Technical efficiency of water use in the irrigated private schemes in Smar watershed, South-Eastern Tunisia

Mahdi N., Sghaier M., Bachta M.S.

in

Technical efficiency of water use in the irrigated private schemes in Smar watershed, south-eastern Tunisia

Naceur Mahdi, Mongi Sghaier and Mohamed Salah Bachta

Institut des Régions Arides de Médenine (IRA), Tunisie

Abstract. In this paper, data envelopment analysis (DEA) is used to asses the farm-level technical efficiency measures and sub-vector efficiencies for water use of a sample of irrigated farms based on surface wells in Smar watershed (south-eastern Tunisia). In the study area, private irrigation schemes play an important role in rural development, but the water scarcity and the increasing pressure on these resources calls for a more efficient water use. With the Data Envelopment Analysis (DEA) techniques used to compute farm-level technical efficiency measures and sub-vector efficiencies for water use, it was shown that under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) specification, substantial technical inefficiencies, of 26% and 15% respectively, exist among farmers. The sub-vector efficiencies for water proved to be even lower, indicating that if farmers became more efficient using the technology currently available, it would be possible to reallocate a fraction of the irrigation water to other water demands without threatening the goal of surface wells irrigation. In a second stage critical determinants of sub-vector efficiency are determined using a Tobit model. Farm size, age of the household head, the number of year of schooling, the type of irrigation scheme, crop choice and the irrigation methods applied showed a significant impact on the sub-vector efficiency for water. Such information is valuable for extension services and policy makers since it can help guide policies towards increased efficiency.

Keywords. Irrigation – Technical efficiency – DEA method – Surface wells – Tunisia.

Efficacité technique de l'utilisation de l'eau dans les périmètres irrigués privés du basin versant de Smar, dans le Sud-est tunisien

Résumé. *Dans le présent travail, nous allons illustrer la méthode DEA (analyse d'enveloppement des données) utilisée pour évaluer les mesures de l'efficacité technique à l'échelle de la ferme et l'efficacité allocative de l'utilisation de l'eau sur un échantillon d'exploitations irriguées utilisant des puits superficiels dans le bassin versant de Smar (Sud-est tunisien). Dans la zone d'étude, les périmètres irrigués privés jouent un rôle important dans le développement rural, mais la pénurie d'eau et la pression croissante sur ces ressources imposent une utilisation plus efficiente de l'eau. Les techniques DEA, employées pour calculer les mesures de l'efficacité technique à l'échelle de la ferme et l'efficacité allocative de l'utilisation de l'eau, ont montré que dans le cas des rendements d'échelle constants (REC) et des rendements d'échelle variables (REV), on observe chez les exploitants des inefficacités techniques significatives, de 26% et 15% respectivement. L'efficacité allocative de l'eau s'est avérée être même plus faible, ce qui indique que si les exploitants pouvaient accroître leur efficacité en utilisant les technologies disponibles actuellement, on réussirait à réallouer une fraction de l'eau d'irrigation à d'autres demandes sans pour autant compromettre l'objectif de l'irrigation par les puits superficiels. Dans un deuxième temps, nous allons parcourir les déterminants critiques de l'efficacité allocative en appliquant le modèle Tobit. La taille de l'exploitation, l'âge du chef de ménage, le nombre d'années de scolarisation, le type de périmètre irrigué, le choix de la culture et les méthodes d'irrigation utilisées ont un effet significatif sur l'efficacité allocative de l'eau. Cette donnée est importante pour les vulgarisateurs et les politiciens dans la mesure où elle peut contribuer à orienter les politiques vers l'objectif d'une plus grande efficacité.*

Mots-clés. *Irrigation – Efficacité – Méthode DEA – Puits superficiels –Tunisie.*

I – Introduction

Water scarcity is a growing problem in Tunisia. Hence, irrigation systems, being a main consumptive user, experience pressure to release water for other uses and to find ways in which to improve performance. South-eastern Tunisia is a water-stressed region. Moreover, because rainfall is low (<200mm per year) and extremely variable in space and time there, irrigation is a key factor indispensable for agricultural production.

Irrigation water is becoming an increasingly scarce resource for the agricultural sector in many regions and countries. A common ground in past policy schemes was the development of adequate irrigation infrastructure to guarantee the supply of irrigation water as the demand for agricultural products was increasing. However, these expansionary policies have resulted in a massive use of irrigation water at a heavily subsidized cost and physical scarcity. Water scarcity has become an increasing social and economic concern for policy makers and competitive water users. Particularly, agriculture is becoming the sector at which policy makers are pointing out at the core of the water problem.

