Measuring irrigation water use efficiency using stochastic production frontier: An application on citrus producing farms in Tunisia

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Abstract

This paper proposes an alternative measure of irrigation water efficiency based on the concept of input-specific technical efficiency. It uses a stochastic production frontier approach, based on Battese and Coelli's (1995) inefficiency effect model, to obtain farm-specific estimates of technical and irrigation water efficiency, and a second-stage regression approach to identify the factors that influence irrigation water efficiency differentials. This methodology was applied to a sample of 144 citrus farms in Nabeul, Tunisia. Technical efficiency varies widely, suggesting that these citrus farmers could increase their production by as much 33% by using inputs more efficiently. Mean irrigation water efficiency is similarly variable, and on average below technical efficiency, suggesting that they could produce the same quantity of citrus using the same quantity of inputs but 47% less water. Finally, the results showed that the farmer's age, education level and agricultural training, and the farm's size, share of productive trees and availability of water tend to affect the degree of both technical and irrigation water efficiency positively.

Keywords: Water efficiency; Stochastic frontier production function; Citrus farms; Tunisia

Cet article propose une mesure alternative de l'efficacité de l'eau d'irrigation basée sur le concept de l'efficacité technique des intrants. Il utilise un modèle d'estimation de la frontière stochastique de production, basé sur les effets d'inefficacité de l'approche de Battese et Coelli (1995), pour obtenir une estimation de l'efficacité technique de l'eau d'irrigation des fermes. Une deuxième phase d'approche régressive est appliquée pour identifier les facteurs qui influent sur les différentiels d'efficacité de l'eau d'irrigation. Cette méthodologie a été appliquée à un échantillon de 144 exploitations agrumicoles de Nabeul en Tunisie. L'efficacité technique varie beaucoup, ce qui suggère que ces agrumiculteurs pourraient

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augmenter leur production jusqu'à 33 pourcent en utilisant les intrants de manière plus efficace. La moyenne de l'efficacité de l'irrigation de l'eau varie de façon similaire et se situe généralement au-dessous de l'efficacité technique, ce qui suggère qu'ils pourraient produire la même quantité d'agrumes en utilisant la même quantité d'intrants mais avec 47% moins d'eau. Finalement, les résultats ont montré que l'âge des agrumiculteurs, leur niveau d'éducation, leur formation agricole, la taille de la ferme, la part d'arbres productifs et la disponibilité de l'eau tendent à influer positivement sur le degré de l'efficacité technique et sur celui de l'irrigation de l'eau.

Mots-clés: *Efficacité de l'eau; Fonction de la frontière stochastique de production; Exploitations agrumicoles; Tunisie*

1. Introduction

Irrigation water is becoming an increasingly scarce resource for agriculture in many regions of the world. Common to past policy schemes was the development of an adequate irrigation infrastructure to guarantee the supply of irrigation water as the demand for agricultural products increased. However, these expansionary policies have led to a massive use of irrigation water at a heavily subsidized cost, and a scarcity of the resource. Water shortage has become an increasing social and economic concern for policy makers and for those who must compete for the resource. In particular, policy makers are beginning to point to agriculture as the sector at the core of the water problem.

Tunisian water reserves are estimated at 4.7 billion m^3/year, of which 2.7 billion m^3 comes from annual rivers in the north, 0.7 billion m^3 from groundwater in the centre, the plains and the coastal area, and approximately 1.3 billion m^3 from the deep groundwater table mainly in the south. Water resources are unevenly distributed across the country, with around 60% located in the north, 18% in the centre and 22% in the south. Water resources that have a salinity of less than 1.5 g/liter are distributed as follows: 72% of surface water resources, 8% of shallow groundwater and 20% of deep groundwater. Water resources management and planning are outlined in the country's five-year development plans. The goals are to mobilize most of the surface water by completing 42 dams and constructing 203 hillside dams, 1000 hillside lakes and 4000 recharge and floodwater diversion structures. This infrastructure, planned for the year 2010, will account for 87% of the potential (4760 million m^3). In addition, the plans emphasize water harvesting and wastewater re-utilization.

Tunisia is known for its saline water: 30% of its water has a salinity of more than 3 g/liter. The salinity of the drinking water supply is mostly less than 1.5 g/liter. Most of the water used for agricultural irrigation has a salinity ranging from 2 to 3.5 g/liter, and the rest is from 3.5 to 4.5 g/liter.

Taking into account the limited water resources and the frequent disparity between supply and demand during dry seasons, Tunisia has engaged over the last three decades in a dynamic program of water mobilization. Several investment projects have been granted, reaching 9% of total investments in the government's Development Plan VIII (1992–1996, in which it has invested 9% in water programs). Agriculture, which accounts for approximately 12% of the GDP, is the sector that consumes the most water (more than 80% of the total demand).

