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A DEA INPUT DISTANCE
FUNCTION APPROACH TO ANALYZE
TECHNICAL AND SCALE EFFICIENCIES
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**Abstract**

Technical and scale efficiencies have been widely studied in agricultural production literature, but many of the inputs used can impact the environment. Environmental impacts can take the form of undesirable output, a non-discretionary production input or, as has been the case in many studies, a conventional input. In this paper, we develop a DEA (Data Envelopment Analysis) model with water salinity as a non-discretionary input and estimate a model of irrigation water demand function based on the role of water in the farm production function. We model production technology by distinguishing six inputs (water, labor, phosphate, farmyard manure, farm size and water salinity) and four outputs (date production, vegetable production, cereal production, and fruit production). The adjusted-DEA model is applied on a transversal data of 138 water users associations farms.

On average, the technical efficiency for our sample observations is 0.63, which means that, on average, the farms can produce the same level of outputs with only sixty three per cent of the inputs if they are operating at the input frontier. Moreover, we also observe that there is wide variation in the measure of technical efficiency across farms. Spearman coefficient of rank correlation is used to test whether the farms' performance rankings, before and after accounting for water salinity, are significantly different. We find that accounting for variations in water salinity does not significantly bias the relative performance of the farms. The mean of scale efficiency levels is about 0.89. The results also show that 70% of farms are operating at below the optimal scale of production and 50% of oases farmers could improve SE (first mention, no full term) if they increased scale in terms of farm size.

The shadow prices of irrigation water derived from the adjusted-DEA model are positive, reflecting that water is a normal input in the production process. The estimation of a model of irrigation water demand function enables us to derive the shadow price elasticities of the inputs. It should be noted that the price elasticity of water is significant and quite high. Thus, the high responsiveness of water demand to price suggests that pricing policies can be a potential instrument for water conservation.

**ملخص**

يكمن الهدف الرئيسي من هذا البحث في تقدير إجراءات قياسات الكفاءة و التقنية ومرونة سعر مياه الري بالنسبة لمزارع الواحات في جنوب غرب تونس. يتم تقدير قياسات الكفاءة والتقنية غير المقيدة بتنوع ملوحة المياه من خلال تحديد ملوحة الماء باعتبارها عنصر إدخال غير تقديري في نموذج تحليل حافظة البيانات الموجه نحو البيانات المدرجة به. وتقدر قيمها بحوالي 63 % و 89% على التوالي. ويسمح وتقدر مرونة سعر مياه الري بـ ـ 0.44. ويتضح أن هذه المرونة على قدر من الأهمية وبالتالي فإن القيام بتسعير المياه قد يشكل وسيلة هامة للقيام بإدارة الموارد المائية بشكل أفضل. وتشير النتائج الخاصة بمرونة الأسعار الصورية فيما يتعلق بمدخلات المزرعة غير المتعلقة بالمياه، مثل الأسمدة والعمالة، إلى أن هذه المدخلات مكملة للمياه.

# 1. Introduction

There are several reasons for analyzing irrigation water demand in the Middle East and North Africa (MENA) and especially in Tunisia. MENA region is characterized by scarce groundwater resources, low and highly variable rainfall. Most of the significant water resources are shared by more than one country. These historic characteristics become crucial problems today because the region is experiencing increased population pressures, improved living standards, growing demands for food, urbanization and industrialization that result in the overexploitation of renewable fresh water and a degradation in its quality. Most MENA countries are classified as water stressed and their consumption already exceeds their annual renewable supplies. By 2050, nearly one billion people living in MENA will have less than 650 cubic meter of water per person (Johansson et al., 2002). In these circumstances, Water Demand Management would be a viable option to complement supply management for alleviating water stress problems.

Our paper will analyze this rationale in the context of Tunisia. Like many other developing countries, and especially MENA countries, Tunisia uses a high percentage of its water resources (80%) for agriculture. This paper contributes to the literature on irrigation-related water use by estimating the irrigation water demand for a transversal data of 138 water user associations farms. The original data comes from a survey conducted with the help of the Tunisian Ministry of Agriculture and Hydraulic Resources and a team of the ETH (Swiss Federal Institute of Technology) in 2002.

The main objective of this research is to estimate the technical and scale efficiency measures and irrigation water price elasticity for oases farms in the South West of Tunisia. Technical and scale efficiencies unconfounded by water salinity variation are estimated by specifying water salinity as a non-discretionary input in an input-oriented adjusted-DEA model which is different from a conventional DEA model.[1] A farm's performance is rated according to its distance from the efficient frontier which is created by DEA from data. The DEA distance function allows the generation of shadow prices of irrigation water which are used to estimate the irrigation water price elasticity.