As in many areas in south-eastern Tunisia, small-scale irrigation schemes are of great importance for the livelihood of many families there.

It is believed that small-scale irrigation schemes could play an important role in rural development because of their potential to provide food security, income and employment opportunities (Al Atiri, 2005). On the other hand, performance and economic success of these schemes have been poor, which raises questions on their level of efficiency (Albouchi, 2007; Chemak, 2007). Moreover, the new water policy regards water as an economic good and thus charges will be levied on its use. Currently, water use of farmers at small-scale irrigation schemes is subsidized. However, these subsidies will gradually decrease and in the future farmers will have to pay to ensure cost recovery (Al Atiri, 2003). Hence, small-scale irrigators will face two new problems in the future: firstly, less water will be allocated to the agricultural sector, due to the increasing water scarcity, and secondly, they will have to pay for the water they use. In other words, they will have to deal with a reality where water becomes a limited input for which they have to pay. The impact of this new reality is unclear, but it will definitely have an impact on the production system and stress the importance of using water in a more efficient way.

This paper analyses the efficiency with which water is used in small-scale irrigation schemes and studies its determinants, with data of a sample of 50 farmers in smar Medenine watershed being used. Although the sample is relatively small, the case study will provide insights that reflect the typical situation of rural areas in south-east Tunisia. It is nevertheless difficult to ascertain whether the use of water is efficient or not, since irrigated agriculture is a multiple input-multiple output process. Furthermore, it is important not to consider water as a resource in an isolated manner (Malana and Malano, 2006; Rodríguez Díaz *et al.*, 2004b).

Studies on efficiency differentials among farms often use simple measures, such as yield per ha or output per m³, which are easy to calculate and understand. However, such measures tell very little about the reasons for any observed differences among farms. Output per m³, for example, does not take into account the differences in non-water inputs among farms (such as labour, fertilizers etc…) (Coelli et al., 2002).

In the first step of the analysis in this paper, a Data Envelopment Analysis (DEA) is used to calculate more consistent measures of efficiency (Fraser and Cordina, 1999). This is a system approach widely used in management science and economics, in which the relationships between all inputs and outputs are taken into account simultaneously (Raju and Kumar, 2006). The method enables the relative efficiency of a farm to be determined and to examine its position in relation to the optimal situation. Moreover, this methodology allows not only technical, but also subvector efficiencies to be calculated, which can be used to specifically monitor the efficiency of water use.

A second step of the study consists of analysing the determinants of efficiency measures. Separate Tobit models are estimated as a function of various attributes of the farms within the sample (Chavas *et al.*, 2005; Binam *et al*., 2003), allowing a pointing out of which aspects of the farms' human and physical resources might be targeted by public investment to improve efficiency (Wadud and White, 2000).

Although there have been several studies that have analysed the efficiency of agricultural production in developing countries (Haji, 2006; Malana and Malano, 2006; Chavas *et al.,* 2006; Abay *et al.,* 2004; Binam *et al.,* 2004; Dhungana *et al.,* 2004; Binam *et al.,* 2003; Coelli *et al.,* 2002, Wadud and White, 2000), most of them have focused on monocropping of major food crops like rice, maize or wheat or on cash crops like coffee and tobacco. However, these studies have not specifically focused on the use of water. The novelty of this paper is that it has a clear focus on water of which the sub-vector efficiencies are calculated and analysed. This is highly relevant given the growing water scarcity and the future introduction of water pricing. It is of significant importance for policy makers, because it not only creates awareness concerning inefficiencies in water use, but also provided insight into possible improvements by exploring the determinants of these inefficiencies.

The remainder of the paper is organised as follows. The next section elaborates on the efficiency concepts and their measurement and discusses the theoretical background for DEA and in section 3, data collection is described. Obtained efficiency scores are presented with the determinants of inefficiency in section 4. Section 5 provides some conclusions.

II – Methodology

1. Efficiency measures

The absolute efficiency position of farmers is usually not known. Therefore the problem is to measure the efficiency of one farm relative to others.