Irrigated agriculture represents 35% of the output value derived from the agricultural sector, 20% of exports and 27% of agricultural employment (Ministry of Agriculture and Water Resources 2003). Irrigated areas contribute 95% of the vegetable production, 70% of the fruit and 30% of the dairy. The average efficiency of the irrigation networks is relatively weak, estimated at approximately 50% (Bachta & Ghersi 2004).

The non-conventional water sources (reclaimed wastewater and desalinated water) represent only 5% of the available resources. The National Office of Water Sanitation (ONAS) collects 178 million m^3 of used water in the public sanitation network, of which 156 million m^3 are treated at 61 purification stations. Sea water is not exploited because desalination is an expensive option.

Tunisia has 411.4 thousand hectares of irrigated land. Tree crops come first, with an area of 152.6 thousand ha (37% of the total surface), vegetables second (30%), followed by forages (16%), cereals (16%), and other industrial crops (1%). The industrial and tourism sectors use 5% and 1% of water resources, respectively. The drinking water service uses 11% in the rural area. This service supplied 38% of the population in 1990 and 80% in 2000.

The objective of this paper is to propose an alternative measure of irrigation water efficiency based on the concept of input-specific technical efficiency, which contrasts with measures previously described in the literature. The proposed measure is a non-radial, input-oriented measure of input-specific technical efficiency. It has an economic rather than an engineering meaning and is defined as the ratio of the minimum feasible water use to observed water use, conditional on production technology and observed levels of output and other used inputs. It provides information on how much water could be saved without altering the output produced and the quantities of other inputs used. This measure explicitly recognizes that each irrigation system could be technically inefficient for several reasons that can be explored through statistical methods.

The remainder of this paper is organized as follows. Section 2 presents the methodological framework, paying special attention to the measurement of irrigation water efficiency in the empirical model, explains the efficiency differentials, and describes the statistical data and variables used in the model. Section 3 presents the empirical results and discussion, and Section 4 concludes with some remarks on policy implications.

2. Methodological framework

2.1. Measuring irrigation water efficiency

Let technology be described by the following stochastic production frontier function (Karagiannis et al. 2003):

$$y_i = f(x_i, w_i,; a) \exp (\varepsilon_i \equiv v_i - u_i) \quad (1)$$

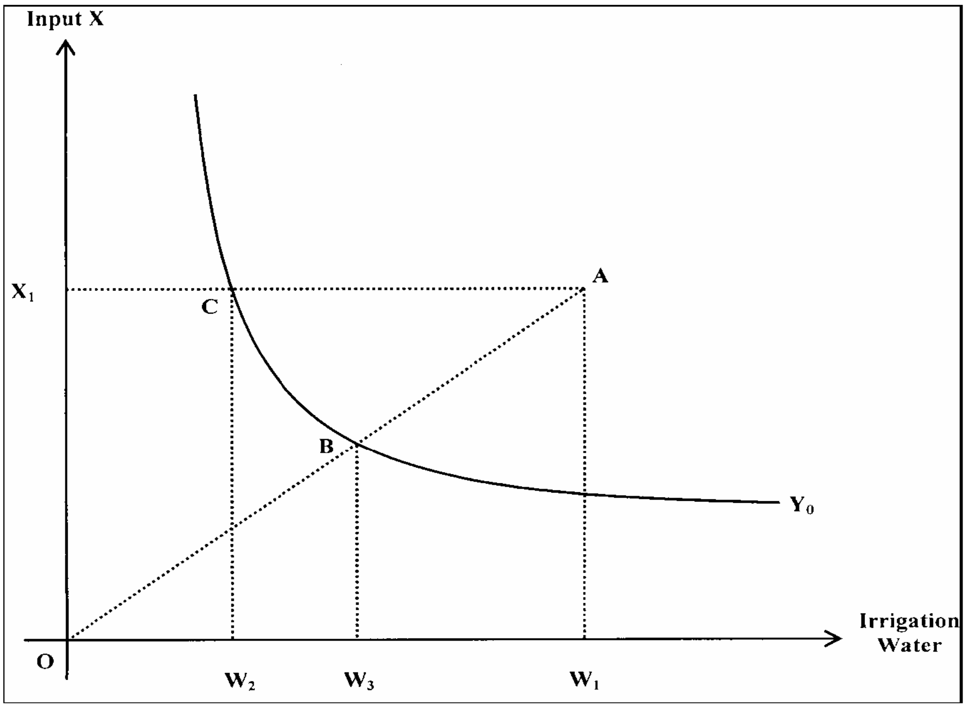
where i = 1,2,....,N refers to farms, $y \in R_+$ is the quantity of output produced, $x \in R_+^m$ is a vector of input quantities used, w is irrigation water, and ε_i is a composed error term consisting of a symmetric and normally distributed error term, v_i, representing those factors that cannot be controlled by farmers (i.e. weather effects), measurement errors and left-out explanatory variables, and a one-sided non-negative error term, $0 \leq u_i$, reflecting the shortfall of a farm's output from its production frontier, because of technical inefficiency. Next, farm specific estimates of output-oriented technical efficiency are obtained as $TE_i^{0} = \exp(-u_i)$ (Kumbhakar & Lovell 2000), while farm-specific estimates of input-oriented technical efficiency are derived using equation (1) with $y_i = f(v_i x_i, v_i w_i; \alpha) \exp(v_i)$ and solving for $TE_i^{1} = v_i$ (Atkinson & Cornwell 1994; Reinhard et al. 1999). Given strict monotonicity, both measures result in the same ranking but in a different magnitude of efficiency scores. TE_i^{0} is greater than, equal to, or less than TE_i^{1} whenever returns to scale are decreasing, constant, or increasing, respectively (Fare & Lovell 1978).