We model production technology by distinguishing six inputs (water, labor, phosphate, farmyard manure, farm size and water salinity) and four outputs (date production, vegetable production, cereal production, and fruit production). We are especially interested in analyzing the following issues:

- What are the technical and scale efficiency measures of farms unconfounded by water salinity variation?
- How changes in model input specification alter the relative performance of farms?
- What can be the per unit shadow price of irrigation use of water?
- What can be said about the price elasticity of irrigation water demand in the South West of Tunisia?

A farm's production technology could be modeled in different ways: the production function, the profit function or the cost function. Then Hotelling's Theorem and Shephard's Lemma allow one to derive compatible input demands and outputs with optimized behavior. Our work is based on a nonparametric approach which uses an input distance function to measure technology and model the production process. The distance functions completely describe multi-input/ multi-output production technologies. Shephard (1970) and Färe and Primont

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[1] Normally, our model reports higher levels of technical efficiency because, as is well known, adding variables to the conventional DEA model raises the efficiency scores. However, only the efficiency scores of farms with high water salinity can change.

(1995) discuss input distance functions. An input distance function describes the degree to which a firm can contract its input vector without changing its output vector. The estimation of distance functions has been attracting attention in the efficiency literature. This interest is most likely due to the fact that distance functions can be used to model multi-input /multi-output production technologies without having to aggregate outputs (or inputs), and without having to make behavioral assumptions such as cost-minimization or profit-maximization even when using parametric approach (Grosskopf et al., 1995). Distance functions can be estimated using parametric and nonparametric techniques.

In our study, we adopt the DEA input distance function approach. Färe et al. (1994) provide a comprehensive discussion of data envelopment analysis, a technique that has the advantage of not needing to specify a functional form for the boundary of the production technology.[2] Moreover, the distance functions allow one to calculate the shadow prices of the inputs, as the observed prices of inputs in the developing countries are not market clearing prices especially for commodities like water.

While a large number of studies have employed conventional DEA models for the purpose of examining technical efficiency (TE) in agricultural production, both in developing countries and developed ones (Piot-Lepetit et al., 1997; Rao and Coelli, 1998; Fraser and Cordina, 1999), few have considered DEA models with non-discretionary production inputs like environmental variables (Piesse et al., 1996; Chapman et al., 1999; Henderson and Kingwell, 2005). We have directly included water salinity into the production function as a non-discretionary fixed input rather than an undesirable output because the degree of salinity measured at the level of a particular farm does not represent the output of that farm's production activity but rather represents the output of the recent activities of all farms. If we consider it as a conventional input as outlined in Coelli et al. (1998), this necessitates making the assumption that it can be reduced or increased like all other inputs and, in effect, is under the control of the farmer. However, this is untrue for water salinity. The farmer has no control over water quality degradation.

The remainder of the paper is organized as follows. Section 2 presents the economic modeling. Irrigation production technologies are represented by the input distance function. The DEA model is the subject matter of section 3. Section 4 presents and discusses the estimation results of the study. Pricing of irrigation water in such developing countries, especially MENA countries is the subject of section 5. The paper closes in section 6 with some concluding remarks.

## 2. The Input Distance Function with Non-Discretionary Inputs

A variety of conventional measures of TE have been proposed in the past. Many studies claim that the approaches used have considered environmental effects as undesirable outputs and recalculated the technical inefficiency accounting for these undesirable environmental effects (Pitman, 1983; Färe et al., 1989; Färe et al., 1993; Ball et al., 1994; Hetemaki, 1996; Tyteca, 1996). This approach raises interest in shadow prices since undesirable outputs are not generally priced in markets.

The above studies have all included three sets of factors: inputs, desirable outputs and undesirable outputs. Environmental effects were incorporated in the output vector, and the measure of technical efficiency incorporated the generation of one or more environmental

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[2] A downside of DEA is that estimated shadow prices are indeterminate at the intersections of the hyper planes, and some may collapse to zero at extreme data points due to the existence of ''slack regions.'' Moreover, the main drawback of DEA is that it estimates a deterministic frontier where all deviations from the frontier are implicitly assumed to be due to inefficiency.

effects as by products of the production process. In this paper, as done by Henderson and Kingwell (2005), we adopt a different strategy. Environmental degradation represented here by water salinity is modeled as an undesirable input which is non-discretionary.

Consider a farm employing a vector of conventional inputs $x = (x_1,.....,x_N) \in R_+^N$ and a vector of non-discretionary inputs to produce a vector of outputs $y = (y_1,...., y_M) \in R_+^M$. We then define the production technology as:

$$T = \{(x,s,y):(x,s) \text{ can produce } y\}. \tag{1}$$

The production function defines the maximum output that can be produced from a vector of conventional and non-discretionary inputs while the cost function defines the minimum cost to produce the exogenously given output. The output and input distance functions generalize these notions to a multi-output case. The input distance function describes "how far" an input vector is from the boundary of the representative input set, given the fixed output vector. An efficiency measure quantifies in one way or another the "distance" to the efficient frontier of the technology. Formally, the input distance function is defined as:

$$D(x,s,y) = \min\{\lambda:[\mathbf{x}/\lambda,(s,\mathbf{y})] \in T\} \tag{2}$$

Equation (2) characterizes the input possibility set by the maximum *equi*-proportional contraction of all conventional inputs consistent with the technology set (1), while keeping outputs and non-discretionary inputs constant. The radial input distance function is used to measure the Debreu-Farrell technical efficiency. It is homogeneous of degree one, concave and non-decreasing in inputs and convex in outputs.[3] It will take a value, which is greater than or equal to one if the input vector is an element of the feasible input set. Furthermore, the distance function will take a value of unity if input bundle is located on the inner boundary of the input set. It is dual to the cost function. That is:

$$D(x,s,y) = \min_{w}\{wx:C(y,w) \geq 1\} \tag{3}$$

$$C(y,w) = \min_{x}\{wx:D(y,x,s) \geq 1\}$$

Where w is a vector of minimum cost deflated input prices and C is a unit cost function if the costs are minimized. This implies that the value of input distance function would be equal to one only when the inputs are used in their cost minimizing proportions,

$$C(y,w) = wx/D(y,x,s) \tag{4}$$

Both the cost function and the input distance function, completely describe the production technology but they have different data requirements. Whereas, both require data on output quantities, the distance function requires data on input quantities rather than input prices. Moreover, by applying the DEA distance function model, the shadow prices of the inputs can be derived. The availability of information on shadow prices of inputs can be used to estimate the irrigation water price elasticity.

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[3] For the properties of input distance function, see Färe and Primont (1995).

## 3. The Adjusted-DEA Model

The input distance function is computed non-parametrically using the Data Envelopment Analysis (DEA) by specifying water salinity as a non-discretionary production input. We choose the distance function approach to calculate Farrell efficiency measure, but the DEA approach is chosen to easily incorporate the inequality restraints dictated by theory. The DEA model used in the analysis is identical to a conventional input-orientated DEA with variable returns to scale (VRS) except that it directly includes water salinity as a non-discretionary production input (s) given by the third constraint.[4] Assuming the situation with N farmers, each producing I outputs by using K inputs. For the $N^{th}$ farmer these are represented by the vectors $y_{in'}$ and $x_{kn'}$, respectively. Below is a mathematical representation of the DEA model that directly includes water salinity as a non-discretionary production input. Thus, the technical efficiency for each farm is computed like this:

$$D(y, x)^{-1} = \text{Minimize } \theta$$
$$(\lambda_1,...,\lambda_{N'}, \theta)$$

Subject to:

$$\sum_{n=1}^{N} \lambda_n\, y_{in} - y_{in'} \geq 0 \qquad\qquad i = 1,\ldots, I \qquad\qquad (5)$$

$$\sum_{n=1}^{N} \lambda_n\, x_{kn} - \theta x_{kn'} \leq 0 \qquad\qquad k = 1,\ldots, K$$

$$\sum_{n=1}^{N} \lambda_n\, s_n - s_{n'} \leq 0$$

$$\sum_{n=1}^{N} \lambda_n = 1$$

$$\lambda_n \geq 0, \qquad\qquad\qquad n = 1,\ldots,\ N.$$

where $\theta$ is a technical efficiency measure of the $N^{th}$ farmer under VRS (Banker et al., 1984)[5] and $\lambda_n$ are weights attached to each of the efficient farmers. This model ensures that inefficient farms are only compared to farms with high or equal water salinity.[6]

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[4] In agricultural production studies, the input reducing and output increasing technical efficiency under variable returns to scale are commonly used.

[5] Estimating a VRS model allows TE to be estimated without the influence of scale efficiencies. The VRS specification forms a production frontier that envelopes data more closely than the CRS specification. Therefore, the resulting efficiency scores are equal to or greater than those obtained with CRS model.

[6] This model is estimated by computing the EMS Software version 1.3. When EMS computes an efficiency score (which is a distance to the efficient frontier) it does not alter the values of non-discretionary data. The distance will only be computed in the directions of the conventional inputs and outputs while the non-discretionary are fixed.

## 4. Data and Estimation Results

The data used in this paper comes from a survey conducted with the help of the Tunisian Ministry of Agriculture and Hydraulic Resources and a team of the ETH (Swiss Federal Institute of Technology) in 2002. Three categories of factors, conventional inputs, desirable outputs and water salinity in the form of undesirable input, (against undesirable outputs as in much of the literature) will be used. Four outputs (date production, vegetable production, cereal production, and fruit production) are considered. Among the inputs considered for inclusion in the model are water, labor, phosphate, farmyard manure, farm size and water salinity. Limiting analysis to the region of Nefzaoua oases, farms can be assumed as homogeneous in terms of soil type, climatic conditions and other physical parameters due to geographic proximity.

