Land	stremmas	5.44	3.52	6.37	3.95	4.10	2.17
	Labor	Hours	591.93	508.98	772.41	551.00	332.98	287.68
	Seeds	Euros	1449.38	1011.23	1573.85	1046.94	1270.80	934.51
	Intermediate inputs	Euros	8886.26	4774.37	9578.78	4760.41	7892.64	4641.44
	Water	M^3	1358.10	967.97	1466.68	1037.80	1202.32	839.06
Determinants	Aridity Index	Score	1.19	0.38	1.14	0.37	1.27	0.37
	Water holding capacity	Cm/s	0.002	0.001	0.002	0.001	0.002	0.001
	Age	Years	41.80	13.66	33.32	5.58	53.98	12.59
	Education	Years	11.77	3.35	13.17	2.17	9.77	3.72
	Extension	N visits	4.06	3.61	5.85	3.57	1.49	1.52
	Farm size		43.52	28.13	50.97	31.64	32.83	17.37
	Subsidies	Euros	703.07	454.60	796.11	426.52	569.59	462.57
Number of observations			224		132		92	

Note: All financial variables were adjusted to reflect 2010 constant prices.

Table 2
Descriptive statistics of efficiency scores over the period 2009–2013.

	TE	WCE	WUE
Pooled sample			
Average	0.891	0.180	0.174
S.D.	0.118	0.248	0.244
Adopters			
Average	0.923	0.220	0.211
S.D.	0.106	0.274	0.271
Non-Adopters			
Average	0.945	0.300	0.295
S.D.	0.085	0.324	0.324

transitional phase, inefficiencies can arise due to factors such as sub-optimal water application, over or under-irrigation, or inadequate system calibration (Genius et al., 2014).

To evaluate whether efficiency scores truly improve over time, our focus is directed towards the adopters as presented in Table 3, covering the period 2009–2013. Results indicate a consistent pattern in TE, which remains relatively stable throughout the four years. In contrast, both WUE and WCE exhibit more dynamic patterns. In the first year following adoption, these efficiencies start relatively high (WUE at 0.564 and WCE at 0.608), indicating an initial boost in water efficiency and conservation efforts. However, there is a notable drop in the second year, with WUE falling to 0.299 and WCE to 0.317. This initial boost in efficiency can be attributed to the structured and informed approach fostered by extension services, which ensures that adopters are well-equipped to handle new systems effectively. This pattern of initial high efficiency followed by a decline aligns with Levidow et al. (2014), who emphasize the crucial role of extension services in the initial implementation phase. Similarly, Wang et al. (2020) point to the significant early impact of social networks and extension services, which may diminish as adopters gain independence. Interestingly, in the third and fourth years after adoption, both WUE and WCE show a recovery and improvement, with WUE rising to 0.362 and then 0.623, and WCE to 0.375 and then 0.659 respectively. This upward trend in the later years can be interpreted as evidence of the adopters' increasing proficiency and effective utilization of the new irrigation technology.

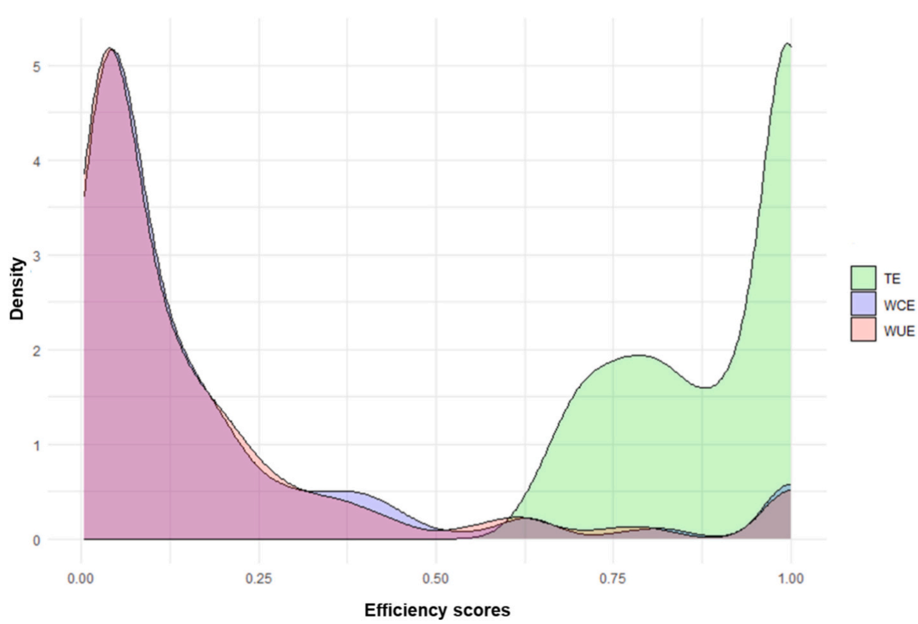

Fig. 2. Density plots of efficiency scores.