The above measures of efficiency cannot identify the efficient use of individual inputs. For this reason, the proposed irrigation water efficiency measure is based on the non-radial notion of input-specific technical efficiency (Kopp 1981). In particular, it is defined as the ratio of minimum feasible to observed levels of outputs and input. Thus, irrigation water efficiency is an input-oriented, single-factor measure of technical efficiency defined as:

$$IE^{1} = [\min\{\lambda: f(x, \lambda w; a) \geq y\}] \rightarrow (0, 1) \qquad (2)$$

Irrigation water efficiency, as defined in (2), has an input-conserving interpretation, which, however, cannot be converted into a cost saving measure owing to its non-radial nature (Kopp 1981).

The proposed measure of irrigation water efficiency is shown in Figure 1 (Karagiannis et al. 2003).



Source: Karagiannis et al. (2003)

Figure 1: Proposed measure of irrigation water efficiency

Let the ith inefficient farmer produce output Y_0 by using x_1 units of all other inputs and w_1 units of irrigation water. Then $TE_i^{\ 1}$ = OB /OA and $IE_i^{\ 1} = x_1 C / x_1 A = w_2 / w_1$. The proposed irrigation water efficiency measure determines both the minimum feasible water use (w_2) and the maximum possible reduction in water use ($w_1 - w_2$) that still permits the production of Y_0 units of output with unaltered use of all other inputs. On the other hand, according to the $TE_i^{\ 1}$ measure, the maximum possible reduction in water use required to make the ith farm technically efficient is ($w_1 - w_3$). From Figure 1 it is clear that the former ($w_1 - w_2$) will always be greater than the latter ($w_1 - w_3$). Consequently, the maximum possible reduction in water use suggested by $IE_i^{\ 1}$ should be considered as an upper bound (Akridge 1989).

Conceptually, measurement of $IE_i^{\ 1}$ requires an estimate for the quantity (w_2), which is not observed. Nevertheless, using $IE_i^{\ 1} = w_2 / w_1$ it can easily be seen that $w2=w1*IE_i^1$. By substituting this into (1) and by noticing that point C in Figure 1 lies on the frontier, i.e. $u_i = 0$, (1) may be rewritten as:

$$y_i = f(x_i, w_i^E; a) \exp(u_i) \tag{3}$$

where $w_i^E = w_2$ (Reinhard et al. 1999). Next, a measure of $IE_i^{\ 1}$ can be obtained by equating (1) with (3) and by using the econometrically estimated parameters α.

Since $IE_i^{\ 1}$ is a non-radial efficiency measure that does not have a direct cost-saving interpretation, the single-factor technical cost efficiency measure can instead be used to evaluate the potential cost savings accruing to more effective management of a single factor (Kopp 1981). Next, irrigation water technical cost efficiency, $ITCE_i$, can be defined as the potential cost savings from adjusting irrigation water to a technically efficient level while holding all other inputs at observed levels. Following Akridge (1989), farm-specific estimates of $ITCE_i$ may be obtained as:

$$ITCE_i = S_{wi} IE_i^I + \sum_{j=1}^{J} S_{ji} \tag{4}$$

where S_{wi} and S_{ji} are the ith farm's observed input cost shares for irrigation water and the jth input, respectively, given that $0 < IE_i^{\ I} \leq 1$ and $S_{wi} IE_i^I + \sum_{j=1}^{J} S_{ji} = 1$ for all i, $0 < ITCE_i \leq 1$.