For details on characteristics of data, see Belloumi and Matoussi (2006). Descriptive statistics of the variables used in the study are given in Table 1.

### 4.1. Technical Efficiency Estimates

Applying Data Envelopment Analysis to a sample of water user associations farms, TE measures unconfounded by water salinity variation are generated by specifying water salinity as a non-discretionary production input in an input-oriented DEA model. These unconfounded TE measures are different from TE measures generated by a conventional DEA model. TE scores obtained from the water salinity-adjusted DEA model are greater than or equal to those obtained from the conventional DEA model because the inclusion of water salinity as a non-discretionary input variable ensures that no farm is compared to another with a lower level of water salinity. The descriptive statistics of technical efficiency measures given by running the water salinity-adjusted and conventional DEA models are presented in Tables 2 and 3. These results show that the mean TE score obtained from the water salinity-adjusted DEA model is a little higher (0.63) than that obtained from the conventional model (0.61). The first (and respectively the second) reflect that on average the farmers can produce the same level of output with only 63% (61%) of the inputs if they were operating at the input frontier. The results displayed in Tables 2 and 3 demonstrate that inclusion of water salinity as an additional non-discretionary input does not change the distribution of efficiency of farms very much. The number of efficient farms is the same.

While changes in TE distributions and scores provide useful information on the effect of incorporating water salinity into the production frontier, the changes in the relative rankings of the farms are more important. If farm rankings between the water salinity-adjusted and conventional TE series are significantly different, then it can be concluded that failure to account for variation in water salinity leads to an incorrect assessment of each farm's relative performance. A simple way to compare the impact of model specification is to check the consistency of two model specifications in terms of the relative ranking of the farms. The Spearman Rank Correlation Coefficient (SRCC) statistically tests if the relative rank of farms changes when employing the different model specifications. The SRCC test statistic is calculated as follows:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \tag{6}$$

where $d_i$ is the difference between the rankings for each farm under the different model specifications and $n$ is the sample size. The hypothesis tested is:

$H_0$: $r_s = 0$; there is no relationship between the model specifications.

$H_1$: $r_s \neq 0$; there is a relationship between the model specifications.

An SRCC test statistic estimate of 0.949 is obtained allowing us to have a t-test statistic equal to 11.45.[7] This result implies the rejection of the null hypothesis at the 1 percent level of significance indicating that a strong, positive and statistically significant correlation exists between the TE estimates obtained by the two models. Thus, the ranking of farms is statistically invariant to the model specifications examined here. In this instance the variation in water salinity across farms is probably not large enough to significantly affect the relative rankings of the sample farms.

### 4.2. Optimal Scale of Production

We now present results examining the optimal scale of production. We estimate variable returns to scale (VRS) and non-increasing returns to scale (NIRS) water salinity-adjusted DEA specifications, so that increasing returns to scale (IRS), constant returns to scale (CRS) and decreasing returns to scale (DRS) can be identified. The CRS assumption is only appropriate when all farmers are operating at an optimal scale. The use of the CRS specification, when not all farmers are operating at the optimal scale, will result in measures of TE which are confounded by scale efficiencies (SE). The use of VRS assumption will permit the calculation of TE devoid of these SE effects. The CRS TE measure can be decomposed into its 'pure' TE and SE components by running a CRS water salinity-adjusted DEA model, which is obtained by deleting the fourth constraint, ($\sum_{n=1}^{N} \lambda_n = 1$) from model (5).

Because the VRS specification forms a production frontier that envelopes data more closely than the CRS specification, the VRS TE measure ($\theta^{VRS}$) is equal to or greater than the CRS measure ($\theta^{CRS}$). The fourth convexity constraint ensures that an inefficient farm is only being compared against farms of similar size. Thus, by estimating both CRS and VRS specifications, SE estimates can be determined as :

$$SE = \theta^{CRS} / \theta^{VRS} \qquad (7)$$

Scale inefficiency arises due to the presence of either increasing or decreasing returns to scale, which can be determined by solving a non-increasing returns to scale DEA model which is obtained by substituting the VRS constraint $\sum_{n=1}^{N} \lambda_n = 1$ with $\sum_{n=1}^{N} \lambda_n \leq 1$. If there is a difference between the CRS and VRS TE scores, this indicates scale inefficiencies exist. SE=1 indicates scale efficiency and SE <1 indicates scale inefficiency. Given that a farm is scale inefficient, in order to assess if the technology in that vicinity is exhibiting increasing or decreasing returns to scale, a non-increasing returns to scale specification needs to be estimated. To determine if IRS and DRS exist, the NIRS TE is compared to the VRS TE estimate. If the two are unequal, this indicates IRS and the scale of farm level operations can be increased. If the two are equal, this indicates that DRS exists and farm operations need to be reduced in size.