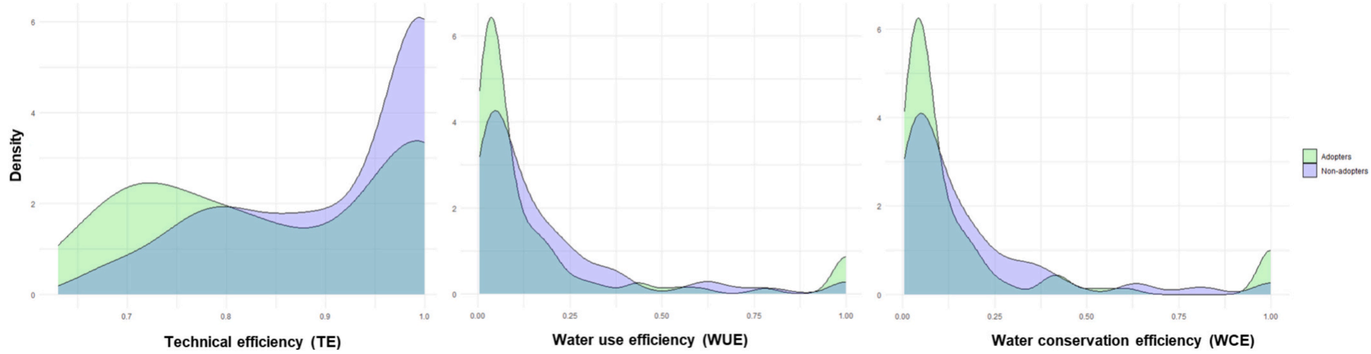

Fig. 3. Density plots illustrating efficiency scores for both adopters and non-adopters.

Table 3
Efficiency scores (average) of adopters over the period 2009–2013.

	1st year after adoption	2nd year after adoption	3rd year after adoption	4th year after adoption
TE	0.954	0.942	0.936	0.948
WCE	0.608	0.317	0.375	0.659
WUE	0.564	0.299	0.362	0.623

4.2. Technology gap ratio results

The analysis of the technological gap ratio (TGR) reveals interesting findings regarding the adoption of the new irrigation technology among adopters and non-adopters (see Table 4). More specifically and in terms of TE, adopters and non-adopters show similar levels of technology adoption, with adopters having a slightly lower TGR (0.944) compared to non-adopters (0.971). This implies that adopters have used a technology that is slightly less productive than non-adopters, though the difference is not substantial. On the other hand, the disparities in WUE and WCE between adopters and non-adopters are more pronounced. Adopters demonstrate higher TGR values for both WUE (0.823) and WCE (0.846) compared to non-adopters (WUE: 0.587, WCE: 0.586). These results suggest that adopters have a more advanced technological infrastructure for water use and conservation, resulting in higher efficiency levels compared to non-adopters. This outcome aligns with the underlying objectives of the project, which aimed to address water limitations in the region. The higher technology adoption levels among adopters, particularly in terms of WUE and WCE, indicate that they have embraced technologies that facilitate more efficient water utilization and conservation.

4.3. Determinants of efficiency scores

Table 5 provides an overview of the regression results examining the relationship between potential influencing variables and the efficiency scores among adopters and non-adopters. The complete regression results can be found in the Appendix, specifically in Tables A1-A8. Furthermore, we incorporated the technical efficiency scores as an explanatory variable in model 2 to explore potential synergies or trade-offs between water use efficiency and the production of intended output.

Table 4
Statistics for technology gap ratio (TGR) for the whole sample over the period 2009–2013.