However, cost saving will vary with factor prices and relatively inefficient water use in a physical sense can be relatively efficient in a cost sense, and vice versa (Kopp 1981).

2.2. Empirical model

Let the unknown production frontier (1) be approximated by the following *translog* specification:

$$\begin{aligned} \ln y_i = {} & \alpha_0 + \sum_{j=1}^{J} \alpha_j \ln x_{ji} + \frac{1}{2}\left(\sum_{j=1}^{J}\sum_{k=1}^{J} \alpha_{jk} \ln x_{ji} \ln x_{ki} \right) + \alpha_w \ln w_i \\ & + \frac{1}{2}\left(\alpha_{ww} \ln w_i^2 + \sum_{j=1}^{J} \alpha_{jw} \ln x_{ji} \ln w_i \right) + v_i - u_i \end{aligned} \tag{5}$$

Using Battese and Coelli's (1995) inefficiency effect model, the one-sided error term is specified as:

$u_i = g(z_i; \delta) + w_i$ (6)

where z is a vector of variables used to explain efficiency differentials among farmers, δ is a vector of parameters to be estimated (including an intercept term), and w_i is an *iid* random variable with zero mean and variance defined by the truncation of the normal distribution such that $w_i \geq -[g(z_i; \delta)]$. The model (5) and (6) can be estimated econometrically in a single stage using ML techniques and the frontier (version 4.1) computer package developed by Coelli (1992). The variance parameters of the likelihood function are estimated in term of $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma^2}$, where the γ parameter has a value between zero and one.

Using the estimated parameters and variances, farm-specific estimates of TE_i^0 are obtained as:

$$TE_i^0 = E\{\exp(-u_i/\varepsilon_i)\} = \exp\left[\left(-\mu_i^0 + 0.5\,G_0^2\right)\left(\frac{\phi[(\mu_i^0/G_0) - G_0]}{\phi(\mu_i^0/G_0)}\right)\right] \qquad (7)$$

Where,

$$\mu_i^0 = \frac{G_v^2\mu_i - G_u^2\varepsilon_i}{G_v^2 + G_u^2},\; G_0^2 = \frac{G_u^2 G_v^2}{G_u^2 + G_v^2}$$

Φ is the cumulative density function of the standard normal random variable and E is the expectation operator.

On the other hand, farm specific estimates of $IE_i^{\,1}$ are derived by using (3) and the following relations developed by Reinhard et al. (1999) for the *translog* specification (5):

$$IE_i^I = \exp\left[\left\{-\xi_i \pm \left(\sqrt{\xi_i^2 - 2\alpha_{ww}u_i}\right)\right\}/\alpha_{ww}\right] \qquad (8)$$

Where,

$$\xi_i = \frac{\partial \ln y_i}{\partial \ln w_i} = \alpha_w + \sum_{j=1}^{J}\alpha_{jw} + \ln x_{ji} + \alpha_{ww}\ln w_i$$

Given weak monotonicity, a technically efficient farm is also irrigation water efficient and thus only the positive root of (8) is used.

2.3. Explaining efficiency differentials

One of the advantages of Battese and Coelli's (1995) model is that it allows measurement of TE_i^0 and examination of its differentials among farmers to be done with a single-stage estimation procedure. The commonly applied two-stage estimation procedure has been recognized as inconsistent with the assumption of identically distributed inefficiency effects in the stochastic frontier, which is necessary in the ML (maximum likelihood) estimation (Reifschneider & Stevenson 1991; Kumbhakar et al. 1991; Battese & Coelli 1995). However, the two-stage estimation procedure can be used without problems for identifying the factors that influence irrigation water efficiency differentials across farms since IE_i is calculated from the parameter estimates and the estimated one-sided error component of the stochastic production frontier in (1), and this procedure is not directly related to distributional assumptions. The relevant second stage regression model has the following form:

$$\text{Ln } IE_i = h(z_i, \delta) + e_i \tag{9}$$

where h (*) is the deterministic kernel of the regression model, δ is the vector of the parameters to be estimated and e_i is an *iid* random variable with zero mean and constant variance. The above model is estimated with the standard OLS (Ordinary Linear Square).

2.4. Data and variables definitions

A panel data of 144 Tunisian citrus producing farms covering the 2002–2003, 2003–2004 and 2004–2005 periods were collected from surveys conducted in two delegations of the governorate of Nabeul, Tunisia (see Table 1). This reason was chosen because of its importance in the national citrus production, transformation and exports sector. Indeed, according to the Ministry of Agriculture statistics (Ministry of Agriculture and Water Resources 2003), this region represents 1.7% of national agricultural land. It contributes 80% of the national citrus production and more than 90% of citrus exports.

