Irrigation water efficiency in wheat production in Chbika (Tunisia): Parametric versus Nonparametric Comparisons

Ali Chebil[(1,a)]**, *Iheb Frija***[(2)] ***and Walid Bahri***[(3)]

(1) Institut National de Recherches en Génie Rural, Eaux et Forêts (INRGREF)
B.P. 10 - 2080 Ariana, Tunisie; Tél. : +216 71 / 719 630 ; Fax : +216 71 / 717 951
(a): Corresponding author : Email: chebil.ali@iresa.agrinet.tn

(2) Institut Supérieur de comptabilité et d'administration des entreprises (ISCAE), Manouba, Tunisie.

(3) Mediterranean Agronomic Institute of Chania
Alsyllio Agrokepiou, PO Box 85
Chania 73100, Crete, GREECE

Abstract

The aim of this paper is to estimate the water use efficiency of wheat farms in irrigated areas in Chbika (Central Tunisia). Both Stochastic Frontier and Data Envelopment Analysis approaches were used for this purpose. Data were collected from 170 wheat farms during 2010-2011cropping season. The empirical results show that the average water use efficiency measured using the Data Envelopment Analysis (DEA) method was around 41% under constant returns to scale and 43% under variable returns to scale while it was 47% when calculated by the Stochastic Frontier Approach (SFA). This suggests that there is substantial scope for improving irrigation water use efficiency in the study region using the existing technology on wheat farms. Spearman's rank correlation coefficient between both methods in measuring irrigation water use efficiency, for our sample of wheat farms it is positive and significant at the 1% level. However, the average technical efficiencies obtained from the Stochastic Frontier method are higher than the ones estimated from Data Envelopment Analysis. This comparison shows that further empirical researches on sub-vectors efficiency calculation approaches are needed in order to obtain more accurate results than these estimations.

Keywords: *Irrigation water efficiency, Stochastic Frontier, Data Envelopment Analysis, Wheat farms, Tunisia.*

1. Introduction

During the last 30 years, irrigated agriculture in Tunisia has increased from 250,000 ha in 1990 to 450,470 ha in 2010 (MA, 2011). Although the irrigated areas represent only 8% of the total agricultural surface, irrigation contributes with 35% of total agricultural production and 20% of agricultural exports. The growth of the agricultural production in the recent years is mainly due to the expansion of irrigated areas (Al Atiri, 2009). However, the increase of irrigated areas has clear consequences on the country's water resources. Considerable efforts have been devoted over the time to introduce policies aiming to increase water efficiency based on the assertion that «more can be achieved with less water through better management» (Allan, 1999). In order to achieve the objective of water conservation, while taking into account its future demand, we must imperatively improve the efficiency of water use in irrigation. This seems to be the main alternative to reach a sustainable irrigation water management.

Stochastic frontier approach (SFA) and Data Envelopment Analysis (DEA) are the most used approaches in literature to measure the irrigation water use efficiency (IWUE). Recent research studies concerning the IWUE at farm level show that a large potential for improvement of the IWUE exists in Tunisia (Dhehibi et al. 2007; Albouchi et al., 2007; Frija et al. 2009; Naceur et al., 2010; Chemak et al. 2010; Chebil et al., 2012; Chemak 2012). Most of these research papers have based their analysis on non-parametric method. Only Dhehibi et al. (2007) and Albouchi et al. (2007) have used the parametric method. Each of these approaches has its advantages and drawbacks. The main advantages of SFA are that it deals with stochastic noise and allows for statistical testing of hypotheses and the construction of confidence intervals. However, SFA imposes a functional form for the technology and assumes a priori distributional forms for the technical inefficiency term. While non-parametric DEA overcome the disadvantage of the parametric approach because it does not impose functional form and there is no distribution of inefficiency, but assumes no random error and it is sensitive to measurement errors or other noise in the data. The relative strengths and weaknesses of DEA and SFA; in addition to the new developments and differences of results drawn from both methods, have been examined in depth in the literature (Bravo-Ureta and Pinheiro,1993; Hjalmarson, et al. 1996; Coelli, 1995; Sharma et al.;1999; Mbaga et al., 2000; Wadud and White, 2000; Sing, 2000; Thiam et al, 2001; Johansson, 2005; Chemak and Dhehibi, 2010; Cooper et al. 2011; Bogetoft et Otto, 2011).