TGR for	Adopters	Non-adopters
TE	0.944 (0.074)	0.971 (0.049)
WCE	0.846 (0.218)	0.586 (0.295)
WUE	0.823 (0.197)	0.587 (0.288)

The results of the truncated regression of the technical efficiency indicate that, overall, most of the examined factors do not have a significant impact on technical efficiency among both adopters and non-adopters. Factors such as age, education, extension services, subsidies, aridity index, and water holding capacity show non-significant coefficients, suggesting that their influence on technical efficiency is weak or indiscernible within the studied context. However, it is noteworthy that farm size emerges as a notable exception, with a significant negative impact on technical efficiency among adopters. The findings suggest that larger farms tend to have lower technical efficiency. This finding aligns with an important and established microeconomic literature that has consistently demonstrated an inverse relationship between economic performance and farm size (Sheng and Chancellor, 2019). According to this literature, smaller farms are often found to be more productive and potentially benefiting from more efficient farming practices. While the lack of significant effects of contextual variables on technical efficiency aligns with previous findings in the literature, it is still somewhat surprising. However, it is important to consider the small sample size in this study, which may have limited the statistical power to detect significant effects. Upon closer examination of the technical efficiency scores, it becomes evident that there is relatively low variation among farmers. Specifically, the coefficient of variation is 9 for adopters and 11.4 for non-adopters, indicating that the farmers in the study exhibit similar performance capabilities. The relatively low variation in technical efficiency scores may contribute to the non-significant findings, as the limited range of performance levels makes it challenging to detect significant relationships with the examined contextual variables.

Considering now the results of the truncated regression of water use and water conservation efficiency against the same set of contextual variables, we find some interesting results. Overall, we find very similar patterns in the impact of the contextual factors on both WCE and WUE. It is widely accepted in economics that higher levels of education among farmers have a positive impact on their performance. Increased education is believed to enable farmers to maximize their output using existing resources effectively and enhance their ability to allocate resources efficiently, particularly in the face of changing environmental conditions. The relationship between education and farmers' efficiency has been extensively explored in agricultural studies (Bravo-Ureta and Pinheiro, 1993). While many studies support a strong positive association between education and farmers' efficiency, other studies have found no significant correlation, and in a few instances, a negative relationship has been uncovered. Our results are against the a priori expectations and suggest that increased education will have a negative impact on WUE and WCE. Assuming that this negative relationship between education and sustainable water management practices is not convincing, one could hypothesize that farmers prioritize profit maximization over non-use values when making decisions about their production factors. This finding aligns with the commonly held belief that farmers tend to prioritize economic considerations over other factors,

Table 5
Parameter Estimates of the regression models.

	Technical efficiency		Water conservation efficiency		Water use efficiency (model 1)		Water use efficiency (model 2)	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Technical efficiency	–	–	–	–	–	–	0.398***	0.349*
Age	−0.106	0.041	0.106	−0.067	0.064	−0.089	0.081	−0.084
Education	0.042	0.095	−0.307***	−0.215***	−0.277***	−0.209***	−0.298***	−0.216***
Extension	−0.004	−0.003	−0.009	−0.011	−0.008**	−0.010	−0.009**	−0.012
Farm size	−0.138***	−0.004	0.055	0.057	0.050	0.053	0.075**	0.057
Subsidies	−0.016	0.007	−0.015	−0.013	−0.022	−0.023	−0.015	−0.008
Aridity Index	−0.050	−0.048	−0.044	−0.318***	−0.046	−0.319***	−0.058	−0.301***
Water Holding Capacity	−0.065	−0.078	−0.255***	0.064	−0.253***	0.034	−0.219***	0.068

Note: *, **, *** indicate significance at the 10 %, 5 %, 1 % level, respectively.

such as environmental or social values, when managing their agricultural operations. Consistent with this finding, the provision of extension services is also found to decrease farmers' efficiencies, although the effect is only significant in the model measuring water use efficiency for adopters.

