

Application of Stochastic Production Frontier in the Estimation of Technical Efficiency of Irrigated Agriculture in Tunisia

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Abstract: In this study, we estimate agricultural technology for Tunisian peasants, accounting for the crop choice of peasants and distinguishing inputs for individual crops such as: vegetable farming cereal and fruit-trees. The study employed the use of cross-section data from distinguishable irrigated crops survey conducted on a sample of 218 farmers from 11 regions in Tunisia. The data were collected with the aid of structured questionnaire and were later analysed. The Cobb Douglas production frontier model is employed in order to analyse data collected. Among the irrigated crop farmers, the significant variables were: farmuar manuar fertiliser quantity, labor, mecanic traction and among of irrigated water applied. The estimated sigma square (σ^2) and gamma (γ) are widely significant for all irrigated crops and revealed that >85% of the variation in the Tunisian irrigated output among farmers in the study area are due to the differences in their efficiencies. However, we find that predicted technical efficiency widely varies across farms and crops from an average of 54.7% for vegetable farming up to 80.6% for fruit-trees. The study also revealed the existing on inefficiency effects among the farmers as: education, farmer's age, irrigation techniques, lack of education, property of land.

Key words: Stochastic, production, frontier efficiency irrigated agriculture, JEL classification: Q₁₂ Q₁₃, gamma (γ), Tunisia

INTRODUCTION

The crucial role that agriculture should play on economic development has been recognized for years. Tunisian agriculture provides 16% to GDP, ensuring the bulk of food supplies of the country and occupying a quarter of the active population. Agricultural and Fishing exports, mostly citrus fruits, dates and fish, represent 11% of total exports.

In Tunisia, the irrigated domain occupies only 7.3% of the useful agricultural area, it contributes much more to the global agricultural output. During the last economic development plan the production share of the irrigated agriculture risen from 29-50% of the total value of agricultural production. Although, agriculture benefits only from 9% of the credits in the economy, most of agricultural investment (60%) is originated from the State Ministere de l' of Agriculture in 2006. Hydraulics accounts for 32% of all agricultural investment and for 4.5% of total investment in Tunisia. The investment not only provides water to peasants but it also participates in improving rural incomes, creating jobs, bringing flexibility to the necessary adaptation of product supply to market

fluctuations. Crop diversification is a core characteristic of the irrigated Tunisian agriculture. Globally, 45% of land is occupied by gardening crops, 34% by fruit trees, 13% by fodder crops and finally 8% by cereals. Water resources in Tunisia come from rain and underground water reserves. Rain is very variable across regions, seasons and years. Neglecting the salinity factor leads to consider that the North of the country possess most water resources (60%), while the Centre and the South have, respectively 17 and 23% of them. From these potential resources, the Ministry of Agriculture assesses that about 88%, i.e., 3,995 Mm³ are immediately exploitable. From this volume, 76% amounting to 3,043 Mm³ are already developed.

Water demand in Tunisia has steadily risen over the last 15 years. Although, the irrigated area has more than doubled, the actual use of water much fluctuates across years depending on the agriculture needs. In part because of this uncertainty, the present water pricing system is far from reflecting the economic value of irrigation water. The official price of water (between 0.032 and 0.06 TD m⁻³) corresponds to the average water cost with total coverage of exploitation costs and partial reimbursement of

investment. However, the contribution of peasants to the investment cost is rarely collected. Similarly, the rental charges that are carried forward only cover from 15-60% of the exploitation costs. The obtained deficit is filled with public subsidies. In practice, the geographical variability of the unit cost of water mostly results from the low irrigation intensity in some regions. Beyond water scarcity, the agricultural sector suffers from several handicaps. The farmers are generally aged and little educated. About 53% of them have a mean age of 53 years in 2006 and 75% are illiterate. Employment is precarious: 60% of salaried and family workers are only employed on a temporary basis. The agricultural workers research on average 140 days year⁻¹, to compare with 250 days for the permanent workers.

In these conditions, farm productivity and efficiency and the question of how to measure them is an important concern for irrigated agriculture in Tunisia. In particular, how water input influences productivity has major consequences on water supply policy. The potential importance of production efficiency has not yielded many focusing on Tunisian agriculture. As a matter of fact this is the first study in this domain. The aim of this study is first to fill the gap in the estimation of efficiency model for Tunisian agriculture and second to explore the use of crop-specific input and output data for this type of models.