However, to our knowledge, no study has been conducted to compare sub-vector efficiency results drawn from both DEA and SFA methods. The combined use of these approaches can improve the results. Consistency between results of IWUE issued from both methods will highlight and strengthen existing results about low values of IWUE in different agricultural systems in Tunisia. Moreover, we applied these methods for the wheat production systems, which are very specific in terms of irrigation techniques and water use patterns. Thus, we do believe that results will add to the existing literature and to the policy makers.

The aim of this paper is to estimate the water use efficiency of wheat farmers, in central Tunisia, using SFA and DEA methods. The same data is used for this purpose in order to make a comparison between results from both approaches. A Spearman rank test will be conducted to see if there will be any significant differences between results issued from both methods.

Wheat is a major cereal in Tunisia in term of its output and cultivated land area. It occupies about 50% of all cereals area (800,000 Ha on average) and represents almost 55% of the total cereals production (average wheat production is around 1.8 million tons) (MA, 2010). Irrigated wheat area is around 80,000 ha (MA, 2011). Considering the social and economic importance of the wheat sub-sector in Tunisia, the potential increase of IWUE should be a major concern for policy makers.

The structure of this paper is as follows. In the second section we describe both parametric and non-parametric estimation methodologies. The third Section presents the study areas and outlines the data used in the analysis. Fourth section discusses the results of our study. Finally, the main conclusions are summarized in the last fifth section.

2. Methodological Framework

Efficiency can be defined as producing a maximum amount of output, for a given set of inputs (Output oriented); or producing a given level of output using a minimum level of inputs (input oriented); or a mixture of both. Efficient farms either use less input than others to produce a given quantity of output, or for a given set of inputs they generate a greater output. Hence, the production function describes a frontier. If the production frontier is known, the technical inefficiency of any particular firm can be assessed easily by simply comparing the position of the firm relative to the frontier.

Farrell (1957) initially introduced the frontier function technique. This original work was of a non-parametric type. It was extended to parametric techniques, including deterministic and stochastic models for the efficiency measurement. This later model appends an error term, assuming two components: one is symmetric, capturing statistical noise and random shocks, and the other is one-sided, representing technical inefficiency effects. Among many authors, Coelli (1995) presents the most detailed review of various techniques used for efficiency measurement, including their limitations, strengths, and applications in agricultural production.

Recently, some methodological advances in sub-vector efficiency calculation using DEA and the SFA are achieved. The sub-vector efficiency measure looks at the possible reduction in the selected subset of inputs holding all other inputs and outputs constant (Färe et al., 1994; Oude Lansink et al., 2002; Oude Lansink and Silva, 2003; Oude Lansink and Silva, 2004; Speelman et al., 2008). The main features of the two methods are described below.

2.1. DEA model of water use efficiency calculation

Efficiency calculation using DEA is based on the simple notion that a production unit which employs fewer inputs than another to produce the same amount of output can be considered as more efficient. The DEA method, used in this study, defines efficiency as the ratio of weighted sum of outputs for a given Decision Making Unit (DMU), to its weighted sum of inputs. Each DMU_k, transforms the non-negative input vector $x^k = (x_{k1},...,x_{kN}) \in R_+^N$ to a non-negative output vector $y^k = (y_{k1},...,y_{kM}) \in R_+^M$. In the DEA model of technical efficiency, the production possibility set (P), which also describes the technology, represents the set of all feasible input-output vectors: $P = \{(x, y) / x \ can \ produce \ y\}$. Simultaneously a production frontier is constructed and efficiency scores for each DMU are calculated. Practically, the surface constructed over the data, allows the comparison of one production method to the others in terms of a performance index. In this way, DEA provides a straightforward approach to calculate the efficiency gap that separates the behaviour of each producer from best practices, based on actual observations of inputs used and outputs generated by efficient firms (Banker et al. 1984; Cooper et al., 2000; Wadud and White, 2000; Malano et al., 2004; Ray, 2004; Haji, 2006; Cooper et al., 2011).

The first DEA model used to assess technical efficiency under the variable returns to scale (VRS) assumption was developed by Banker et al. (1984) and called the BCC (Banker, Charnes and Cooper) model. In this study we also opt for this assumption because in agricultural production increasing the inputs does not usually result in a proportional increase in output (Speelman et al., 2008).