The aridity index, calculated by dividing the average yearly temperature by the total annual rainfall in a specific area, serves as a measure of climate changes and its impact on water availability. It provides insight into the overall dryness or aridity of a specific area, considering the balance between temperature and precipitation patterns. A higher aridity index indicates a drier climate with less precipitation relative to the average temperature, while a lower index suggests a more humid environment with greater precipitation relative to temperature. Consistent with this idea, the aridity index is found to have a negative and significant impact on both water use and water conservation efficiency among non-adopters. When the aridity index is higher, indicating a drier climate with limited precipitation relative to temperature, it becomes challenging for farmers to conserve and efficiently use water resources. This negative impact highlights the difficulties faced in water conservation as aridity increases, leading to lower efficiency in water utilization. Furthermore, an interesting observation emerges when considering adopters. In this case, the analysis shows that the aridity index does not significantly impact water efficiency scores. This suggests that the adoption of advanced irrigation technologies allows farmers to overcome the negative effects of aridity on water management. By implementing more efficient irrigation techniques, such as sprinklers, farmers can optimize water usage and adapt to arid conditions more effectively.

Water holding capacity is another environmental factor that can affect farmers' water usage and their ability to conserve water effectively. It serves as an indicator of the soil's hydraulic conductivity, which refers to how well water can move through the soil. The negative impact of high water holding capacity on water use and water conservation efficiency for farmers who have adopted sprinkler irrigation technology is quite surprising. The adoption of alternative technologies like sprinklers is generally expected to enhance irrigation practices and thus water use and conservation efficiency. However, in the case of soils with high water holding capacity, this expectation is not met. The excessive water retention characteristic of such soils can lead to over-irrigation, as they hold more water than necessary for optimal plant growth. This results in wastage of water and reduced conservation efficiency (Chartzoulakis and Bertaki, 2015). Additionally, the slower water infiltration rates in soils with high water holding capacity can lead to surface runoff and insufficient water reaching the root zone, further decreasing efficiency (Basche and DeLonge, 2019). Lastly, poor drainage in these soils also contributes to waterlogging issues, reducing crop productivity and increasing the risk of root damage (Kaur et al., 2020). Overall, while the adoption of sprinklers holds potential benefits, the unexpected negative impact of high water holding capacity on water use and conservation efficiency highlights the importance of considering soil characteristics in irrigation practices to optimize water management efforts. Results also show that the farmers' age and subsidies do not have a statistically significant effect on the efficiency scores.

Finally, to explore the potential synergies or trade-offs between water use efficiency and desired output production, the second model assessing water use efficiency was employed. This model incorporated technical efficiency as an explanatory variable. The regression results indicated a significant and positive relationship between technical efficiency and water use efficiency. This finding suggests a complementary association, indicating that improving technical efficiency can contribute to enhanced water use efficiency. Moreover, the results from model 2 provide further confirmation and support the findings obtained in model 1, reinforcing the notion that these relationships are not coincidental or misleading.

5. Discussion and policy implications

Our result shows that a high level of technical efficiency is associated with a lower level of water use and water conservation performance. This finding supports earlier research that indicated high levels of technical efficiency are associated with relatively poor environmental performance. In fact, the relationship between economic performance and water use efficiency in agriculture can be positive or negative, depending on the context and the indicators used. For example, a positive relationship can be observed when farmers adopt improved irrigation technologies or practices that increase crop yields and reduce water losses, resulting in higher water productivity and lower water footprint (Dinar and Zilberman, 1991). While a negative relationship can be observed when farmers over-irrigate their crops due to low water prices or subsidies, resulting in lower productivity and higher water footprint (Oweis and Hachum, 2009). Our study findings indicate a positive correlation between technical efficiency and water use efficiency, suggesting that improvements in one can complement the other. However, interpreting this relationship becomes more complex when considering the sector as a whole. At the farm level, enhanced technical performance leads to a reduction in water usage for producing the same amount of vegetables, resulting in improved water use efficiency. To enhance water use efficiency at the sector level, it is important to encourage newly established farms or the next generation of farmers to adopt environmentally friendly practices and advanced technologies in their production techniques. However, if the sole aim of improving technical efficiency is to increase vegetable production, the impact on water use efficiency may not be significant or could even be negative. The extent to which enhancements in technical efficiency translate into better water use efficiency or increased agricultural outputs depends on factors such as technological innovations, market dynamics, and changes in the policy environment.