There are two main competing paradigms for estimating the relative efficiency of farms: parametric and non-parametric. The parametric approach assumes a functional relationship between outputs and inputs and uses statistical techniques to estimate the parameters of the function. The sampling theory estimators that are typically used have statistical properties that are known in large samples. The non-parametric approach, in contrast, constructs a linear piecewise function from empirical observations on inputs and outputs without assuming any a priori functional relationship between them. Simar and Wilson (2000) show how a simple statistical model of the data generating process can be used to determine the statistical properties of a non-parametric (DEA) estimator, which is analogous to the parametric method. However, DEA is also not without criticism – it is deterministic rather than stochastic, so it is sensitive to outliers and data measurement errors. Comprehensive reviews of the two approaches are provided by Kalirajan and Shand (1999); Coelli (1995); Lovell (1993); Bravo- Ureta and Pinheiro (1993); Bjurek et al (1990) and Bauer (1990).

Given the alternative empirical tools available, the choice as to the 'best' method is unclear (Olesen *et al.*, 1996). Few rigorous empirical analyses have been carried out in assessing the sensitivity of efficiency measures to the choice of DEA and parametric methodology in agriculture (e.g., Sharmaet al.,1999; Wadud and White, 2000). The limited findings show that efficiency score estimates from each approach differ quantitatively, although the ordinal efficiency ranking of farms obtained from the two approaches appear to be quite similar. The evidence would suggest that the choice is somewhat arbitrary, though to a certain degree the choice between alternative modelling approaches depends upon the objectives of the research, the type of farms and assumptions regarding the data generating process. We used the non-parametric DEA technique developed

by Charnes et al. (1978) (CCR) and Banker et al. (1984) (BCC). We could have used a stochastic frontier approach instead, but we expect qualitatively the results would be similar under both approaches.

2. Data envelopment analysis

Data envelopment analysis (DEA) was developed by Charnes, Cooper, and Rhodes (1978) based on M.J. Farrel's contribution to productive efficiency. The data envelopment analysis technique uses linear programming methods to construct a non-parametric frontier. The technique also identifies efficient production units, which belong to the frontier, and inefficient ones, which remain below it.

Data envelopment analysis (DEA) uses a non-parametric piecewise linear production frontier in estimating technical efficiency. A DEA model may be either input-oriented or output-oriented. Both output-oriented and input-oriented DEA models produce the same technical efficiency estimate for a farm under the assumption of constant returns to scale in production.

In deciding on the orientation of a DEA model, one should also consider over which variables decision making units (DMUs) have most control. If DMUs have more control over output variables than input variables, the DEA model should be output-oriented; otherwise, the model should be input-oriented. Agricultural farms, such as irrigated private perimeters (surface wells), usually have more control over their inputs than their outputs. Input-oriented models were chosen in this study to reflect the reality where the main aim is not to increase production but to use different resources more efficiently (Rodríguez Diaz *et al.*, 2004a).

The model is presented here for the situation with n firms or decision making units (DMUs), each producing a single output by using m different inputs. Here, Y_i is the output produced and X_i is the $(m \times 1)$ vector of inputs used by the ith DMU. Y is the $(1 \times n)$ vector of outputs and X is the $(m \times n)$ matrix of inputs of all n DMUs in the sample.

The DEA model to calculate the technical efficiency (TE) is in this case (equation 1):

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

$$\text{Subject to} \qquad -y_i + Y\lambda \geq 0$$

$$\theta_i x_i - X\lambda \geq 0$$

$$\sum_{i}^{n} \lambda_j = 1$$

$$\lambda \geq 0$$

Where θ_i is a TE measure of the ith DMU and λ is an $n \times 1$ vector of weights attached to each of the efficient DMUs. A separate linear programming (LP) problem is solved to obtain TE score for each of the n DMUs in the sample. If $\theta = 1$, the DMU is on the frontier and is technically efficient under CRS. If $\theta \prec 1$, then the DMU lies below the frontier and is technically inefficient. It should also be noted that equation 1 has a variable returns to scale (VRS) specification which includes a convexity constraint ($\sum_{i}^{n} \lambda_j = 1$). Without that constraint, equation (1), would have constant returns to scale specification (CRS). Using that specification, it is assumed that farms are operating at their optimal scale (Fraser and Cordina, 1999). In the case of agriculture, increased amounts of inputs do not proportionally increase the amount of outputs. For instance, when the amount of water to crops is increased, a linearly proportional increase in crop volume is not necessarily obtained, one reason why the variable return to scale option might be more suitable for our problem (Rodriguez-Diaz *et al.*, 2004b). Coelli *et al.* (2002) and Haji (2006) on the other hand