MATERIALS AND METHODS

The production frontier literature: The original frontier function model introduced by Farrell (1957) uses the efficient unit isoquant to measure economic efficiency and to decompose this measure into technical efficiency and allocative efficiency. In this model, Efficiency (TE) is defined as the firm's ability to produce maximum output given a set of inputs and technology. Stated differently, technical inefficiency reflects the failure of attaining the highest possible level of output given input and technology. In contrast, Allocative (or price) Efficiency (AE) measures the firm's success in choosing the optimal input proportions, i.e., where the ratio of marginal products for each pair of inputs is equal to the ratio of their market prices.

In Farrell's framework, economic efficiency is a measure of overall performance and is equal to TE times AE. A large number of frontier models have been developed. They are based on Farrell's work can be classified into two basic types: parametric and non-parametric. Parametric frontiers rely on a specific functional form while non-parametric frontiers do not. Due to the data limitations, we follow the parametric approach. Another important distinction is between deterministic

and stochastic frontiers. The deterministic model assumes that any deviation from the frontier is due to inefficiency. The deterministic parametric approach was initiated by Aigner and Chu who estimated a Cobb-Douglas production frontier through linear and quadratic programming techniques.

In contrast, the stochastic approach allows for statistical noise. This is the option that we pursue given the prevailing ignorance about actual agricultural technical processes. In the stochastic production frontier, technical efficiency is measured with one-sided disturbance term. When explicit assumptions for the distribution of the disturbance term are introduced, the frontier function can be estimated using the maximum likelihood method. If no assumption are made concerning the distribution of the error term, the frontier can also be estimated by the Corrected Ordinary Least Squares method (COLS) which consists of shifting the intercept term of the frontier function upwards until no positive error term remains.

The stochastic production function model: Given the inherently stochastic nature of data production, we prefer to use the stochastic frontier production function approach in order to assess the technical efficiency of data farmers in the irrigated agriculture.

The stochastic frontier production model incorporates a composed error structure with a two sided symmetric component and a one-sided component. The one-sided component reflects inefficiency, while the two sided error captures the random effects outside the control of the production unit, including measurement errors and other statistical noise typical of empirical relationships. The Aigner *et al.* (1977), Meeusen and van den Broeck (1977) and Battese and Coelli (1995) model for the cross-sectional data is defined in two equations as:

$$y_i = f(X_i, \beta) e^{\varepsilon_i} \quad (1)$$

Where:

- y_i = The production of the i th farmer in the sample ($i = 1, 2, \dots, n$)
- X_i = A $(1 \times k)$ vector of input quantities used by the i th farmer
- β = A $(k \times 1)$ vector of parameters to be estimated
- $f(X_i, \beta)$ = An appropriate parametric form for the underlying technology
- ε_i = A stochastic error term consisting of two independent components u_i and v_i

$$\varepsilon_i = v_i - u_i \quad (2)$$

The symmetric component v_i accounts for random variation in output due to factors outside the farmer's control, such as weather and plant diseases. It is assumed

to be independently and identically distributed as $N(0, \sigma_v^2)$ independent of u_i . The asymmetric component u_i is a non-negative random variable, associated with technical inefficiency. It is assumed to be independently distributed with truncations (at zero) of the normal distribution with mean, μ_i and variance, σ_u^2 [$N(\mu_i, \sigma_u^2)$]. Under these assumptions the mean of the technical inefficiency effects, μ_i can be specified as follows:

$$\mu_i = \sum \delta_k Z_{ik}$$

Where:

Z = A $(1 \times m)$ vector of observable farm-specific variables hypothesized to be associated with technical inefficiency

δ = An $(m \times 1)$ vector of unknown parameters to be estimated

The variance of ϵ is therefore: $\sigma^2 = \sigma_u^2 + \sigma_v^2$, while the ratio of two standard errors is defined as:

$$\gamma = \frac{\sigma_u^2}{\sigma_v^2}$$

Parameter γ can determine whether a stochastic frontier model is warranted as opposed to a simple production function. The rejection of the null hypothesis, $H_0: \gamma = 0$, implies the existence of a stochastic production frontier. Jondrow *et al.* (1982) have shown how measures of efficiency at the individual farm level can be obtained from the error terms. For each farm, the inefficiency measure is the expected value of u conditional on ϵ , i.e.,

$$E(u_i / \epsilon_i) = \frac{\sigma_u \sigma_v}{\sigma} \left[\frac{\phi(\epsilon_i \lambda)}{1 - \Phi(\epsilon_i \lambda / \sigma)} - \frac{\epsilon_i \lambda}{\sigma} \right] \quad (3)$$