Mathematically, the BCC model of input orientation can be written as follows (See Cooper et al. (2000) for more details about the standard DEA model):

$$\begin{aligned} & Min_{\theta,\lambda}\theta \\ \text{s.t.} \quad & \sum_{k=1}^{K}\lambda_k y_{m,k} \ge y_{m,o} \\ & \sum_{k=1}^{K}\lambda_k x_{n,k} \le \theta . x_{n,o} \qquad (1) \\ & \sum_{k=1}^{K}\lambda_k = 1 \\ & \lambda_k \ge 0 \end{aligned}$$

Here θ is the technical efficiency and hence the percentage of radial reduction to which each of the inputs could be subjected; λ_k is a vector of k elements representing the contribution of each farm in determining the technical efficiency of the farm under consideration (farm$_0$); x_{n0} and y_{m0} are, respectively, the input and the output vectors of farm$_0$. Finally, equation $\sum_{k=1}^{K}\lambda_k = 1$ is a convexity constraint, which specifies the VRS framework. Without this convexity constraint, one obtains the CCR model (Charnes et al., 1978).

As an extension to this basic model the concept of “subvector efficiency” (see Oude Lansink and Silva, 2004; Oude Lansink et al., 2002; Färe et al., 1994) can be introduced to account a specific IWUE score for each farm. The IWUE score can be calculated for a given farm by looking at the possible reduction in the water use (*w*) holding all other inputs (*n-w*) and outputs constant. Mathematically, this can be done by splitting the second constraint of model (1) into the following two inequalities:

$$\sum_{k=1}^{K}\lambda_k x_{n-w,k} \le x_{n-w,o}, \quad \text{and} \quad \sum_{k=1}^{K}\lambda_{k,w} \le \theta^{w} x_{w,o} .$$

Technical subvector efficiency for the variable input (*w*) can be determined for each farm (*k*) by solving the following transformed model (2)

$$Min_{\theta,\lambda}\theta^{w}$$

s.t.
$$\sum_{k=1}^{K} \lambda_k y_{m,k} \geq y_{m,o}$$
$$\sum_{k=1}^{K} \lambda_k x_{n-w,k} \leq x_{n-w,o}$$
$$\sum_{k=1}^{K} \lambda_k x_{w,k} \leq \theta^{w}.x_{w,o} \qquad (2)$$
$$\sum_{k=1}^{K} \lambda_k = 1$$
$$\lambda_k \geq 0$$

Where θ^{w} is the IWUE score of the farm$_{\text{O}}$. For more information about the use of a subvector-DEA model for the calculation of IWUE see e.g. Lilienfeld and Asmild (2007), Speelman et al. (2008) and Frija et al. (2009).

2.2. Stochastic frontier model of water use efficiency calculation

Calculation of irrigation water efficiency through the SFA is based on Karagiannis et al., *(*2003). This assumes the following stochastic production frontier function:

$$y_i = f(x_i, w_i; a)\exp(\varepsilon_i = v_i - u_i) \qquad (3)$$

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, respecting 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, $u_i \geq 0$, reflecting the shortfall of farm output from its production frontier, due to the existence of technical inefficiency.

Then, farm specific estimates of output-oriented technical efficiency are obtained as $TE_i^0 = \exp(u_i)$ (Kumbhakar and Lovell, 2000), while farm-specific estimates of input oriented technical efficiency are derived by equation (3) with $TE_i^0 = f(\vartheta_i x_i, \vartheta_i w_i; \alpha)\exp(v_i)$ and solving for $TE_i^I = \vartheta_i$ (Atkinson and Cornwell, 1994; Reinhard et al., 2000). Given strict monotonicity, both measures result in the same ranking but in different magnitude of efficiency scores. TE_i^0 is greater, equal, or less TE_i^I than whenever returns to scale are decreasing, constant, or increasing, respectively (Färe and Lovell, 1978).

The above measures of efficiency are incapable of identifying 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). Specially, it is defined as the ratio of minimum feasible to the observed levels of outputs and input. Thus, irrigation water efficiency is an input-oriented, single-factor measure of technical efficiency defined as:

$$IE^{I} = \left[\min\{\lambda : f(x, \lambda w; a) \geq y\}\right] \rightarrow (0,1] \qquad (4)$$

Irrigation water efficiency, as defined in (4), has an input-conserving interpretation which, however, cannot be converted into a cost saving measure due to its non radial nature (Kopp, 1981).The proposed measure of irrigation water efficiency is illustrated in figure 1 (Karagiannis et al*.,* 2003).