found that for small farms like the ones considered in this study, little scale economies could be realised, hence both specifications will be modelled. In addition, a comparison of both scores is interesting because it provides information on scale efficiency (SE). Coelli *et al.* (2002) showed that the relation is as follows:

$$SE = \frac{\theta^{CRS}}{\theta^{VRS}}$$

To calculate the efficiency of use of an individual input or subset of inputs, the "sub-vector efficiency" concept can be introduced. This measure generates a technical efficiency for a subset of inputs while remaining inputs are held constant (Speelman *et al.*, 2007). Using the notion of sub-vector efficiency proposed by Färe *et al.* (1994), the technical sub-vector efficiency for the variable input k is determined for each farm i by solving following programming problem (equation 2):

$$Min_{\theta k}\theta^k,$$
$$subject \ to \qquad -y_i + Y\lambda \geq 0$$
$$\theta^k x_i^k - X^k \lambda \geq 0$$
$$x_i^{n-k} - X^{n-k} \lambda \geq 0$$
$$\sum_{i=1}^{n} \lambda_j = 1$$
$$\lambda \geq 0$$

Where θk is the input k sub-vector technical efficiency score for farm i. The terms x_i^{n-k} and X^{n-k} in the third constraint refer to x_i and X with the kth input (column) excluded, whereas, in the second constraint, the terms x_i^k and X^k include only the kth input. All other variables are defined identically as in equation 1.

3. Determining factors affecting efficiency

Analysis of the effects of firm-specific factors on productive efficiency has generated considerable debate in frontier studies (Sharma *et al.*, 1999). Use of a second stage regression model to determine the farm specific attributes in explaining inefficiency is suggested in a number of studies (e.g., Parikh and Shah, 1995; Hallam and Machado, 1996; Sharma *et al.*, 1999; Shafiq and Rehman, 2000; Wadud and White, 2000). An alternative to this approach is to incorporate farm specific attributes in the efficiency model directly (e.g., Battese *et al.*, 1989; Kumbhakar et al., 1991; Battese and Coelli, 1995).

The present study employs the former approach and uses a model to analyse the role of farm specific attributes in explaining inefficiency of water uses in private irrigated farms based on surface wells. To motivate our empirical model we assume

$$θk* = β0 + β1z1 + β2z2 + ... βjzj + e \quad =Zβ+e \tag{3}$$

where θ_k is the DEA sub-vector efficiency index used as a dependent variable. Z is a vector of independent variables related to farm specific attributes, β is the unknown parameter vector associated with the farm specific attributes, and e is an independently distributed error term assumed to be normally distributed with zero mean and constant variance, σ^2. The dependent variable in the regression equation (3) cannot have a normal distribution. The efficiency parameters vary between 0-1, they are censored variables and thus a Tobit model needs to be used. The variables included in the Tobit model are discussed in the following section.

4.   Study area and data collection

The watershed of Smar is located in south-eastern Tunisia (South west of the city of Médenine). It covers an area of 55,700 ha. The population is estimated, according to the census of 2004, at 48,188 inhabitants. The region is marked by high dependence of its predominantly rural population on smallholder agriculture and wage labor.

The groundwater resources are scarce and over-exploited. This exploitation reaches 183% with annual renewable resource of 1.39 Mm3. Two subsystems can be distinguished: the sub-system of private irrigated farms is based on surface wells (432 surface wells). The subsystem of public irrigation schemes is based on collective tube-wells (3 collective tube-wells), normally established by the state. The water management is ensured by a water user association known as the 'GDA'. The agricultural production is based on vegetables and fruit trees.

Data was collected from private irrigated farms based on surface wells situated in Smar Watershed (South-eastern Tunisia) from February to March 2008. The data was obtained from interviews with 50 randomly selected irrigated farming households selected from the 240 households. During the interviews information was gathered on the irrigation schemes, household characteristics, farm activities, quantities and costs of inputs used in production, quantities and value of output, the quantity of water consumed and irrigation practices. For the purpose of efficiency analysis, output is aggregated into one category (vegetable production) and inputs are aggregated into four categories, namely, land, water, labour, fertilizers, seeds and pesticides. Summary statistics of these variables is given in table 1.

Table 1. Descriptive statistics on outputs and inputs used in efficiency analysis.