Descriptive statistics of SE indexes are reported in Table 4, as well as the number of farms operating at constant, increasing, and decreasing returns to scale. The scale efficiency index for the water user associations farms varies from 6.6% to 100%, with a sample mean of 89.6%. In terms of scale efficiency, 41 (29.72%) farms exhibit CRS. Among the scale inefficient farms, 70 (50.72%) show increasing returns to scale and 27 (19.56%) show

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[7] With $n > 30$, $r_s$ is approximately normally distributed with mean zero and standard deviation $1/(n-1)^{0.5}$, so that the Z test is $Z = r_s(n-1)^{0.5}$.

decreasing returns to scale. These results show that many farms are operating at below the optimal scale of production (70.28%). Farms are generally small because when property in the oasis passes from one generation to the next, the size of the farm is fragmented until it becomes sometimes economically unfeasible to use. Upward of 50 percent of oases farmers could improve SE if they increased scale in terms of farm size.

### 4.3. Shadow Prices of Water

The shadow prices for water are computed by running the water salinity-adjusted DEA model specified above by equation (5). The shadow price is the maximum price the farmer is willing to pay to relax the water constraint by one (marginal) unit. It is also called the shadow price of the water constraint. Notice that this shadow price varies with the level of the constraint and will be positive only when the constraint is binding. Notice also that it is equal to the inverse derived demand for water (Tsur, 2005).

If farmers pay for irrigation water on a per area basis or any other non-volumetric way, then the water fee, once paid, is basically a sunk cost and farmers will use irrigation water up to the point where its value of marginal productivity is zero. In our study, farmers pay for irrigation water on a per area basis. The estimation results would then be expected to give a shadow price of about zero. In addition, in Tunisia like in many other developing countries, water is a scarce resource in the sense that farmers face a stringent water resource constraint and water is often under priced. In such a context, farmers are likely to overuse water resources and the marginal productivity of the water tends to be low, as reported by Wang and Lall (2002). These shadow prices are positive, reflecting that water is a normal input in the production process. For instance, the average shadow price for water is very low.

### 4.4. Analysis of Derived Demand for Water

Water is one of many inputs of agricultural production. As a productive input, it is valued for its contribution to farm outputs, rather than as a commodity for final consumption. The relationships between irrigation farm inputs are complex and seldom linear. Some inputs are essentially fixed in the short run (such as land), while others are variable (such as fertilizers). Because some inputs are fixed, diminishing returns occur at some point such that the continued addition of variable inputs eventually yields smaller and smaller additional units of output.

Overall, the quantity of water demanded is derived from its price, its contribution to production (which depends on the prices of all inputs) and the prices of outputs (which determine the optimal quantities to produce). If a demand curve for water is presented for a given level of other inputs, changes in the price of water will lead to a movement along the demand curve. Changes in output prices, or in input prices, technological changes in production methods (investment in capital, such as more efficient irrigation systems) and use of other interdependent inputs, will lead to shifts of the demand curve for water.

The change in the amount of water demanded, due to changes in price, is measured by price elasticity. It is likely that the elasticity for water demand will vary over space, time and between irrigators. The price elasticity of water demand is the percentage change in the quantity demanded which results from a one percent change in price. Irrigators have an incentive to reduce the quantity of water demanded if the price of water rises, therefore, water price elasticity is negative. Elasticity is measured at a specified level of price or quantity, and will generally be different at other prices and quantities. If it is between −1 and minus infinity, demand is said to be relatively elastic. That is, quantity demanded responds by more than the proportionate change in price. In such a case, the irrigator's expenditure on water

will fall as the price rises. If it is between zero and –1, demand is said to be relatively inelastic. That is, the quantity demanded, responds by less than the proportionate change in price. In such a case, the farmer's expenditure on water will increase in response to an increase in price even though their consumption of water has fallen.

Data of prices and quantities of water exchanged is required to estimate the responsiveness of demand but this kind of data has been difficult to obtain. It is rare to find published empirical estimates of the price responsiveness of demand for irrigation water in developing countries from observing irrigators' behavior in historical water purchases. Many previous studies of agricultural water demand rely on simulated data and linear programming techniques (Bontemps and Couture, 2002; Hooker and Alexander, 1998; Appels et al. 2004).

Analysis of the responsiveness of demand for irrigation water using shadow prices derived from the model has been done in this work.

The water demand equation we estimate is of total water use by a farmer with the explanatory variables including shadow prices for irrigation water and the income of the farmer. However, the problem is about the choice of the functional form for the estimation equation. Previous work on residential water demand has generally used linear, log-log, or log-linear functional forms. Information on the crop production function influences the decision of the appropriate functional form. Some research has shown that a quadratic production function provides a good fit for observed yields and water input levels in agriculture. A quadratic production function implies that we estimate a linear input-demand function. In addition, in contrast to a Cobb-Douglas production function, which assumes a constant price elasticity of demand, a quadratic production function allows the elasticity to differ depending on the price observed.