Our results may justify the need to prioritize and promote the adoption of advanced technological infrastructure in agriculture for water use and conservation. Policymakers should focus on increasing awareness about the benefits of water-efficient technologies, while also providing financial support through incentives, subsidies, and low-interest loans especially at the first years after adoption while the farmers are still learning on how to use the new agricultural technology. Additionally, to ensure the effectiveness of these policies, it is important to establish monitoring systems that track technology adoption rates and evaluate the impact of implemented measures (Klerkx et al., 2019). Furthermore, education can help farmers understand the potential cost savings, increased productivity, and environmental benefits associated with using water-efficient technologies. However, it is worth considering the challenge posed by the negative impact of farmers' education level on water use efficiency. To address this, targeted training programs can be developed to enhance farmers' knowledge and skills in water-efficient practices (Bitsch and Olynk, 2007). Additionally, demonstrating the benefits through projects and collaborations with agricultural extension services can also be effective (Polasky, 2009). By implementing these strategies, farmers can be empowered with the necessary education and skills to effectively implement water-efficient techniques and improve overall water use efficiency.

Moreover, our results reveal the adoption of sprinkler irrigation technology alone is not sufficient to improve water use and conservation efficiency in agriculture, especially in soils with high water holding capacity. Therefore, policy makers should consider implementing complementary measures to address the challenges posed by such soils, such as providing technical guidance and training to farmers on how to adjust their irrigation schedules and amounts according to the soil moisture status and crop water requirements. Promoting the use of soil amendments or practices that can improve the soil infiltration rate and drainage, such as organic matter, mulching, cover crops, or subsoiling (Martey and Kuwornu, 2021). Encouraging the adoption of crop varieties or species that are more tolerant to waterlogging or excess soil moisture (Kaur et al., 2020). Finally, implementing incentives or regulations that can discourage over-irrigation and encourage water conservation, such as water pricing, subsidies, quotas, or audits.

6. Concluding remarks

The importance of water management issues in agriculture is underscored by the need for an integrated approach that considers both economic and environmental indicators in farm performance measures. This study specifically focuses on incorporating water-related indicators into performance evaluations to assess the eco-efficiency (EE) of farms. Eco-efficiency is defined as the ratio between the production of intended outputs and the negative environmental impacts resulting from the production process, with a particular emphasis on irrigation practices. Here, we utilize a combination of Data Envelopment Analysis (DEA) and econometric analysis to calculate efficiency scores and identify the factors influencing efficiency for a sample of small-scale greenhouse farms in Crete during the period 2009–2013.

The study's findings include a number of key findings. First off, the pooled sample's average technical efficiency score is 0.891, which denotes a comparatively high level of economic performance. However, as evidenced by the bimodal distribution of technical efficiency scores, there is an economic performance heterogeneity. Second, with average scores of 0.180 and 0.174, respectively, the scores for water conservation efficiency and water use efficiency indicate room for improvement. Moreover, the distribution of efficiency scores is strongly right-skewed, indicating the need for better water management practices. Thirdly, adopters of an alternative irrigation technology demonstrate higher levels of technical efficiency compared to the pooled sample, while non-adopters exhibit even higher levels. However, adopters have relatively higher water conservation and use efficiency, indicating the benefits of adopting advanced technologies for water management. Finally, contrary to expectations, increased education among farmers has a negative impact on water conservation and use efficiency. Additionally, a higher aridity index adversely affects water management efficiency among non-adopters. These findings emphasize the need for targeted interventions to improve water management practices, considering factors such as technology adoption, education, and climatic conditions.

As this work presents a novel application for evaluating water conservation behavior through an eco-efficiency analysis at the farm-level, it is subject to a number of limitations. First, our water loss estimation is an approximation of actual water loss. Given the dynamic nature of climatic and soil conditions, variations over time may introduce some degree of imprecision. Additionally, our method focuses solely on water loss and does not account for broader farm management practices that encompass conservation efforts beyond water volume reduction. Second, our eco-efficiency measure does not capture all ecological pressures. Instead, it concentrates specifically on water conservation. Consequently, we are unable to address potentially significant interactions between water resource management and other ecological impacts, such as nutrient leaching or water quality deterioration.

Finally, we would like to suggest several directions for future research. From a methodological perspective, prioritizing dynamic assessment models that account for temporal variations in climatic and soil conditions would enhance the adaptability and resilience of greenhouse farming systems. Such models could offer more accurate evaluations of water use and eco-efficiency, particularly under changing environmental conditions. Furthermore, incorporating additional sustainability indicators, such as soil health and energy efficiency, would provide a more comprehensive understanding of resilience and reveal synergies between water management and ecological sustainability. Lastly, it would be valuable to conduct similar studies using alternative datasets, covering different regions and time periods, to compare and contextualize results across varying environmental and agricultural settings.