Table 1: Distribution of citrus farms surveyed by delegation and by land area

Delegations	**Private farms**			
	< 1Ha	1 – 2 ha	> 2ha	Total
Beni Khalled	20	31	19	70
Menzel Bouzelfa	12	27	35	74
Total Nabeul	32	58	54	144

The selected sample comprises 32 farms smaller than one hectare (22.22% of the sample), 58 ranging between one and two hectares (40.27%) and 54 larger than two hectares (37.50%). It represents a total agricultural surface of about 392.22 ha. In this area there are 105,921 productive citrus trees, of which 8.63% are younger than five years, 8.49% from five to ten years, 19.23% from ten to 20 years and 63.6% over 20 years. The density of plantation is about 270 trees/ha on average. The production of citrus during 2002/2003, 2003/2004 and 2004/2005 was 2390.7 metric tons per year, on average, which corresponds to 67.7kg/tree and 18.3t/ha.

As we explained at the outset, the dependent variable is the total annual citrus production measured in kg. Aggregate inputs considered in the analysis are: (1) land measured in hectares, (2) total labor measured in working days, (3) chemical inputs measured in Tunisian dinars (TND), (4) irrigation water measured in m^3, and (5) other costs, comprising the rest of inputs used in producing citrus (mechanization, etc.) and measured in TND. Summary statistics of these variables are shown in Table 2. From the surveyed farms, it appears that the average age of respondents is 55.8 years, ranging from 29 to 80. It is also important to indicate that, on average, land holding is 2.61 ha, ranging from 0.2 to 18.5 ha. Of the sample of farmers, 35.33% are illiterate, 30.66 have primary level education, and 34% have at least six years of schooling. It appears that 81.33% of farmers in the sample inherited their farms and the other 18.66% purchased theirs. Most of the farmers (86%) never followed a training program on managing a citrus plantation. Moreover, only 71% of them agree with official estimates of the availability of water, especially during summer. A significant proportion of the surveyed farmers (90.6%) resort to using fertilizer. It is important to note that a large proportion of the total labor is family labor (68.65%), especially for citrus production (82.38%). Finally, in terms of machinery, only 28% of the farmers in the sample have their own tractors. The other 72% have to hire them.

Table 2: Summary statistics of the variables used in the frontier model for citrus producing farms in Tunisia

Notation	Variables	Mean	Std dev	Min	Max
P	Production (in kg)	47814.27	54577.96	2096.76	415129.1
S	Area (in ha)	2.61	3.04	0.2	18,5
L	Labour (in working days)	428.44	364.93	46.5	2950.0
CI	Chemical inputs (in TND)	1937.83	2491.76	0.00	14000.0
IW	Irrigation water (in m^3)	97.90	121.83	0.00	900.00
OC	Other costs (in TND)	631.77	1206.49	0.00	11300.00
AF	Age of farmer (in years)	55.88	10.64	29.00	80.00
SFL	Share of family labour (in %)	0.68	0.36	0.00	1.00
SPT	Share of productive trees (in %)	0.86	0.19	0.00	1.00

Note: 1 TND (Tunisian dinar) = 0.65 euros

4. Results and discussion

4.1. Production structure

The estimated parameters of the *translog* stochastic production frontier are presented in Table 3. From this table it can be seen that all the first-order parameters (α_i) have the anticipated (positive) sign and magnitude. On the other hand, the ratio of farm specific to total variability,

γ, is positive and statistically significant at the 5% level. The value of 0.81 indicates that output-oriented technical efficiency is important in explaining the total variability of output produced. The remaining portion (0.19) is due to factors beyond the farmer's control (weather, diseases, etc.).

Table 3: Parameter estimates and t-values of the inefficiency frontier model of a sample of Tunisian citrus producing farms

Parameters	Estimates	t-student
Stochastic frontier model		
Cte	0.43	5.89**
Ln(S)	0.34	2.98**
Ln(L)	0.03	0.34
Ln(CI)	0.22	3.83**
Ln(IW)	0.33	3.39**
Ln(OC)	0.24	0.51
$Ln(S)^2$	-0.19	-3.91**
$Ln(L)^2$	0.16	2.43**
$Ln(CI)^2$	0.067	2.37**
$Ln(IW)^2$	-0.029	-0.54
$Ln(OC)^2$	-0.003	-0.029
Ln(S)*Ln(L)	0.98	3.87**
Ln(S)*Ln(CI)	-0.38	-2.52**
Ln(S)*Ln(IW)	0.002	1.12
Ln(S)*Ln(OC)	0.79	3.27**
Ln(L)*Ln(CI)	-0.07	-0.43
Ln(L)*Ln(IW)	0.017	2.95**
Ln(L)*Ln(OC)	-0.74	-3.38**
Ln(CI)*Ln(IW)	-0.08	2.25**
Ln(CI)*Ln(OC)	0.44	3.23**
Ln(IW)* Ln(OC)	0.065	4.21**
Variance parameter		
σ^2	0.38	4.86**
γ	0.81	8.45**
Log-likelihood	-79.46	