	Unit	Mean	St.dev.	Min	Max
Output	TD	19240,5	11466	1590	51200
Inputs					
Land	ha	1,94	0,9	0,5	4
Expenditure on Seeds	TD	2957,77	1586,99	253,125	8475,25
Expenditure on pesticides	TD	530,8	545,24	30	3000
Expenditure on fertilizers	TD	1505,1	1457,28	200	8900
Labour man	Days	471,64	295,68	40	1588
Water	m³	22755,4	1988	3942	94608

In the Tobit analyses various farm-specific factors are analysed to asses their influence on the sub-vector efficiencies for water. The share of family labour, farmer's age and its square, farmer's education, land fragmentation index, Irrigated area equipped with water saving technologies and farmer's training.

To examine the role of relevant farm-specific factors in sub-vector efficiency the following equation is estimated:

$$\theta_i = \beta_0 + \beta_1 \text{FA} + \beta_2 \text{EDU} + \beta_3 \text{AGT} + \beta_4 \text{FSA} + \beta_5 \text{FA} + \beta_6 \text{FS} + \beta_7 \text{EIA} + \varepsilon_i \qquad (4)$$

Where:

- θ_i is the DEA sub-vector efficiency index;

- FA is the farmer's age, measured in years;

- EDU is education dummy variable, = 1 if farmer accumulated at least 6 years of schooling, 0 otherwise;

- AGT is agricultural training dummy variable, = 1 if the farmer has gone through agricultural training, 0 otherwise;

- FSA is the square of farmer's age measured in years;

- FL is the share of family labour;

- FS denotes the size of a farm, defined in terms of the number of hectare;

- EIA is the irrigated area equipped with water saving technologies (drip and PVC irrigation technologies); and ε_i is random error.

III – Results

1. Data envelopment analysis efficiency measures

Both the CRS and the VRS DEA models for overall technical efficiency (equation 1) are estimated using the program DEAP (Coelli, 1996). Sub-vector efficiencies were modelled in GAMS using the methodology proposed by Färe *et al.* (1994) and the modelling suggestions of Kalvelagen (2004).

Table 2 gives the frequency distribution of the efficiency estimates obtained by the DEA methods. The average overall technical efficiencies for the CRS and the VRS DEA approaches are 0.74 and 0.86 respectively, indicating that substantial inefficiencies occurred in farming operations of the sample farm households. The average efficiency provides information about the potential resource saving that could be achieved while maintaining the same output level. In our case, results show that the same level of output can be reached by only using 74% and 86% of the used inputs under CRS and VRS specification respectively. Average scale efficiency, which can be calculated as the ratio between CRS and VRS efficiencies, is around 86%. This measure indicates that many farms are not operating at an efficient scale and that adjusting the scale of operation could improve the efficiency.

Table 2. Overall technical and water-subvector efficiencies under constant and variable returns to scale specifications.

Efficiency score	Tech CRS		Tech VRS		Water subvec CRS		Water subvec VRS	
	N° Farms	% of farms	N° Farms	% of farms	N° Farms	% of farms	N° Farms	% of farms
0-10	0	0	0	0	4	8	0	0
10-20	0	0	0	0	11	22	3	6
20-30	0	0	0	0	7	14	3	6
30-40	4	8	0	0	1	2	6	12
40-50	8	16	3	6	3	6	7	14
50-60	5	10	5	10	5	10	2	4
60-70	5	10	3	6	1	2	3	6
70-80	6	12	6	12	1	2	1	2
80-90	5	10	5	10	0	0	1	2
90-100	1	2	5	10	1	2	1	2
100	16	32	23	46	16	32	23	46
Average	0.74		0.86		0.52		0.69	
Scale Efficiency	0.86				0.75			