Where:

$\phi(\cdot)$ and $\Phi(\cdot)$ = The standard normal density function and the standard normal distribution function evaluated at $(\epsilon \lambda / \sigma)$

Estimated values for ϵ , $\lambda = (\sigma_u / \sigma_v)$ and σ are used to evaluate the density and distribution functions. Finally, the technical efficiency of the i th sample farm, denoted by TE_i , is defined in terms of the ratio of the observed output to the corresponding frontier output, conditioned on the levels of inputs used by that farmer. It is given as:

$$TE_i = \exp(-u_i) = Y_i / [f(X_i, \beta) \exp(v_i)] \quad (4)$$

where, $f(X_i, \beta) \exp(v_i)$ describes the stochastic frontier production.

The estimation of technical efficiencies is based on the conditional expectation in expression (Eq. 4), given the model specifications (Battese and Coelli, 1988).

$$TE_i = E(\exp\{-u_i\} / \epsilon_i) = \left[\frac{1 - \Phi(\sigma_u - \mu_i / \sigma_u)}{1 - \Phi(-\mu_i / \sigma_u)} \right] \exp\left\{-\mu_i + \frac{1}{2} \sigma_u^2\right\}$$

Where:

$$\mu_i = -\epsilon_i \sigma_u^2 / \sigma^2 \text{ and } \sigma_u^2 = \sigma_u^2 \sigma_v^2 / \sigma^2$$

In recent years, the Battese and Coelli (1995) model for the technical inefficiency effects has become popular thanks to its computation simplicity as well as its ability to examine the effects of various farm-specific variables on technical efficiency in an econometrically consistent manner. This is as opposed to a traditional two-step procedure which is inconsistent with the assumption of independently and identically distributed technical inefficiency effects in the stochastic frontier. The main advantage of this technique over the two-stage approach is that it incorporates farm-specific factors in the estimation of the production frontier on the ground that these factors may have a direct impact on efficiency. We first tested and rejected a translog functional form for the production frontier. On the basis of this generalized likelihood ratio test, the Cobb-Douglas form is found to be a preferable representation of the data. Although, the Cobb-Douglas specification is restrictive, it provides a useful representation of production, as the interest lies also on efficiency measurement and not only on analysis of production structure. The model estimated for the common sample is specified as:

$$\ln(y_i) = \beta_0 + \sum_{k=1} \beta_k \ln x_{ik} + v_i - u_i \quad (5)$$

Where:

- (i) = Refers to the i th farmer in the sample
- y_i = The output for this farmer
- X_k = Input variables
- β_k = Parameters to be estimated
- v_i and u_i = The random variables

This model is estimated separately for the different crops. Following Battese and Coelli (1995), the mean of technical inefficiency effects, μ_i is further defined as:

$$\mu_i = \delta_0 + \sum \delta_k Z_{ik} \quad (k = 1, \dots, 6) \quad (6)$$

Where:

- Z = Farm-specific variables
- δ_k = Unknown parameters

The Z_{ik} variables included in the model of technical inefficiency are socioeconomic factors as in Yao and Liu (1998) and Battese *et al.* (1989).

With cross-section data, the technical inefficiency model can be estimated only if the u_i 's are stochastic and have given distributional properties (Battese and Coelli, 1995). It is of interest to test various null hypotheses such as the following:

- Technical inefficiency effects are not stochastic, $H_0: \gamma = 0$
- Technical inefficiency effects are absent from the production function model

$$H_0: \gamma = \delta_0 = \delta_1 = \delta_2 = \dots = \delta_6 = 0$$

These and other relevant null hypotheses can be tested using the generalized likelihood ratio statistic, λ given by:

$$\lambda = -2 \{ \ln(L(H_0)) - \ln(L(H_1)) \} \quad (7)$$

Where $L(H_0)$ and $L(H_1)$ denote the values of likelihood function under the null (H_0) and alternative (H_1) hypotheses, respectively. If the given null hypothesis is true λ has approximately chisquare distribution or mixed chisquare distribution when the null hypothesis involves $\lambda = 0$ (Coelli and Battese, 1996). We now present the data used in the estimations.

The data: The data are taken from a national survey focusing of irrigated agriculture conducted by the Tunisian Ministère de l'agriculture in 2006.