** significant at 5% level *significant at 10% levelSeveral hypotheses about the model specifications are presented in Table 4. From this table it is evident that the traditional average production function does not adequately represent the production structure of citrus farms in the sample as the null hypothesis $\gamma = 0$ is rejected at the 5% level of significance. Thus, the technical inefficiency effects are in fact stochastic and a significant part of output variability is explained by the existing differences in the degree of output-oriented technical inefficiency.

In addition, the hypothesis that the inefficiency effects are absent (i.e. $\gamma = \delta_0 = \delta_m = 0$) is also rejected at the 5% level of significance. This indicates that the majority of farms in the sample operate below the output-oriented technically efficient frontier. Finally, our model specification cannot be reduced either to Aigner et al.'s (1977) or to Stevenson's (1980) model as the null hypotheses $\delta_0 = \delta_m = 0\ \forall$ m and $\delta_m = 0\ \forall$ m are rejected at the 5% level of significance.

Table 4: Tests of hypotheses for the parameters of the stochastic frontier inefficiency model of a sample of Tunisian citrus producing farms

Null hypotheses	λ -statistic	D.f	Critical value at 5%	Decision
$\gamma = 0$	22.18	2	5.99	Reject of H_0
$\gamma = \delta_0 = \delta_m = 0\ \forall$ m	46.2	20	31.4	Reject of H_0
$\delta_0 = \delta_m = 0\ \forall$ m	41.8	19	30.1	Reject of H_0
$\delta_m = 0\ \forall$ m	38.9	18	28.9	Reject of H_0

Average estimates of production elasticities and returns to scale are presented in Table 5 for the region of study. The estimated production elasticities of all five inputs are positive. They indicate that in the Nabeul region chemical inputs are the most important inputs, followed by irrigation water, other costs and land, while labor has the lowest point estimate, with an average standing at 0.117. In economics terms, the latter means that, holding all other inputs constant, a 1% reduction in irrigation water requires a sacrifice of 0.298% of marketable output. On the other hand, the hypothesis of constant returns to scale is rejected at the 5% level of significance, and returns to scale were found to be increasing (1.106).

A shadow price of irrigation water may be computed by using the mean values of the relevant variables shown in Table 2 and the estimated production elasticity of irrigation water. By combining these figures we find that a reduction of 0.979 m^3 of irrigation water would 'cost' approximately 1.42486 kilograms in terms of foregone quantities and TND0.5429 in terms of foregone revenue. This in turn implies that the shadow price of irrigation water is equal to TND0.546 per m^3, a value that is much higher than the market price charged in Nabeul region, (0.09 and 0.1 TND per m^3). This shadow price should be considered as the upper bound of the true shadow assumption that all other inputs are held constant at their observed levels, which might not be palatable for greater changes in the quantity of irrigation water.

Table 5: Production elasticities and returns to scale of a sample of Tunisian citrus producing farms

Production elasticities	Average
Land	0.133
Labour	0.117
Chemical inputs	0.321
Irrigation water	0.298
Other costs	0.235
Returns to scale	**1.106**

4.2. Technical and irrigation water efficiency

Results for estimates of technical efficiency (TE^0_i), irrigation efficiency (IE^I_i), and irrigation water technical cost efficiency ($ITCE_i$) are showed in Table 6 in the form of frequency distribution within a deciles range. The estimated mean output-oriented technical efficiency ranges from a minimum of 12.8% to a maximum of 90.7% with an average estimate of 67.7%. This result means that a 32.3% increase in production is possible with the present state of technology and unchanged input uses, if technical inefficiency is completely removed. Thus, improving technical efficiency will significantly increase farmers' revenue and profit. On the other hand, mean irrigation water efficiency is found to be 53%, which is much lower than technical efficiency and also exhibits greater variability, ranging from 1.6% to 98.87%. The estimated mean irrigation water efficiency implies that the observed quantity of marketable citrus could have been maintained by using the observed values of other inputs while using 47.0% less irrigation water. This means that farmers can achieve significant savings in water use by improving the way they use the irrigation system and by using more advanced irrigation techniques.