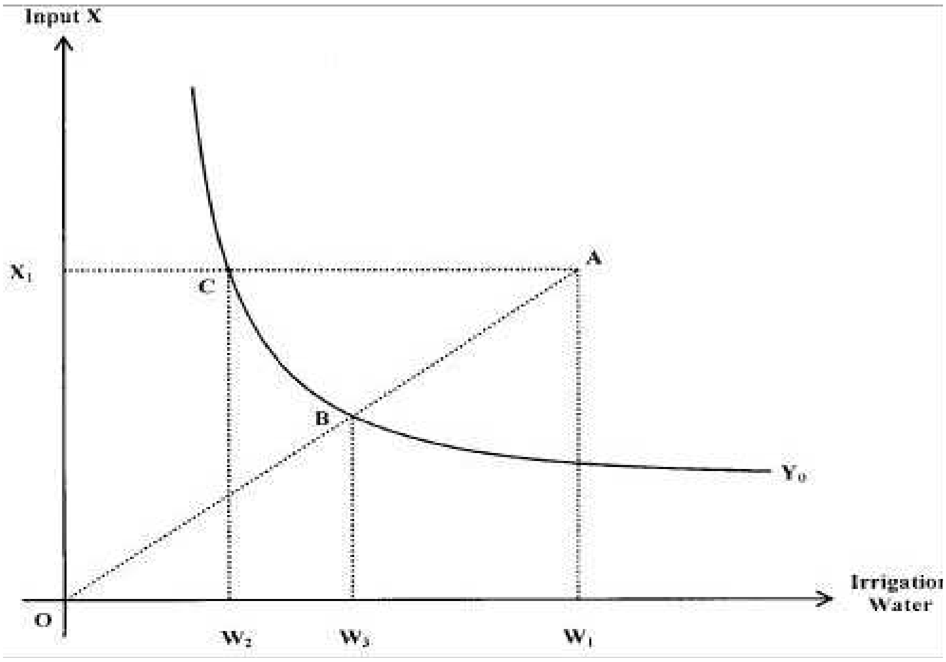

Figure 1: *Irrigation water efficiency*

Let the i^{th} inefficient farmer producing output Y_0 by using x_1 of all other inputs and w_1 units of irrigation water. Then $TE_i^I = OB/OA$ and $IE_i^I = x_iC/x_iA = w_2/w_1$. 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 the use of all other inputs. On the other hand, according to the TE_i^I 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^I should be considered as an upper bound (Akridge, 1989).

Conceptually, measurement of IE_i^I requires an estimate for the quantity (w_2), which is not observed. Nevertheless, when using $IE_i^I = w_2/w_1$ it can easily be seen that $w_2 = w_1.IE_i^I$. By substituting this into (3) and by noticing that point C in Figure 1 lies on the frontier, i.e., $u_i = 0$, (3) may be rewritten as:

$$y_i = f(x_i, w_i^E; a)\exp(v_i) \qquad (5)$$

Where $w_i^E = w_2$ (Reinhard et al., 2000). Then, a measure of TE_i^I can be obtained by equating (3) with (5) and by using the econometrically estimated parameters a (for more details see Reinhard et al., 2000 and Karagiannis et al., 2003).

3. Data and empirical model

3.1. Data and variables definition

The data employed in this study consist of the information about the production structure of 170 Tunisian wheat farms. In order to ensure homogeneity in land and weather conditions, the farms in the sample have been chosen from Chbika region located in Kairouan province, which is located in the center of Tunisia. Chbika is facing growing problems of water scarcity. It belongs to the semi-arid bioclimatic lower floor and characterised by a moderate winter. Groundwater represents the main water source. The data used in the study were collected in 2011 with the collaboration of the extension service in the region, through a questionnaire to cereal-growing farmers.

The value of wheat production per ha is used as an output. In addition, three inputs (labour, water and fertilizers) are also included in the estimation of the frontier production function and the DEA model. Table 1 presents a summary statistics of output and inputs data used in this study. As it can be seen, the annual value of wheat production is 2226.26 Tunisian National Dinar (TND) per farm ranging from a minimum of 1016 to 4370 TND/ha. The standard deviation of the water input vector indicates a large variability of the irrigation volume among the farms.