We estimate water demand using the specification log-log:[8]

$$Log(q_i)= \beta_0 +\beta_1 Log(w_{1i}) +\beta_2 Log(w_{2i}) +\beta_3 Log(w_{3i}) +\beta_4 Log(w_{4i}) +\beta_5 Log(p_{1i})$$

$$+\beta_6 Log(p_{2i}) +\beta_7 Log(p_{3i}) +\beta_8 Log(p_{4i}) +\varepsilon_i \qquad (8)$$

where $q_i$ is the observed quantity of water used by the *ith* farmer; $w_{1i}$, $w_{2i}$, $w_{3i}$ and $w_{4i}$ are respectively the shadow prices for inputs (water, labor, phosphate and manure); and $p_{1i}$, $p_{2i}$, $p_{3i}$ and $p_{4i}$ are respectively the shadow prices for outputs (date production, vegetable production, cereal production, and fruit production). The shadow price for water is perhaps the variable of most interest to this study. We expect the coefficient on water price to be negative since farmers will be more careful with water application at a higher water price.

The results of the water demand estimation are presented in Table 5. We find that the water price coefficient is still negative and significant, with a price elasticity close to -0.44. The price elasticity of irrigation water has the expected negative sign, implying that an inverse relationship between the price of water and the quantity demanded. This finding demonstrates that marginal price can influence farm water demand. The significance of water price in this equation suggests that better management alone can result in a significant amount of conservation, and can do so in the short run. The result suggests that pricing policies can be a potential instrument for water conservation. The results also show that the coefficients associated to shadow prices of other inputs are all negative but insignificant except for the manure which is significant. These results indicate that the other non-water farm inputs such as fertilizers and labor are complementary to water. Many previous results, in both economics

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[8] Using the same data and applying the LM ratio test, we found that the frontier production function assumes the form Cobb-Douglas against translog when we consider only the main output which is date production.

and agronomy, show that there are very few substitutes for effective water in crop production. The coefficients of shadow prices of the outputs are negative for date and fruit production and positive for vegetable and cereal production. They are significant at ten percent except for cereal output. These results indicate that even if the prices of outputs increase, the water demand could decrease.

Previous econometric studies which have estimated irrigation water demand have found varying results. Nieswiadomy (1988) found a price elasticity of water demand of -0.25, while Moore et al. (1994) found no response of farmers to increased water rates. The study of Schoengold et al. (2005) used an econometric analysis to decompose water use by both crop and irrigation technology to estimate the effect of land quality characteristics in determining total applied water. They found evidence that these characteristics (soil permeability, slope, and temperature levels) are significant in determining water demand. All the studies reported by Appels et al. (2004) used mathematical models of representative farm production systems to estimate elasticity of demand for water in major irrigation regions within the Murray-Darling Basin. All the models estimated a very inelastic demand for irrigation water at low prices and a slightly less inelastic demand at higher prices.

## 5. Pricing of Irrigation Water

The costs of providing irrigation water include a fixed cost of operation and maintenance and a variable cost, which depends on the quantity of water supplied. In addition, there is a capital cost of constructing a water project. The World Bank (1993) argues that the pricing of water resources will give users an incentive to pursue efficiencies in utilization. The argument goes that water has been under-priced as a scarce resource. The conceptualization of water as a free resource can result in conflicts between users and negative environmental externalities. Negative environmental externalities can be reduced by 'correct' pricing whereby environmental costs are internalized in production and ultimately borne by consumers and/or by the application where appropriate of the 'polluter pays' principle.

There are many pricing systems used for recovering some or all the costs involved. In some developing countries such as India and Pakistan, which have benefited greatly from irrigation, the revenues received fall far short of the costs of supplying irrigation water to users, and often do not recover even the initial capital costs (Schoengold and Zilberman, 2005). Water pricing systems can be designed to encourage users of water for low value purposes to conserve water -thus freeing up water for transfer to other uses - or to adopt water-conserving technologies. Water pricing is thus conceived as a tool for increasing economic efficiency and for internalization of environmental externalities. The most common pricing systems are per-hectare fees, increasing or decreasing block rates, and volumetric fees. A volumetric fee provides an incentive to limit water use, while a per-hectare fee provides an incentive to cultivate agriculture more intensively. Under per area pricing, changing the (per hectare) water fee across crops can be used to improve efficiency by affecting farmers' crop selection.

The block rates can either be fixed or may depend on the area and time of year. Israel has introduced a pricing structure giving high incentive to save water with an increasing block rate pricing structure. A pricing system in progressive blocks, where the price of water increases according to the volume consumed, can have a really dissuasive effect on the consumption of water depending on the progression of the prices and their level, but it is seldom applied to irrigation in MENA countries except in Israel and Jordan.

Some countries like Brazil adopt a combination of these systems; for example charging a per-hectare fee for access to water, and then a reduced volumetric fee for water delivered. The

extreme case, where structure is of little importance, is where water is free (Egypt), which does not encourage water saving at all. In Egypt, irrigators are only responsible for the maintenance of canals that are attached to their fields.