Table 6: Frequency distribution of efficiency ratings of a sample of Tunisian citrus producing farms

Efficiency (%)	**IE^I**	**TE^O**	**ITCE**
$E \leq 20$	23	1	0
$20 < E \leq 30$	10	1	0
$30 < E \leq 40$	11	6	0
$40 < E \leq 50$	16	12	0
$50 < E \leq 60$	17	20	0
$60 < E \leq 70$	27	27	0
$70< E \leq 80$	16	44	9
$80< E \leq 90$	6	30	33
$E > 90$	18	3	102
N	**144**	**144**	**144**
Mean efficiency	53.00	67.73	70.81
Min. efficiency	1.6	12.82	70.21
Max. efficiency	98.87	90.69	99.90

However, the cost savings that could be attained by adjusting irrigation water to its efficient level would be small since its outlays constitute only a small proportion of the total cost. For this reason, the estimated mean $ITCE_t$ is much higher than IE^I_i. The results in Table 6 show that the average technical efficiency of the cost of irrigation, which is in the order of 70.81%, suggests a potential reduction of 29.19% of the total cost if irrigation water is adjusted to its efficient level. In addition, the vast majority of farms have achieved irrigation water technical cost efficiency greater than 90% (71% of farms). The other 29% are using water less efficiently in the technical sense, and there is not much incentive to become efficient, because the potential cost saving is small.

In order to enrich the analysis, the second step of the analysis addresses the sources of efficiency differentials among farmers. For this reason, the inefficiency effects model (equation 6) and the second stage regression (equation 9) have been estimated. Estimation results from these models are presented in Table 7. In the first model of the inefficiency effects, it is important to note that a negative sign of the estimated parameter indicates a positive relationship between technical efficiency and the variable under consideration, while in the second a positive sign depicts a positive relationship between irrigation water efficiency and the corresponding variable.

According to the empirical findings, the farmer's age squared does not seem to affect either technical or irrigation water efficiency. In contrast the farmer's age affects technical and irrigation water efficiency positively. This finding indicates that young farmers are becoming relatively more technically efficient over time by improving learning by doing. On the other hand, farm size, education level, agricultural training, the share of productive trees and the perception of the availability of water tend to affect the degree of both technical and irrigation water efficiency positively. Finally, it is important to note that the share of family labor affects the efficient use of irrigation water positively, but technical efficiency negatively.

Table 7: Explaining efficiency differentials

Parameter	TE^O		IE^I	
	Estimate	**Std error**	**Estimate**	**Std error**
δ_0	0.911	0.291	1.415	0.5068
δ_{FS}	-0.0079	0.0044	-0.0016	0.0078
δ_{AG}	-0.0073	0.0106	-0.0197	0.0174
δ_{AAGG}	0.000008	0.0000	0.0001	0.00015
δ_{EDC}	-0.0081	0.0334	-0.0177	0.0580
δ_{AT}	-0.012	0.0381	-0.0132	0.0661
δ_{FL}	0.007	0.0422	-0.0184	0.0733
δ_{SPT}	-0.035	0.0673	-0.1351	0.1168
δ_{WDP}	-0.012	0.0295	-0.0154	0.0512
R^2			**0.42**	

Notes:
FS –farm's size in hectares
AG and AAGG – farmer's age and age squared in years
EDC – level of schooling (1 = illiterate, 2 = primary, 3 = secondary, 4 = high school)
AT – dummy variable indicating the citrus plantation training programs the farmer has followed
FL – proportion of family labour
SPT – share of productive trees measured in %
WDP – dummy variable indicating farmer's perception of availability of water

5. Concluding remarks

This paper has proposed an alternative measure of irrigation water efficiency based on the concept of input-specific technical efficiency, which contrasts with measures previously described in the literature. The proposed measure provides information on how much water use could be reduced without altering the production output and the quantities of other inputs used. This measure explicitly recognizes that each irrigation system could be technically inefficient for several reasons that can be explored through statistical methods.

The proposed methodology was applied to a randomly selected sample of 144 citrus growing farms in Nabeul, Tunisia. A stochastic production frontier approach, based on Battese and Coelli's (1995) inefficiency effect model, was used to obtain farm-specific estimates of technical and irrigation water efficiency. In addition, a second-stage regression approach was used to identify the factors that influence irrigation water efficiency differentials across citrus growing farms.

The empirical results as regards the estimated parameters of the *translog* stochastic production frontier indicate that all the first-order parameters (α_i) have the anticipated sign and magnitude. On the other hand, the ratio of farm specific to total variability indicates that output-oriented technical efficiency is important in explaining the total variability of output produced. Moreover, it appears that the technical inefficiency effects are in fact stochastic and a significant part of output variability is explained by the existing differences in the degree of output-oriented technical inefficiency. In addition, the hypothesis that the inefficiency effects are absent is also rejected. This indicates that the majority of farms in the sample operate below the output-oriented technically efficient frontier.