The sub-vector efficiencies for water demonstrated even larger inefficiencies. Average water efficiency was only 0.52 under CRS and 0.69 under VRS. Figure 1 gives a graphical representation of the cumulative efficiency distributions for the different measures. Again it is clear that under both returns to scale specifications more farms were highly inefficient in the use of water compared to overall technical efficiency.
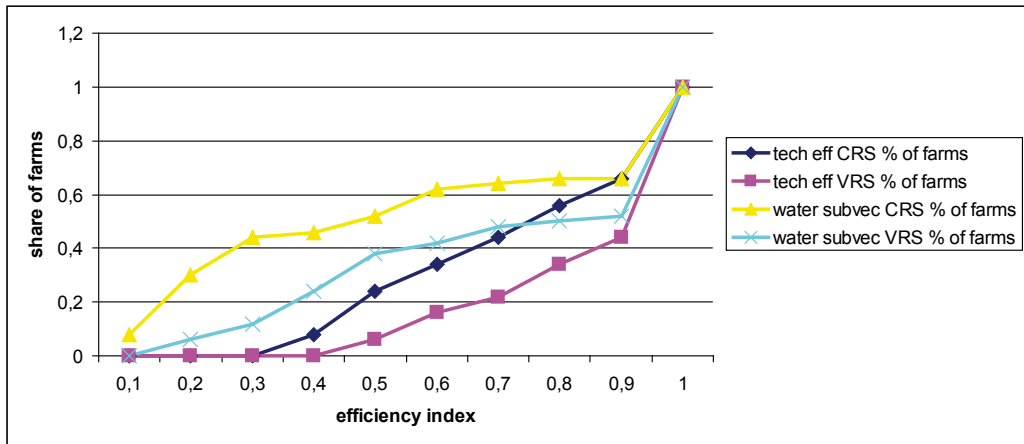

Figure 1. Cumulative efficiency distribution for technical and subvector efficiency for water under VRS and CRS specification.

Table 3 gives the correlation statistics between sub-vector efficiency for water and the overall technical efficiency, which help us to determine the relationship between the two efficiency measures. Technical efficiency and sub-vector efficiency were highly positively correlated both under CRS and VRS specification.

Table 3. Pearson correlations between efficiency measures

	CRS	VRS	SubCRS	SubVRS
CRS	1			
VRS	0,67**	1		
Sub CRS	0,85**	0,69**	1	
Sub VRS	0,609**	0,875**	0,79**	1

Note: ** indicates a 99% significance level

A paired sample t-test to analyse the equality between sub-vector efficiencies and overall efficiencies was statistically significant. Furthermore, sub-vector efficiencies for water were significantly lower than overall technical efficiency measures, both under CRS and VRS specification (table 4).

Table 4. Paired samples t-tests demonstrating the difference between overall technical efficiency and sub-vector efficiency

	Mean difference	Std dev.	t-statistic
CRS: subvector-overall technical efficiency	-0,21	0,21	-7,24**
VRS: subvector-overall technical efficiency	-0,16	0,19	-6,21**

Note: ** indicates a 99% significance level

2. Farm specific factors related to farm inefficiency

The second part of the analysis consists of identifying the characteristics that determine the sub-vector efficiencies for water of these private irrigated farms based on surface wells. Two separate Tobit regressions for CRS and VRS specifications were estimated using the Shazam's Tobit estimation procedure. The results are presented in table 5.

Table 5. Tobit regression coefficients (n=50).

Variable	Sub-vector CRS efficiency	Sub-vector VRS efficiency
Constant	0,907c	2,06a
Age (FA)	- 2,01	-2,52 b
Education (EDU)	1,5c	1,42b
Agricultural training (AGT)	-0,32	-0,44c
Age2 (FSA)	0,025	0,03b
Share of family labour (FL)	0,01	0,08
Size of a farm (FS)	-0,005c	-0,006b
Equipped irrigated area (EIA)	0,495a	0,56a
Log likelihood	-123,19	- 134,7

a Significant at 1% level

b Significant at 5% level

c Significant at 10% level

The estimated coefficients in the technical inefficiency model are also as expected. The farm size, agricultural training and age negatively influenced water efficiency, while the other significant variables had a positive effect on the efficiency measures.

The results in table 5 showed that the farmer's age has a negative, but a positive quadratic effect on all efficiency measures. However, the parameters are only significant for Sub-vector VRS efficiency at the 5 per cent significance level. This suggests that younger farmers are more likely to be inefficient than their older counterparts. The quadratic age variable has a positive coefficient indicating that inefficiency drops with age, perhaps because of the experience.

Farm size has a negative and significant effect on inefficiency levels, with suggests that, on average, large farms operate at higher efficiency levels than small farms.

Concerning the farmer training (AGT), variable of particular interest to policy maker, had a negative effect under both specifications, but were only significant under the VRS specification. Consequently, the negative and statistically significant at 10% level coefficient suggests that an increase in the training programs related to the irrigated agricultural contributes to higher technical efficiency levels of surface wells production on these farms.

Education (EDU) also has a positive impact on technical efficiency. Schooling helps farmers to use information efficiently since a better educated farmer acquires more information and is able to produce from a given input vector.

In addition, the results reveal statistically insignificant but consistently positive relationships between the share of family labour (FL) and all efficiency measures under both specifications.