In volumetric pricing systems, water is priced based on direct measurement of volume of water consumed. A special case of volumetric fee is marginal cost pricing where efficiency requires that the price of water reflect the marginal cost of water supply disregarding water allocation between crops. Volumetric pricing methods encourage water conservation. However, in many developing countries, the installation of a volumetric fee system is difficult due to their inability to measure the quantity of water an individual uses and prices based on marginal costs are often too high for low farm incomes. Most of developing countries use a per-hectare fee system (Tsur et al. 2004).

In Tunisian oases, water user associations are considered a useful medium through which cost recovery procedures can be implemented. They are responsible for a wide range of management activities. Delivery of water to user groups gives them the responsibility for both water distribution and fee collection at the local level. A rotational method for equitable allocation of irrigation water fixes flows by day, time and duration of supply proportional to irrigated area.

In Tunisia, the regular increase in the price of irrigation water since the mid-1980s has enabled water authorities to recover operation and maintenance costs. Besides that, other institutional measures have enabled the stabilization of water demand since 1997 (Dinar and Subramanian, 1997; Belhaj, 2002). Some Tunisian experiments on price increases for water show an impact on consumption and have proved that water pricing could be a good tool for water conservation.

In Morocco, water administration is currently undergoing a structural transformation from a centralized political structure towards a decentralized system of governance. The pricing adjustment plan, proposed for schemes in financial imbalance, should improve covering the cost of recurrent charges (operation, maintenance and renewal by 2010). The adjustment plan is expected to achieve a budget balance within 1 to 6 years for schemes in slight deficit, which represent 40% of irrigated land. On the other hand, in schemes with severe deficit – 12% of land area, where water is lifted to be put under pressure – it should reach a recovery rate of 65 to 80% (Chohin - Kuper et al., 2003).

Other countries in MENA region have increased or expect to make limited increases, to recover more of the water costs: Lebanon, Israel and Jordan. A price increase of 20 to 30% is expected in Lebanon.

Pricing experiments in the majority of MENA countries (except oil countries) are oriented towards cost recovery objectives in general, and have contributed to the reduction of public financing - at least with respect to operation and maintenance costs of irrigation schemes. However, these price increases did not contribute significantly to water demand management objectives and there is a need for complementary tools and policies in order to tackle the water resource issue.

Most MENA countries now face challenges to satisfy future water demands that could reach development requirements and environmental issues. Such challenges would require not only long term planning, but also the consideration of the inter-linkages between technical, economical, social and environmental issues. For this reason new resources such as non-conventional resources are to be used to close the gap between the volume of water available and the volume of water needed for use. The most common non-conventional resources are: desalination of brackish water, water harvesting and treated wastewater. For example, for future agricultural uses, the reuse of treated wastewater and drainage water is considered an

important element of water policies. Both these resources have health and environmental implications, and hence, a functional system of monitoring and continuous evaluation is absolutely essential. Long-term potential environmental impacts of reusing drainage water and criteria for use should be clearly identified. Institutional and legal implications of establishing a water quality data monitoring and management system has to be prepared and implemented.

## 6. Conclusions

Freshwater resources are increasingly limited in many arid regions, and understanding the patterns of how individuals use those water resources is crucial for a better understanding of water demand, with the goal improving water management. One available mechanism to change those patterns of use is the price of water. Hence, the measurement of the price elasticity of water demand has been the subject of many previous studies. The majority of these studies have focused on urban water demand, despite the fact that agricultural producers use the majority of water resources in many areas of the world.

In this paper, we develop a DEA model with water salinity as a non-discretionary input and estimate a model of irrigation water demand based on the role of water in the farm production function. We consider production technology with an input distance function, which is dual compared to the more commonly used cost function. This duality is employed to retrieve the shadow price of water which is used to estimate the derived demand for irrigation water by using the establishment-level data for 138 farms belonging to different water users associations in the oases of Tunisia.

In the literature, cost, production and demand functions have been used to estimate the derived demand of irrigation water use. These three approaches are based on the maintained axioms of optimization and assume that farms are operating at their frontiers, and that cost and demand functions require an established market for water and information regarding costs and prices. In the absence of a well established water market and information about prices and costs, the DEA input distance function approach can be used to asses the shadow prices of irrigation water if information about quantities of inputs and outputs is available when farms are not operating at their frontiers. Thus the DEA input distance function also provides estimates of farms' technical efficiency.