According to our findings, the estimated production elasticities of all five inputs are positive. They indicate that in the Nabeul region chemical inputs are the most important inputs, followed by irrigation water, other costs and land, while labor has the lowest point estimate, with an average of 0.117. In economics terms, this means that, holding all other inputs constant, a 1% reduction in irrigation water requires a sacrifice of 2.98% of marketable output. On the other hand returns to scale were found to be increasing (1.106).

The results for estimates of technical efficiency (TE^0_i) indicate that the estimated mean output-oriented technical efficiency ranges from a minimum of 12.9% to a maximum of 90.7% with an average estimate of 67.7%. This result means that a 32.3% increase in production is possible with the present state of technology and unchanged input uses, if technical inefficiency is completely removed. Thus, improving technical efficiency will result in significant increases in farmers' profits. On the other hand, mean irrigation water efficiency (IE^I_i) is found to be 53%, which is much lower than technical efficiency and also exhibits greater variability ranging from 1.6% to 98.87%. The estimated mean irrigation water efficiency implies that the observed quantity of marketable citrus could have been maintained by using the observed values of other inputs while using 47.0% less irrigation water. This means that farmers can achieve significant savings in water use by improving the way they use the irrigation system and by using more advanced irrigation techniques. However, the cost savings that could be attained by adjusting irrigation water to its efficient level would be small since its outlays constitute only a small proportion of the total cost. For this reason, the estimated mean $ITCE_t$ is much higher than IE^I_i.

Finally, the analysis of the sources of efficiency differentials among farmers showed that farmer's age has a positive effect on technical and irrigation water efficiency. This finding indicates that young farmers are becoming relatively more technically efficient over time by improving their techniques. On the other hand, farm size, education level, agricultural training, the share of productive trees and the perception of water availability tend to affect the degree of both technical and irrigation water efficiency positively.

This study highlights the need for government policies, through extension activities, not only to set up training programs on managing citrus and improving pruning and irrigation techniques but also to encourage the setting up and implementation of a rejuvenating pruning program for old citrus plantations, since the old unpruned trees use more water than the others.

References

Aigner, DJ, Lovell CAK & Schmidt, P, 1977. Formulation and estimation of stochastic frontier production function models. Journal of Econometrics 6, 21–37.

Akridge, JT, 1989. Measuring productive efficiency in multiple product agribusiness firms: A dual approach. American Journal of Agricultural Economics 71, 116–25.

Atkinson, SE & Cornwell, C, 1994. Estimation of output and input technical efficiency using a flexible functional form and panel data. International Economic Review 35, 245–55.

Bachta, MS & Ghersi, G, 2004. *Agriculture et alimentation en méditerranée : Les défis de la mondialisation*. Montpellier, France: Editions Karthala/CIHEAM/IRESA.

Battese, GE & Coelli TJ, 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20, 325–32.

Coelli, TJ, 1992. A computer program for frontier production function estimation: Frontier version 2.0. Economics Letters 39, 29–32.

Fare, R & Lovell, CAK, 1978. Measuring the technical efficiency of production. Journal of Economic Theory 19, 150–62.

Karagiannis, G, Tzouvelekas, V & Xepapadeas, A, 2003. Measuring irrigation water efficiency with a stochastic production frontier: An application to Greek out-of-season vegetable cultivation. Environmental and Resource Economics 26, 57–72.

Kopp, RJ, 1981. The measurement of productive efficiency: A reconsideration. Quarterly Journal of Economics 96, 477–503.

Kumbhakar, SC & Lovell, CAK, 2000. Stochastic Frontier Analysis. New York: Cambridge University Press.

Kumbhakar, SC, Ghosh, S & McGuckin, JT, 1991. A generalised production frontier approach for estimating determinants of inefficiency in US dairy farms. Journal of Business and Economic statistics 9, 279–86.

Ministry of Agriculture and Water Resources, 2003. *Rapports d'activité* 1995–2003.

Reifschneider, D & Stevenson, R, 1991. Systematic departures from the frontier: A framework for the analysis of firm inefficiency. International Economic Review 32, 715–23.

Reinhard, S, Lovell, CAK & Thijssen, GJ, 1999. Econometric estimation of technical and environmental efficiency: An application to Dutch dairy farms. American Journal of Agricultural Economics 81, 44–60.

Stevenson, RE, 1980. Likelihood functions for generalised stochastic frontier estimation. Journal of Econometrics 13, 58–66.