Table 1. *Summary statistics of the sample variables*

Variable		Mean	Standard deviation	Min	Max
Output	Production value (TND/ha)	2226.26	636.46	1016	4370
Inputs	Water (m^3/ha)	2696.24	1110.80	500	4500
	Labor expenses (TND/ha)	66.46	22.30	31.50	178.75
	Fertilizer expenses (TND/ha)	142.23	60.02	33	338

1 TND ≈ 0.70$

3.2. Empirical models

Using the parametric approach and the selected variables, the production function of the stochastic frontier will have the following form (6):

$$\begin{aligned} LnY_i &= \beta_0 + \beta_1 LnW_i + \beta_2 LnF_i + \beta_3 LnL_i + 1/2\beta_4 (LnW_i)^2 + 1/2\beta_5 (LnF_i)^2 \\ &+ 1/2\beta_6 (LnL_i)^2 + \beta_7 LnW_i\, LnF_i + \beta_8 LnW_i\, LnL_i + \beta_9 LnF_i\, LnL_i + v_i - u_i \end{aligned} \tag{6}$$

where:
Y_i = the output (production value/ha) for the i-th farm
$i = 1, 2. \ldots, N$, N is the number of farm
X_{ji} = the j-th input of the i-th farm
W = water (m^3/ha)
F = fertilizers (Dinars/ha)

L = labour (Dinars/ha)
β = parameters to be estimated
v_i and ε_i are random errors

Concerning the nonparametric approach, the input oriented model presented in section 2.1 is estimated for the same sample of farms and for the same output/input variables as for the stochastic frontier.

4. Empirical results and Discussion

4.1. Estimation of efficiency

The SFA which is going to be estimated is defined in the equation (6) above. The maximum likelihood (ML) estimates the parameters of the translog stochastic frontier production which are obtained using the program FRONTIER 4.1 (Coelli, 1994). As can be seen from the table, the estimated values for the variance parameters are statistically significant from 0. This implies existence of technical inefficiencies among the wheat farmers.

The results of the estimation show that most of the estimated coefficients of the stochastic production frontier are statistically significant at 5% and the expected signs of the coefficients. The estimated elasticity for water, fertilizer, and labour are 0.16, 0.19 and, 0.27 respectively, which indicate a decreasing returns to scale. Therefore, the null hypothesis of constant returns to scale is rejected. The calculated F statistics was 9.68, which exceeded the critical F value ($F^{0.01}_{(4,160)} = 3.34$) at the 1% level of significance

Table 2: *Parameters estimates and t-values of the stochastic production frontier of a sample of Tunisian wheat farms*

Parameters **Stochastic frontier model**	**Estimates**	***t*-student**
Cte	0.202	4.98*
Ln water	0. 13	2.54*
Ln fertilizer	0.12	3.36*
Ln labour	0.28	3.41*
Ln water*Ln water	-0.20	-1.47
Ln fertilizer*Ln fertilizer	0.037	0.23
Ln labour*Ln labour	-0.13	-0.35
Ln water*Ln fertilizer	-0.052	0.54
Ln water*Ln labour	-0.047	-0.25
Ln fertilizer*Ln labour	0.26	5.68*
Variance parameter		
σ^2	0.08	4.73*
γ	0.73	5.68*
Log-likelihood	26.33	

Notes: *: indicates significance at the 5% level

Table 3 shows the frequency distribution of both technical and irrigation efficiencies estimates obtained from the SPF application. The overall technical efficiency varies from 50% to 95.1%, with an average of 83%. This result means that, if technical inefficiency is completely removed, 17% increase in production is possible using the same current technology and without changing levels of the inputs use.

On the other hand, the average input-oriented IWUEis only about 47%, which is much lower than technical efficiency. The average irrigation water use efficiency estimated implies that the observed output of wheat could have been maintained by using the observed values of other inputs, while using 53% less irrigation water. A wide variation in water efficiency across the farms is observed. The range of water efficiency ratings is 12-84%. Frequency analysis of efficiency scores show that 70% of the sample farms have TE below 50%, whereas 5.3% of the farms have an IWUE level of more than 75%. The rest have an IWUE level between 50 and 75% (Table 3).

Table 3: *Frequency distribution of technical and water use efficiencies estimates for a sample of Tunisian wheat farms.*

Econometric Model				
Efficiency level (%)	**Technical efficiency**		**Water Use Efficiency**	
	Number of farms	**% of farms**	**Number of farms**	**% of farms**
0 < EL < 25			14	8.2
25 < EL < 50			106	62.3
50 < EL < 75	34	20	41	24.1
75 < EL < 1	136	80	9	5.3
Average	83.2		47.0	
Min	50.5		10.5	
Max	95.2		83.8	
Standard Deviation	8.3		16.3	

4.2. DEA results

DEA model is estimated using the program GAMS (General Algebraic Modelling System). The frequency distributions of overall technical efficiency and IWUE scores are summarized in Table 4.

The average of the overall technical efficiency of the farms in the sample is about 69% for VRS DEA and 62% for CRS DEA. This implies that the current level of output can be produced using 38% less inputs on average. The DEA results reveal a wide variation in individual efficiency scores across farms, ranging from 35.5% to 100% under VRS and from 26.4% to 100% under CRS.