The objective of the survey was to gather basic data about producers, their production unit and the use of water. About 250 agricultural producers have been surveyed, leaving 218 observations (Table 1) because of missing or erroneous data. The sampling scheme is stratified by zone (11 regions equally distributed on an East-West axis across the three agro-climatic region: North, Centre and South), irrigation source, perimeter size and perimeter age. Note a rare opportunity: we dispose of input and output information that is specific to three crops: fruit-trees, vegetable farming and cereal. The main variables entering the stochastic frontier function are as follows (Table 2). A few descriptive statistics for the sample by crop are shown in Table 3. Data on each input and output were collected by crop. Inputs include the use of farmyard manure fertiliser, human labor, mechanic traction, animal traction irrigated water.

Land is generally scarce and average holding is small. Average land for each crop ranges from 0.03 ha/household for cereal to 18 ha/households for fruit-trees. The average labor input ranges from 25 days (fruit-trees) to 1080 days (vegetable farming). Labour

Table 1: Interviewed perimeters

Region	Perimeter surveyed	No. of households
Ariana	El Battan, Sidi Naji	24
Bizerte	Mateur, Ghezala	13
Nabeul	Menzel Bouzelfa, Lebna	27
Ben Arous	Mornag	13
Jendouba	S.Essebt, Bouhertma	19
Zagouane	Zagouane	15
Kairouan	Sidi Saad	11
	Hajeb	22
Mahdia	Bir Ben Kamla, Hiboun	14
Sousse	Chott Meriam, Sidi Bouali	20
Gabés	Metouia, Zerig, Ketana	21
Kebeli	Matrouha	19
Total		218

Table 2: Description of output, input and farm-specific variables

Variables	Description
Output (Y)	Output for a particular crop (in tons)
Input variables	
Manure (X_1)	Farmyard manure fertiliser, tons
Labor (X_2)	Regular and casual labor (in days)
Mecanization (X_3)	Mechanic traction (h)
Animal traction (X_4)	Animal traction (days)
Irrigated water (X_5)	Among of water applied (m^3)
Farm size (X_6)	Total farm size (acres)
Farm specific variables	
Farmer's age (Z_1)	Age, number of years
Price of water (Z_2)	In 10^{-3} dinars m^{-3}
Farmer's education dummy (Z_3)	1 if analphabet farmer and 0 otherwise
Propriety dummy (Z_4)	1 if owner farmer and 0 otherwise
Region dummy (Z_5)	1 if north region and 0 otherwise
Technique of irrigation dummy (Z_6)	Value 1 if traditional technique of irrigation and otherwise
Monetary variables	
Price of output (p_o)	Market price of output, 10^3 dinars kg^{-1}
Cost	Cost of production (dinars)

input is more important than mechanization because of the small land size. Often, statistical demand curves for irrigation water are specified with demanded water quantity a function of, price, income and rainfall. This approach may not be appropriate in Tunisia since water irrigation demand is correlated with the political importance of crop.

For example, cereals is seen as a politically sensitive crop fostered by the government in order to ensure food self-sufficiency. This crop requires an average of 5107 m^3 by household. For irrigation water, a small variation in price of water occurs across farms (an average of 0.055 $TND^{-2} m^{-3}$). The official price of water (between 0.024 and 0.07 $TND m^{-3}$) corresponds to the average cost including integral coverage of exploitation costs and partial reimbursement of the investment cost. However, the contribution of peasants to the investment cost is rarely perceived. Similarly, the rental charges of irrigation water that are carried forward only cover from 15-60% of the exploitation costs.

The deficit is filled with public subsidies. The farmers are generally aged (mean age 54 years). The education of the head and member of the household is generally very low. Over 53% of them cannot read and write a letter. We now turn to the estimation results.