CRediT authorship contribution statement

Amer Ait Sidhoum: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Maria Vrachioli:** Conceptualization, Investigation, Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

footnote 2

Appendix A. Appendix

Table A1
Full results of the truncated regression analysis (Water use efficiency- Non-adopters – Model 1).

					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
TE	0.349	0.198	1.770	0.077	−0.046	0.775
Age	−0.084	0.072	−1.170	0.242	−0.221	0.052
Education	−0.216	0.051	−4.200	0.000	−0.317	−0.118
Extension	−0.012	0.012	−1.030	0.303	−0.037	0.009
Farm size	0.057	0.047	1.210	0.224	−0.033	0.150
Subsidies	−0.008	0.028	−0.280	0.776	−0.064	0.043
Aridity Index	−0.301	0.066	−4.600	0.000	−0.437	−0.176
Water Holding Capacity	0.068	0.130	0.520	0.603	−0.187	0.318
D2010	−0.068	0.055	−1.250	0.211	−0.165	0.041
D2011	−0.147	0.050	−2.930	0.003	−0.241	−0.049
D2012	−0.052	0.051	−1.020	0.310	−0.152	0.046
Constant	1.481	0.950	1.560	0.119	−0.352	3.286

Table A2
Full results of the truncated regression analysis (Water use efficiency- Non-adopters – Model 2).

					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
Age	−0.089	0.071	−1.250	0.212	−0.226	0.058
Education	−0.209	0.051	−4.050	0.000	−0.311	−0.099
Extension	−0.010	0.012	−0.850	0.395	−0.032	0.014
Farm size	0.053	0.048	1.100	0.272	−0.040	0.153
Subsidies	−0.023	0.027	−0.840	0.403	−0.080	0.029
Aridity Index	−0.319	0.070	−4.570	0.000	−0.455	−0.175
Water Holding Capacity	0.034	0.138	0.250	0.805	−0.239	0.309
D2010	−0.078	0.054	−1.450	0.147	−0.181	0.026
D2011	−0.150	0.051	−2.930	0.003	−0.260	−0.056
D2012	−0.062	0.054	−1.140	0.256	−0.166	0.045
Constant	1.357	0.996	1.360	0.173	−0.630	3.300

Table A3
Full results of the truncated regression analysis (Water conservation efficiency- Non-adopters).

					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
Age	−0.067	0.070	−0.950	0.343	−0.211	0.062
Education	−0.215	0.052	−4.130	0.000	−0.314	−0.108
Extension	−0.011	0.012	−0.870	0.385	−0.034	0.015
Farm size	0.057	0.046	1.230	0.218	−0.035	0.146
Subsidies	−0.013	0.026	−0.490	0.627	−0.066	0.038
Aridity Index	−0.318	0.070	−4.540	0.000	−0.456	−0.183
Water Holding Capacity	0.064	0.134	0.480	0.633	−0.209	0.323
D2010	−0.067	0.054	−1.260	0.208	−0.180	0.037
D2011	−0.152	0.050	−3.030	0.002	−0.252	−0.060
D2012	−0.065	0.050	−1.300	0.195	−0.157	0.032
Constant	1.403	0.972	1.440	0.149	−0.540	3.289

Table A4
Full results of the truncated regression analysis (Technical efficiency- Non-adopters).

TE non-adopters					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
Age	0.041	0.133	0.310	0.757	−0.233	0.294
Education	0.095	0.083	1.150	0.250	−0.081	0.247
Extension	−0.003	0.017	−0.170	0.863	−0.034	0.033
Farm size	−0.004	0.126	−0.030	0.974	−0.279	0.234
Subsidies	0.007	0.040	0.180	0.860	−0.073	0.085
Aridity Index	−0.048	0.093	−0.520	0.602	−0.249	0.119

(*continued on next page*)

Table A4 (*continued*)

TE non-adopters					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
Water Holding Capacity	−0.078	0.171	−0.450	0.650	−0.405	0.278
D2010	−0.119	0.073	−1.640	0.100	−0.265	0.028
D2011	−0.048	0.064	−0.740	0.457	−0.178	0.082
D2012	−0.099	0.068	−1.470	0.143	−0.243	0.030
Constant	0.108	1.225	0.090	0.930	−1.991	2.677

Table A5
Full results of the truncated regression analysis (Water use efficiency- Adopters – Model 1).