The average IWUE is about 43.2% and 40.5% under VRS and CRS, respectively. Farmers are then less efficient in the use of water compared to the use of other inputs. Thus, increase in the efficiency of water use results is an increase in overall efficiency. A large range of water efficiencies are observed across 170 farms. As showed in the table 4 below, there are 116 farms under VRS (129 under CRS) with IWUE scores below 50%, 35 farms under VRS (25 farms under CRS) between 50-75%, and 19 farms under VRS (16 farms under CRS) with scores more than 75%.

***Table 4:** Frequency distribution of efficiency ratings of wheat farms in Chbika*

DEA model	**Technical efficiency**				**Irrigation water use efficiency**			
	VRS		**CRS**		**VRS**		**CRS**	
Efficiency level (%)	**Number of farms**	**Percentage of farms**	**Number of farms**	**Percentage of farms**	**Number of farms**	**Percentage of farms**	**Number of farms**	**Percentage of farms**
<25					35	20.6	38	22.4
25-50	20	11.8	38	22.3	81	47.6	91	53.5
50-75	101	59.4	105	61.8	35	20.6	25	14.7
>75	49	28.8	27	15.9	19	11.2	16	9.4
Average	69.1		61.8		43.2		40.5	
Min	35.5		26.4		11.9		10.4	
Max	1		1		1		1	
S.D.	13.9		15.6		22.5		21.3	

4.3. Discussion

The empirical results show that significant irrigation water use inefficiencies of wheat production exist in our farm sample. These inefficiencies are present whether the frontier is parametric or non-parametric. This means that a large potential to increase IWUE is always possible. Our results are in-line with other case studies in Tunisia which were focused into the calculation of IWUE in irrigated Farms, such as works of Chemak et al. (2010) on Sidi Bouzid farmers (Tunisian semi-arid region), Chebil et al. (2012) on vegetables farms in Nadhour region, Dhehibi et al. (2007) on citrus producing farms in Cap Bon region and Frija et al. (2009) on horticultural greenhouses in Teboulba.

Empirical studies listed above have used only one approach to measure water use efficiency. However, in the present study, two approaches have been used in order to test whether the IWUE scores depend on the kind of estimation method. Table 5 shows that Spearman rank test is statistically significant at 1% level which indicates the same scores trend for both parametric and non-parametric methods.

***Table 5:** Spearman rank test of IWUE measures of sample wheat farms based on SFA and DEA approaches*

	SFA	**DEA (VRS)**	**DEA (CRS)**
SFA	1		
DEA (VRS)	0.87*	1	
DEA (CRS)	0.91*	0.96*	1

* Significant at the 1% level

The comparison made between measures of IWUE using SFA and DEA approaches suggested that estimating sub-vectors efficiencies could be used in further future investigations for better comparison. In fact, there are no other studies that we are aware of to compare sub-vector efficiency scores. Results from other studies, which compare overall efficiency scores estimated from both methods, show similar (Sharma et al., 1999; Walud and White, 2000; Johansen, 2005; Chemak and Dhehibi, 2010) and dissimilar results (Hjalmarsson, et al., 1996; Sing, 2000; Mbaga M., et al., 2000) obtained from SFA and DEA methods.

5. Conclusions

This study aims to measure the irrigation water use efficiency of a sample of Tunisian wheat farms and to compare parametric and nonparametric results. The frontier functions were estimated using data based on a sample of 170 wheat farms for the 2009-2010 productions periods. The survey was conducted in Chbika region situated in Kairouan province, which is located in the center of Tunisia.

The empirical results show that the average water use efficiency measured by the Data Envelopment Analysis method was around 41% under constant returns to scale and 43% under variable returns to scale while it was 47% when measured by the Stochastic Frontier Approach scale. Thus, the results from both approaches reveal considerable inefficiencies in water use for wheat production in the region. The estimated mean technical efficiencies in the use of irrigation water obtained from the parametric technique are slightly higher than those from DEA. According to of these research results, it seems that substantial decreases in water use could be attained by using the existing irrigation technology on wheat farms. This result is consistent with previous studies in Tunisian agriculture (Albouchi et al., 2007; Dhehibi et al., 2007; Frija et al., 2009; Naceur et al., 2010; Chemak et al., 2010; Chebil et al. 2012; Chemak, 2012). Thus, policy makers in Tunisia should be more concerned by the low levels of irrigation water use efficiency. Deeper solutions, such as enhancement of water saving technology, improving extension services for better water scheduling and irrigation systems management at the farm level should be proposed.