Table 3: Summary statistics of output, input and farm-specific variables

Variables	Fruit-tree			Vegetables			Cereal		
	Mean±SD	Min.	Max.	Mean±SD	Min.	Max.	Mean±SD	Min.	Max.
Output (Y)	11.28±20.37	0.03	120	17±31.92	0.15	300	14.28±19.2	0.9	150
Input variables									
Manure (X ₁)	32.23±56.91	0	401.5	39.7±163.3	0.75	2007	13.54±14.8	0.4	72
Labor (X ₂)	86.47±154.4	25	980	88.6±129.6	250	1080	46.04±43.6	30	200
Mecanization (X ₃)	6.383±36.55	0	400	4.97±5.841	0	38	406.9±97.6	328	606
Animal traction (X ₄)	18.3±39.36	0	360	12.3±26.93	0	200	12.29±16.6	0.5	100
Irrigated water (X ₅)	4478±9382	200	32930	1815±2298	126	15000	5107±4509	1040	3300
Farm size (X ₆)	1.682±2.266	0.05	18	1.02±1.282	0.05	10	2.486±2.28	0.03	12
Farm specific variables									
Farmer's age (Z ₁)	54.31±14.26	20	97	54±13.97	22	84	53.9±13.5	29	84
Price of water (Z ₂)	53.98±9.893	33	70	57.5±9.055	24	70	57.61±7.5	48	70
Farmer's education dummy (Z ₃)	0.541±0.501	0	1	0.58±0.495	0	1	0.567±0.5	0	1
Propriety. dummy (Z ₄)	0.892±0.311	0	1	0.71±0.457	0	1	0.881±0.33	0	1
Region dummy (Z ₅)	0.546±0.5	0	1	0.57±0.497	0	1	0.866±0.34	0	1
Technique of irrigation (Z ₆)	0.515±0.502	0	1	0.37±0.484	0	1	0.134±0.34	0	1
Farm benefit	5570.823±9552.623	110	47750	3132.635±4847.695	100	39000	1861.888±1429.912	295	6080
Price of output	357.3±88.64	220	450	242±70.14	150	300	333.7±164	200	950
Cost of production	776.6716±915.7247	100	4280	926.605±922.215	100	6000	1322.102±1016.356	150	5000
No. of observation	130				201				67

RESULTS AND DISCUSSION

The parameters (β_k) ($k = 1, \dots, 6$) of the stochastic Cobb Douglas production frontier model and those for the technical inefficiency model (δ_k) ($k = 1, \dots, 6$) are simultaneously estimated by the maximum likelihood method. The model 6 and 7 is estimated for three different crops: fruit-trees, vegetables and cereal. The estimates are shown in Table 4. The estimate of technical efficiency model is based on the half-normal specification. The slope coefficients of the stochastic frontier describe the output elasticities of inputs. The estimated signs of the parameters are as expected.

The significant input variables include: fertilizers, labor, mechanic traction, amount of irrigated water and farm size. Even if animal traction is not significant at 5% level, it is significant at 10% level for fruit-trees. Moreover, the estimated output elasticities with respect to irrigation water are significant and range from 0.022-0.224. Labor input, mechanization and animal traction coefficients are statistically significant. However, even though the land size has a positive elasticity, it is not significant at 5% level. This may be because it is a fixed factor.

The estimated sigma square (σ^2) of the irrigated crop farmers are 0.701, 0.854 and 0.596, respectively for cereal, fruit trees and vegetable farming (all significant at 1% level). This result indicates a good fit of the model. The estimate gamma (γ) parameter of the irrigated crop farmers are 0.948, 0.896 and 0.903, respectively for cereal, fruit-trees and vegetables (highly significant at 1% level). That is: over 89% of the variation in the irrigated crop output among the farmers in Tunisia is due to the differences in their technical efficiencies. This results is consistent with

the finding of Yao and Liu (1998). In the efficiency model, the coefficients of age, land property and traditional irrigation are significantly negative. In particular, the younger the farmer, the more technically inefficient. Education has a positive and significant relationship with technical efficiency.

The traditional OLS estimates of a production function, without technical inefficiency effects is not an adequate representation of irrigated crop involved in this study. We conduct generalized likelihood ratio tests of the nullity of the variance parameter γ ($H_0: \gamma = 0$). The test results that inform of the importance of the inefficiency component are shown in Table 5. The null hypothesis specifies that the irrigated crop farmers in Tunisia were technically efficient in their production. The null hypothesis is rejected for all the considered crops in the study area. Given that there are differences in efficiency levels among irrigated crop farmers in this study, it is appropriate to question why some farmers can achieve relatively high efficiency, while others are technically less efficient. Variations in the technical efficiencies of farmers may arise from farm characteristics that affect the ability of the farmer to use the existing technology adequately.