					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
TE	0.398	0.119	3.330	0.001	0.173	0.640
Age	0.081	0.082	0.990	0.323	−0.094	0.233
Education	−0.298	0.089	−3.340	0.001	−0.473	−0.122
Extension	−0.009	0.004	−2.160	0.031	−0.016	−0.001
Farm size	0.075	0.035	2.130	0.034	0.006	0.142
Subsidies	−0.015	0.024	−0.640	0.524	−0.058	0.032
Aridity Index	−0.058	0.045	−1.290	0.197	−0.149	0.027
Water Holding Capacity	−0.219	0.078	−2.800	0.005	−0.368	−0.062
D2010	0.047	0.039	1.220	0.222	−0.026	0.124
D2011	−0.079	0.037	−2.130	0.033	−0.148	−0.004
D2012	−0.011	0.038	−0.300	0.764	−0.085	0.060
Constant	−0.811	0.650	−1.250	0.212	−2.048	0.417

Table A6
Full results of the truncated regression analysis (Water use efficiency- Adopters – Model 2).

					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
Age	0.064	0.087	0.730	0.467	−0.106	0.244
Education	−0.277	0.095	−2.930	0.003	−0.465	−0.094
Extension	−0.008	0.004	−1.980	0.047	−0.016	0.000
Farm size	0.050	0.036	1.380	0.167	−0.017	0.122
Subsidies	−0.022	0.024	−0.920	0.358	−0.071	0.024
Aridity Index	−0.046	0.048	−0.960	0.336	−0.146	0.046
Water Holding Capacity	−0.253	0.080	−3.140	0.002	−0.409	−0.089
D2010	0.053	0.042	1.260	0.209	−0.030	0.134
D2011	−0.078	0.040	−1.980	0.048	−0.160	−0.004
D2012	−0.015	0.040	−0.360	0.715	−0.100	0.062
Constant	−0.917	0.679	−1.350	0.177	−2.183	0.456

Table A7
Full results of the truncated regression analysis (Water conservation efficiency- Adopters).

WCE adopters					95 % Conf. Interval	
	Coef.	Bootstrap Std. Err.	z	P > |z|	Lower bound	Upper bound
Age	0.106	0.091	1.170	0.244	−0.077	0.275
Education	−0.307	0.099	−3.100	0.002	−0.495	−0.107
Extension	−0.009	0.004	−2.140	0.032	−0.018	−0.001
Farm size	0.055	0.039	1.410	0.157	−0.021	0.132
Subsidies	−0.015	0.025	−0.610	0.540	−0.066	0.033
Aridity Index	−0.044	0.049	−0.910	0.362	−0.146	0.045
Water Holding Capacity	−0.255	0.084	−3.040	0.002	−0.408	−0.093
D2010	0.057	0.042	1.340	0.181	−0.026	0.143
D2011	−0.084	0.040	−2.090	0.037	−0.159	−0.005
D2012	−0.016	0.042	−0.380	0.704	−0.094	0.069
Constant	−1.054	0.714	−1.480	0.140	−2.517	0.287

Table A8
Full results of the truncated regression analysis (Technical efficiency- Adopters).

	Coef.	Bootstrap Std. Err.	z	P > |z|	95 % Conf. Interval	
					Lower bound	Upper bound
Age	−0.106	0.096	−1.110	0.265	−0.297	0.099
Education	0.042	0.116	0.360	0.719	−0.186	0.283
Extension	−0.004	0.006	−0.680	0.498	−0.014	0.007
Farm size	−0.138	0.052	−2.660	0.008	−0.245	−0.033
Subsidies	−0.016	0.029	−0.550	0.582	−0.072	0.043
Aridity Index	−0.050	0.049	−1.020	0.309	−0.143	0.045
Water Holding Capacity	−0.065	0.094	−0.700	0.485	−0.237	0.131
D2010	0.005	0.047	0.110	0.914	−0.084	0.102
D2011	−0.013	0.045	−0.280	0.783	−0.101	0.079
D2012	0.014	0.043	0.310	0.753	−0.070	0.099
Constant	1.395	0.826	1.690	0.091	−0.301	2.989

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