Applying the Spearman rank test, the estimated efficiencies of irrigation water use from parametric and non-parametric methods are found positive and statistically significant at 1% level, which indicates the same efficiency scores trend for the sample wheat farms. Amara and Romain (2000) conclude that "similarities and differences of parametric and non-parametric technical efficiency results depend on data".

Therefore, further research is needed in order to confirm these results. First, the number of farms included in the dataset needs to be increased. Secondly, the estimation of water use efficiency should be studied in other regions with different irrigation systems. Finally, deeper analysis should be made to other crops and approaches such as Stochastic DEA method (Land et al., 1993; Olesen and Petersen, 1995; Cooper et al., 2011).

References

Al Atiri, R. 2009. Politique du pays en matière de gestion de l'eau. Journée nationale de l`économie d`eau, INAT, 22 Mars, Tunis.

Albouchi, L., Bachta, M.S. and Jacquet, F. 2007. Efficacités productives comparées des zones irriguées au sein d'un bassin versant, New Medit 3,4-13.

Allan, T. 1999. Productive efficiency and allocative efficiency: why better water management may not solve the problem. Agricultural Water Management 40,71-75.

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

Atkinson, S.E. and Cornwell, C. 1994. Estimation of output and input technical efficiency usinga flexible functional form and panel data. International Economic Review 35, 245–55.

Amara, N. and Romain, R. 2000. Mesure de l'efficacité technique : revue de la littérature. Cahiers de CREA, Canada, 32 p.

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. 1992. Frontier production functions and technical efficiency: a survey of empirical application in agricultural economics, Agricultural economics **7**, 185-208.

Bogetoft P. and Otto L. 2011. Benchmarking with DEA, SFA, and R, Springer, New York.

Bravo-Ureta, B.E. and Pinheiro, A.E. 1993. Efficiency analysis of developing country agriculture: a review of the frontier function literature. Agricultural Research Economic Review 22, 88-101.

Charnes, A., Cooper W.W. and Rhodes, E. 1978. Measuring the efficiency of Decision Making Units, European Journal of Operational Research 2, 429-444.

Chebil, A., Frija, A. and Abdelkafi, B. 2012. Irrigation water use efficiency in collective irrigated schemes of Tunisia: determinants and potential irrigation cost reduction, Agricultural Economic Review 13 (1), 39-48.

Chemak, F., Boussemart, J.P. and Jacquet, F. 2010. Farming system performance and water use efficiency in the Tunisian semi-arid: data envelopement analysis, International Transactions in operational research 17, 381-396.

Chemak, F and Dhehibi, B. (2010). Efficacité technique des exploitations en irrigué: une approche paramétrique versus non paramétrique. New Medit 2, 32-41.

Chemak, F. (2012). Water demand management by monitoring the technology performance and the water use efficiency. American Journal of Environmental Sciences 8(3), 241-247.

Coelli, T. 1995. Recent Developments in Frontier Modelling and Efficiency Measurement, Australian Journal of Agricultural Economics 39(3), 219–45.

Cooper, W.W., Seiford, L.M. and Tone, K. 2000. Data Envelopment Analysis: A comprehensive text with models, applications, references and DEA-solver software. Kluwer Academic Publishers, Boston/Dordbrecht/London.

Cooper, W.W., Seiford, L.M. and Zhu J.2011. Handbook on data envelopment analysis, second edition, Springer, New York.

Dhehibi, B., Lachaal, L., Elloumi, M. and Messaoud, A. 2007. Measuring irrigation water use efficiency using stochastic production frontier: An application on citrus producing farms in Tunisia, AfJARE 1 (2), 99-114.

Färe, R. and Lovell, C.A.K. 1978. Measuring the technical efficiency of production, Journal of Economic Theory 19, 150–62

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

Farrell, M.J. 1957. The measurement of technical efficiency. Journal of the Royal Statistical

Society 120, 253-281.

Frija, A., Chebil, A., Speelman, S., Buysse, J. and Van Huylenbroeck, G. 2009. Water use and technical efficiencies in horticultural greenhouses in Tunisia, Agricultural Water Management, 96 (11), 1509-1516, doi:10.1016/j.agwat.2009.05.006 .

Forsund, F. R., Knox Lovell, C. A. and Schmidt, P. 1980. A Survey of Production Functions and of their Relationship to Efficiency Measurement. Journal of Econometrics 13, 5-25.