The found discrepancies could also be due to heterogeneous technical knowledge. Many researchers have suggested that the technical efficiency of farmer is much determined by socio-economic and demographic factors. The distributions of technical efficiency measures are summarized in Table 6. The mean value of technical efficiency for all farms is estimated to be 0.547, for vegetables (from 0.202-0.998); 0.772 for cereals (from 0.248-0.979) and 0.806 for fruit-trees (from 0.472-0.962). Then, output could be increased on average by,

Table 4: Maximum likelihood estimates for the parameters of the stochastic frontier production function and technical inefficiency models

Parameters	Cereal		Fruit-trees		Vegetable farming	
	Co-eff.	t-ratio	Co-eff.	t-ratio	Co-eff.	t-ratio
Stochastic frontier						
Constant (β_0)	0.091	0.348	1.712	6.868	1.206	9.005
ln (farmyard manure) (β_1)	0.353	3.474*	0.219	1.735**	0.268	1.721**
ln (labor) (β_2)	0.206	1.952*	0.125	2.545*	0.138	6.188*
ln (Mechanization) (β_3)	0.024	1.692**	0.150	2.789*	0.138	1.621
ln (animal traction) (β_4)	0.166	1.657**	0.003	0.038	0.194	1.154
ln (irrigated water) (β_5)	0.224	3.261*	0.166	9.304*	0.022	1.951*
ln (farm size) (β_6)	0.109	1.639	0.242	1.596	1.018	1.552
Inefficiency models						
Constant (δ_0)	-2.021	-0.776	0.030	0.061	0.983	2.270
Farmer's age (δ_1)	-0.004	-0.355	-0.005	-0.975	-0.001	-0.839
Price of water (δ_2)	0.039	1.165	-0.005	-1.066	0.000	0.189
Education dummy (δ_3)	0.081	0.512	0.129	1.305	0.026	1.076
Propriety dummy (δ_4)	-0.105	-0.352	-0.013	-0.091	-0.033	-0.825
Region dummy (δ_5)	0.190	0.562	-0.131	-0.689	-0.190	-5.163
Technique of irrigation (δ_6)	-0.104	-0.422	-0.161	-1.475	-0.052	-1.417
Variance parameters						
σ^2	0.701	3.285	0.854	3.058	0.596	6.994
γ	0.948	5.571	0.896	4.576	0.903	5.170
Ln (likelihood)	-37.072		-102.093		-205.706	
No. of observation	67.000		130.000		210.000	

* = Significant at the 5% level; ** = Significant at the 10% level

Table 5: Likelihood ratio test of $H_0: \gamma = 0$

Irrigated crops	L (H_0)	L (ha)	χ^2_c	Critical value ($\chi^2_{3,0.05}$)	No. of observation
Vegetables	-242.050	-205.710	72.6842	15.51	210
Cereals	-66.985	-37.072	59.8260	15.51	67
Fruit-trees	-119.010	-102.090	33.8320	15.51	130

Table 6: Frequency distributions of technical efficiency estimates

Efficiency index (%)	Vegetable farming	Cereal	Fruit-tree
<25	19 (9.4%)	1 (1.5%)	0 (00.0%)
25-50	133 (66.2%)	2 (3.0%)	8 (06.2%)
50-75	41(20.4%)	24 (35.8%)	51 (39.2%)
75-100	8 (4.0%)	40 (59.7%)	71 (54.6)
No. of observation	201	67	130
Mean	0.547	0.772	0.806
Minimum	0.202	0.248	0.472
Maximum	0.998	0.979	0.962
Standard deviation	0.138	0.162	0.109

respectively 45.3% (vegetables), 22.8% (cereals) and 19.4% (fruit-trees) with the current technology and the same amount of inputs, if technical inefficiency is removed. Three quarters (75.7%) of the surveyed farmers are below 50% efficiency in the case of vegetables. About 96.1% of the farmers are below 75% if efficiency.

Thus, there is considerable room for efficiency improvement for vegetables in Tunisian agriculture. However, cereals and fruit-trees correspond to more reasonable efficiency levels. Over 40% of the farmers have efficiency levels under 75%.

These statistics are comparable to those reported by previous frontier studies in agriculture in developing countries. For example, the overall average level of technical efficiency computed from all the studies presented by Thiam *et al.* (2001) is 68%. The parametric studies relying on the

Cobb-Douglas form reported technical efficiency measures ranging from 52-84%, with an average of 71%.

Policy implications: Agricultural policy in Tunisia is much determined by considerations of food security self-sufficiency and import-substitution strategies. The water resources manager in the semi-arid and arid zones is interested in knowing how far agricultural production can be expected to increase by raising its productive efficiency without absorbing further resources, given the involved technology.