One objective of our analysis is to measure technical and scales efficiencies of farms unconfounded by water salinity variation and the price elasticity of irrigation water use in the South West of Tunisia, as it provides important information about the effectiveness of using price reforms to manage water demand. We find that the mean of technical efficiency levels for the farms is about 63%. This result indicates that for the same amounts of outputs, the inputs could be contracted by up to 37% if the farmers are operating at the input frontier. Spearman coefficient of rank correlation is used to test whether the farms' performance rankings, before and after accounting for water salinity, are significantly different. We find that the fact to account for variations in water salinity does not significantly bias the relative performance of the farms. This is partly attributed to a lack of variation in water salinity between farms. The mean of scale efficiency levels is about 89%. The results also show that about 70% of farms are operating at below the optimal scale of production and 50% of oases farmers could improve SE if they increased scale in terms of farm size. Our results also support the hypothesis that farmers respond to an increase in the marginal price of water by reducing their water applications. The price elasticity of irrigation water is close to –0.44. It is shown to be significant, thus water pricing would be a pertinent instrument for better management and water conservation. This result will prove to policy makers the relevance of this alternative over other costly and inefficient tools. The results of shadow price elasticities

of the other non-water farm inputs such as fertilizers and labor indicate that these inputs are complementary to water.

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**Table 1. Summary Statistics for Output and Input Variables**

| Variables | Mean | Std.dev | Min. | Max. | Median |
|---|---|---|---|---|---|
| Date production (kg) | 2556.5 | 5189.5 | 20 | 47050 | 1100 |
| Vegetable production (kg) | 28.55 | 133.56 | 0 | 1000 | 0 |
| Cereal production (t) | 0.858 | 1.408 | 0 | 6.666 | 0 |
| Fruit production (kg) | 22.95 | 78.03 | 0 | 500 | 0 |
| Irrigated water (m3) | 11390.5 | 15391.7 | 104 | 129600 | 6912 |
| Labour (hour/year) | 131.77 | 179.04 | 0 | 1760 | 90 |
| Phosphate (kg) | 84.72 | 161.66 | 0 | 1200 | 0 |
| Manure (t) | 3.265 | 3.837 | 0 | 20 | 2 |
| Farm size (are) | 88.45 | 120.59 | 0.15 | 1000 | 50 |
| Water salinity (g/l) | 4.128 | 1.74 | 1.8 | 7 | 3.6 |
| Sample size | 138 | 138 | 138 | 138 | 138 |

**Table 2. Frequency Distributions of TE Estimates from Water Salinity-Adjusted DEA Model**

| Efficiency Index (%) | Count | Percent | Cum. percent |
|---|---|---|---|
| <20 | 13 | 9.42 | 9.42 |
| 20-40 | 35 | 25.36 | 34.78 |
| 40-60 | 20 | 14.49 | 49.28 |
| 60-80 | 13 | 9.42 | 58.70 |
| 80-100 | 13 | 9.42 | 68.12 |
| 100 | 44 | 31.88 | 100.00 |
| Mean | 63.19 | | |
| Median | 60.73 | | |
| Maximum | 100.00 | | |
| Minimum | 12.28 | | |
| Standard deviation | 32.08 | | |
| Observations | 138 | | |

**Table 3. Frequency Distributions of TE Estimates from Conventional DEA Model**

| Efficiency Index (%) | Count | Percent | Cum. percent |
|---|---|---|---|
| <20 | 15 | 10.87 | 10.87 |
| 20-40 | 37 | 26.81 | 37.68 |
| 40-60 | 18 | 13.04 | 50.72 |
| 60-80 | 16 | 11.59 | 62.32 |
| 80-100 | 8 | 5.80 | 68.12 |
| 100 | 44 | 31.88 | 100.00 |
| Mean | 61.11 | | |
| Median | 57.07 | | |
| Maximum | 100.00 | | |
| Minimum | 12.28 | | |
| Standard deviation | 32.15 | | |
| Observations | 138 | | |

**Table 4 . Optimal Scale of Production**

| Scale Efficiency Index (%) | | | | Number CRS farms | Number IRS farms | Number DRS farms |
|---|---|---|---|---|---|---|
| Mean | Maximum | Minimum | Std. Dev | | | |
| 89.61 | 100.00 | 6.61 | 18.74 | 41(29.72%) | 70 (50.72%) | 27 (19.56%) |

**Table 5. Estimation Results of Irrigation Water Demand Function**

| Variable | Coefficient | t-Statistic | Prob. |
|---|---|---|---|
| $Log(W_1)$ | -0.442 | -7.625 | 0.00 |
| $Log(W_2)$ | -0.063 | -1.451 | 0.15 |
| $Log(W_3)$ | -0.024 | -1.142 | 0.26 |
| $Log(W_4)$ | -0.043 | -2.368 | 0.02 |
| $Log(p_1)$ | -0.096 | -1.853 | 0.07 |
| $Log(p_2)$ | 0.111 | 1.941 | 0.06 |
| $Log(p_3)$ | 0.004 | 0.196 | 0.84 |
| $Log(p_4)$ | -0.109 | -1.934 | 0.06 |
| Constant | 3.047 | 5.583 | 0.00 |
| R-squared | 0.79 | - | - |