Finally, the equipped irrigated area (EIA) was highly significant and had a positive effect on the sub-vector efficiency for water under both specifications at 5 per cent significance level.

IV – Conclusions and Policy Implications

The study used a DEA approach to measure the technical and sub-vector efficiency for water of irrigated private schemes based on surface wells in Smar watershed in south-eastern Tunisia.

Detailed survey data collected in 2008 on 50 sampled farmers were used to compute the efficiency measures. The results indicate that the mean technical efficiency under the CRS and VRS is 74% and 86%, respectively. This suggests that, on average, private irrigated farmers could increase their production by as much as 26% through more efficient use of production inputs. This result implies that improvement of technical efficiency should be the first logical step for considerably increasing irrigated production in the study region. Furthermore, considering that international competition is increasing and environment regulations are being tightened, the potential for increasing production by using more traditional inputs is limited.

The sub-vector efficiencies for water are with 52% (CRS) and 69% (VRS), even lower than the overall technical efficiencies. This might be an indication that farmers have little incentives to use water in an efficient manner, in the absence of a water price.

On the other hand, these low efficiencies suggest that substantial decreases in water use can be attained given existing technology, without compromising the key role in rural development played by small-scale irrigation. In this way there is room for lifting part of the increasing pressure on water resources by reallocating a fraction of the irrigation water elsewhere.

In a second step, the relationship between the sub-vector efficiency for water and various attributes of the farm and farmer was examined. The results of the Tobit models can help policy makers or extension services to better aim efforts to improve water use efficiency.

Estimation results from the technical inefficiency effects model suggest that the share of family labour (FL), the agricultural training (AGT), the equipped irrigated area (EIA), the education level (EDU) of the farmer and the square age of the farmer (FSA) variables have a significant and positive relationship with technical efficiency.

Furthermore, education level (EDU) and agricultural training (AGT) particularly used for pruning are associated with higher levels of technical efficiency. This highlights the need for government policies, through extension activities, to set up training programs on irrigated crops in arid zone

More research would also be needed to generalise the results. This paper builds on information of 50 farmers, spread over a significant number of irrigation schemes, but a similar approach in other irrigation schemes in rural areas could provide an interesting comparison.

References

Abay C., Miran B. and Gunden, C., 2004. An analysis of input use efficiency in Tobacco production with respect to sustainability: The case study of Turkey. *Journal of Sustainable Agriculture* 24(3), 123-143.

Al Atiri, R., 2003. Décentralisation et gestion participative de l'irrigation en Tunisie. Forum sur la Gestion de la Demande en Eau. Le Caire, Egypte – Février 2003.

Al Atiri R., 2004. Les efforts de modernisation de l'agriculture irriguée en Tunisie. In : Hammani A.,Kuper M., Debbarh A. (éd.). La modernisation de l'agriculture irriguée. Actes du séminaire euroméditerranéen, 19-23 avril 2004, Rabat, Maroc, projet INCO-Wademed.

Al Atiri R., 2005. WP2 de WADEMED sur les instruments économiques de la modernisation de l'agriculture irriguée. Analyse des politiques hydrauliques. Cas de la Tunisie. Sousse, Tunisie, novembre 2005.

Albouchi L., 2007. Gestion de l'eau en Tunisie : d'une politique de mobilisation à une politique de réallocation de la ressource selon sa valorisation économique. Thèse de Doctorat, université de Montpellier I

Banker. R.D., Charnes. A., and Cooper. W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 30:1078-1092.

Battese, G.E. and Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics.* 20, 325-332.

Battese, G.E., Coelli, T.J. and Colby, T.C., 1989, 'Estimation of frontier production function and the efficiency of Indian farms using panel data from ICRISAT's village level studies', *Journal of Quantitative Economics*, vol. 5, pp. 327–348.

Bauer, P.W. 1990, 'Recent development in the econometric estimation of frontiers', *Journal of Econometrics*, vol. 46, pp. 39–56.

Binam J.N., Sylla K., Diarra I., Nyambi G., 2003. Factors Affecting Technical Efficiency among Coffee Farmers in Côte d'Ivoire: Evidence from the Centre West Region. *R&D Management* 15, 66-76.

Binam J.N., Tonyè J., Wandji N., Nyambi G. and Akoa M., 2004. Factors affecting the technical efficiency among smallholder farmers in the slash and burn agriculture zone of Cameroon. *Food Policy*, 29, 531-545.