The econometric estimates of the farm-level technical inefficiencies reveal that the farmers produce well below their potential agricultural output. It has been estimated that for the same amounts of inputs, output could be increased on average respectively by 36% for vegetables, 26% for fruit-trees, while only 16% for cereals. Observed levels of benefits and full-efficiency-benefits (Belloumi and Matoussi, 2006) are presented in Table 6 for the three crops.

By reaching full efficiency levels, farmers would be able to increase their actual benefits by 87.3, 82.8 and 69.7%, respectively for vegetables, fruit-trees and cereals. Various benefit levels with and without in efficiency shown in Table 7. Understanding the different efficiency levels among farmers can help policymakers. For example, agricultural development programs can be targeted to

Table 7: Various benefit levels with and without inefficiency

Crops	π = Observed benefit levels	π^* = Benefit levels at full efficiency		
	(Mean)	Mean \pm SD	Min.	Max.
Vegetable farming	3132	5867 \pm 8322	96	74548
Fruit-tree	5570	10186 \pm 18018	68	93289
Cereal	1861	3159 \pm 3373	74	14278

those types of farms that are more efficient and provide most benefits to the community. This is important in Tunisia because food self-sufficiency, which is a government objective, can only be reached by promoting output growth.

CONCLUSION

In this study, we have used survey data on input and output by farms to estimate farm-level inefficiency of Tunisian irrigated crop production for three crops (cereals, fruit-trees and vegetables). We find some evidence of substantial inefficiencies. On average, cultivation of cereals and fruit-trees is found to be more efficient than vegetables farming.

We find that irrigated production for the three crops is mainly determined by five variables: farmyard manure fertiliser, labor, mechanization, water quantity and farm size. Output elasticities of all inputs are found to be positive and significant except for the farm size. For the technical inefficiency model, none of the introduced socio-economic variables seems to matter.

This result may be due to the lack of variability in these variables in these data where the majority of the farmers have similar socio-economic characteristics. From a policy standpoint, more accurate technical efficiency estimates are crucial in guiding policy decisions dealing with farm extension and training programs, among others. On average, vegetable production is found to be technically less efficient than cultivation of cereals and fruit-trees.

However, water resource scarcity continues to characterize water demand and supply environment in Tunisia. Agriculture by far the largest user of water, accounts for roughly 80% of water use. In this sector, the application of highly subsidized associated inputs such

as water has drained public budgets. Then, attention has turned towards better usage of the existing irrigation infrastructure and improving water conservation.

REFERENCES

- Aigner, D.J., C.A.K. Lovell and P. Schmidt, 1977. Formulation and estimation of stochastic frontier production models. *J. Econ.*, 6: 21-37.
- Battese, G. and T. Coelli, 1988. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *J. Econ.*, 28: 387-399.
- Battese, G.E. and T.J. Coelli, 1995. A model for technical inefficiency effect in stochastic frontier production function for panel data. *Empirical Econ.*, 20: 325-332.
- Battese, G.E., T.J. Coelli and T.C. Colby, 1989. Estimation of frontier production functions and the efficiencies of indian farms using panel data from ICRISAT's village level studies. *J. Quantitative Econ.*, 5: 327-348.
- Belloumi, M. and M.S. Matoussi, 2006. A stochastic frontier approach for measuring technical efficiencies of date farms in Southern Tunisia. *Agric. Resour. Econ. Rev.*, 35: 1-10.
- Coelli, T.J. and G. Battese, 1996. Identification of factors which influence the technical inefficiency of Indian farmers. *Aust. J. Agric. Econ.*, 40: 103-128.
- Farrell, M.J., 1957. The measurement of productive efficiency. *J. R. Stat. Soc.*, 120: 253-290.
- Jondrow, J., C.A.K. Lovell, I.S. Materov and P. Schmidt, 1982. On the estimation of the technical inefficiency in the stochastic frontier production function model. *J. Econ.*, 13: 233-238.
- Meeusen, W. and J. van den Broeck, 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *Int. Econ. Rev.*, 18: 435-444.
- Thiam, A., B.E. Bravo-Ureta and T.E. Rivas, 2001. Technical efficiency in developing country agriculture: A meta-analysis. *Agric. Econ.*, 25: 235-243.
- Yao, S. and Z. Liu, 1998. Determinants of grain production and technical efficiency in China. *J. Agric. Econ.*, 49: 171-184.