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.

Hjalmarsson, L., Kumbhakar, S. and Hesmati, A. 1996. DEA, DFA and SFA: A Comparison, Journal of Productivity Analysis **7**, 303-327.

Johansson, H. 2005. Technical, allocative and economic efficiency in Swedish dairy farms: The Data Envelopment Analysis versus the Stochastic Frontier Approach, XI international congress of the EAAE, Copenhagen, Denmark, August 24-27, 2005; 17 pages.

Jondrow, J., Lovell, C. A., Materov, I. S. and Schmidt, P. 1982. On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model. Journal of Econometrics 19, 233- 238.

Karagiannis, G, Tzouvelekas, V and 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.

Koopmans, T. C. 1951. An Analysis of Production as an Efficient Combination of Activities, in (T.C. Koopmans, ed.), Activity Analysis of Production and Allocation, Cowles Commission for Research in Economics. Monograph n°13. New York: John Wiley & Sons, Inc.

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

Land, K. C., Lovell A. A. K., and Thore S. 1993. Chance-Constrained Data Envelopment Analysis. Managerial and Decision Economics 14, 541–554.

Lilienfeld, A. and Asmild M. 2007. Estimation of excess water use in irrigated agriculture: a data envelopment analysis approach, Agricultural Water Management 94, 73-82.

Malano, H., Burton, M. and Makin, I. 2004. Benchmarking performance in the irrigation and drainage sector: a tool for change, Irrigation and Drainage 53, 119–133.

Mbaga, M., Romain, R., Larue B. and Lebel, L. 2000. Assessing technical efficiency of Quebec Dairy Farms, la Série Recherche des cahiers du CREA, Octobre 2000, 22 pages. echerche/2000/SR-00-10.pdf.

Meusen W. and Van den Broeck, J. 1977. Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error, International Economic Review 18: 435-44.

Ministère de l'Agriculture (MA), 2010. Annuaire des statistiques agricoles, Tunisie.

Ministère de l'Agriculture (MA), 2011. Enquête sur les périmètres irrigués, Tunisie.

Naceur, M., Sghaier M. and Bachta, M.S. 2010. Water Use and Technical Efficiencies in Private Irrigated Perimeters in Zeuss-Koutine Watershed, South-Eastern Tunisia, BALWOIS 2010 - Ohrid, Republic of Macedonia - 25, 29 May 2010.

Olesen, O.B. and Petersen, N.C. 1995. Chance constrained efficiency evaluation. Management Science 41, 442–457.

Oude Lansink, A., Pietola, K. and Bäckman, S. 2002. Efficiency and productivity of conventional and organic farms in Finland 1994-1997, Eur Rev Agric Econ. 29(1), 51-65.

Oude Lansink, A. and Silva, E. 2004. Non-parametric production analysis of pesticides use in the Netherlands, Journal of productivity analysis 21, 49-65.

Ray, S.C. 2004. Data Envelopment Analysis: Theory and techniques for economics and operation research, Cambridge University Press, United Kingdom.

Reinhard, S., Lovell, C.A. and Thijssen, G.J. 2000. Environmentally efficiency with multiple environmentally detrimental variables estimated with SFA and DEA, European Journal of Operational Research 121**,** 287-303.

Seiford, L.M. 1996. Data Envelopment Analysis: the evolution of the state of the art (1978-1995), Journal of Productivity Analysis **7**, 99-138.

Sharma, K. R., Leung; P.S. and Zaleski, H. M. 1999. Technical, Allocative, and Economic Efficiencies in Swine Production in Hawaii: A Comparison of Parametric and Non-parametric Approaches, Agricultural Economics 20 (1), 23-35.

Singh, S., Coelli, T. and Fleming, E. 2000. Performance of Dairy Plants in the cooperative and private sectors in India, CEPA working paper 2/2000, Department of Econometrics, University of New England, Amidale, NSW, Australia

Speelman, S., D'Haese, M., Buysse, J. and D'Haese, L. 2008. A measure for the efficiency of water use and its determinants, a case study of small-scale irrigation schemes in North-West Province, South Africa, Agricultural Systems: 98, 31-39.

Thiam A., Bravo-Ureta B.E. and Rivas T.E. 2001. Technical efficiency in developing country agriculture: a meta-analysis. Agricultural economics 25, 235-243.

Wadud, A. and White, B. 2000. Farm household efficiency in Bangladesh: A comparison of stochastic frontier and DEA models Methods, Applied Economics 32: 1665-1673.