Bjurek H.L., Hjalmarsson L. and Forsund F.R. 1990. 'Deterministic parametric and nonparametric estimation in service production', *Journal of Econometrics*, vol. 46, pp. 213–227.

Bravo-Ureta B.E. and Pinheiro A.E., 1993. 'Efficiency analysis of developing country agriculture: a review of the frontier function literature', *Agriculture and Resource Economics Review*, vol. 22, pp. 88–101.

Charnes A., Cooper W.W. and Rhodes E., 1978. 'Measuring the efficiency of farms', *European Journal of Operational Research*, vol. 2, pp. 429–444.

Chavas J., Petrie R. and Roth M., 2005. Farm household production efficiency: evidence from the Gambia. *American Journal of Agricultural Economics*, 87, 160-179.

Coelli T.J. 1995, 'Recent developments in frontier modelling and efficiency measurement', *Australian Journal of Agricultural Economics*, vol. 39, pp. 219–245.

Coelli, T.J. and Battese, G.E. 1996, 'Identification of factors which influence the technical inefficiency of Indian farmers', *Australian Journal of Agricultural Economics*, vol. 40, pp. 103–128.

Coelli, T., 1996. A Guide to DEAP Version 2.1: A data envelopment analysis (computer) program. CEPA Working Papers n°8/96, University of New England, Australia.

Coelli T., Rahman S. and Thirtle C., 2002. Technical, Allocative, Cost and Scale Efficiencies in Bangladesh Rice Cultivation: A non-parametric Approach. *Journal of Agricultural Economics*, 53 (3) 607-627.

Chemak F., 2007. Comportement des producteurs agricoles et efficacité d'usage de la ressource en eau : cas des périmètres irrigués de la région de Sidi Bouzid en semi aride Tunisien. Thèse de Doctorat, université de Montpellier I

Dhungana, B.R., Nuthall, P.L. and Nartea, G.V., 2004. Measuring the economic inefficiency of Nepalese rice farms using data envelopment analysis. *The Australian Journal of Agricultural and Resource Economics* 48 (2), 347-369.

Färe R., Grosskopf S. and Lovell C.A.K., 1994. *Production frontiers*, Cambridge, Cambridge University Press.

Fraser I. and Cordina D., 1999. An application of data envelopment analysis to irrigated dairy farms in Northern Victoria, A*ustralia. Agricultural Systems* 59, 267-282.

Haji J., 2006. Production Efficiency of smallholders' vegetable-dominated Mixed Farming System in Eastern Ethiopia: A non-parametric Approach. *Journal of African Economies* 16(1), 1-27.

Kalirajan K.P. and Shand R.T., 1999. 'Frontier production functions and technical efficiency measures', *Journal of Economic Surveys*, vol. 31, pp. 149–172.

Kumbhakar S.C., Ghosh S.C. and McGuckin J.T., 1991. 'A generalised production frontier approach for estimating determinants of inefficiency in US dairy farms', *Journal of Business and Economic Statistics*, vol. 9, pp. 279–286.

Rodríguez Díaz J.A., Camacho Poyato E., López Luque R., 2004a. Applying Benchmarking an Data Envelopment Analysis (DEA) Techniques to irrigation districts in Spain. *Irrigation and Drainage* 53, 135-143.

Rodríguez Díaz J.A., Camacho Poyato E., López Luque R., 2004b. Application of Data Envelopment Analysis to Studies of Irrigation Efficiency in Analusia. *Journal of irrigation and drainage engineering* 130, 175-183.

Sharma K.R., Leung P. and Zaleski H.M., 1999, 'Technical, allocative and economic efficiencies in swine production in Hawaii: a comparison of parametric and nonparametric approaches', *Agricultural Economics*, vol. 20, pp. 23–35.

Simar L. and Wilson P., 2000, 'Statistical inference in non-parametric frontier models: the state of the art', *Journal of Productivity Analysis*, vol. 13, pp. 49–78.

Speelman S., D'Haese M., Buysse J., and D'Haese L., 2007. Technical efficiency of water use and its determinants, study at small-scale irrigation schemes in North-West Province, South Africa. Paper presented at the 106th EAAE Seminar "Pro-poor development in low income countries. Food, agriculture, trade and environment". October 2007, Montpellier, France

Wadud A. and White B., 2000. 'Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods', *Applied Economics*, vol. 32, pp. 1665–1673.