Impacts of Soil Salinity on the Productivity of Al-Musayyeb Small Farms in Iraq: An Examination of Technical, Economic and Allocative Efficiency

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Abstract

The objective of the study was to investigate how smallholder farm communities could sustain economically viable agricultural production in the salt-affected areas of Al-Musayyeb in 'Central Iraq'. It aims at opening a new dimension to farmers and policy makers on how to increase production in soil-affected areas by determining the extent to which it is possible to raise efficiency for salt-affected farmers with the existing resources base and available technology. There were 220 households, randomly stratified, interviewed based on severity of salinity indicators. The scores and determinants of technical efficiency (TE) and allocative efficiency (AE) were identified using stochastic frontier cost and production functions. Empirical findings show that the estimated AE of the farms in the Al-Musayyeb area varied in the range of 56–94%, with a mean of 59%. This suggests that the average farmer needs a cost-saving of 41% to attain the status of the most allocatively efficient farmer. Findings show that technical efficiency was in the range of 57–98%, with mean of 89%; and economic efficiency was 32–84%, with mean of 52%. These widely varying indices of efficiency among Al-Musayyeb farmers in a similar agro-ecological locality indicate great potential to achieve productivity growth through improved efficiency, using existing technologies and the available resource base in the study area. Results of the estimated coefficients indicated that family labor and land tenure are significantly and positively correlated with technical and allocative efficiencies, while off-farm income contributed to technical efficiencies. These results suggest that land tenure in this farming system and increased investment in extension services could jointly contribute to improved efficiency in in the studied area. Therefore, efforts directed to generation of new technologies should not be neglected.

***Keywords**: Technical efficiency, Allocative efficiency, Economic efficiency, Inefficiency determinants, NDVI, Iraq.*

1. Introduction

Salinity has emerged as the major factor responsible for low crop production in Iraq (Hatem et al., 2012; Wu *et al.*, 2014a and 2014b). In recent years, various regions have lost significant agricultural productivity due to soil salinity. This situation is particularly critical for the Al-Musayyeb area, which produces an important share of crops for the whole country (Hatem et al., 2012). In the past, the Iraqi economy was heavily dependent on agriculture for employment generation through exports of agricultural goods and agro industries such as the cotton crop for the textile sector. In the last 15 years there has been a phenomenon of increased reliance on women in the agricultural sector. In 2000, women represented more than 50% of all workers in agriculture and were expected to increase to about 60% in 2010 (Telleria *et al.*, 2012).

Annual loss of cultivated lands in Iraq is about 5% due to salinization and water logging (FAO, 2003). Of the total land area of Iraq (43 million ha), 8.2 million ha (18.8%) is agricultural area, 4 million ha (9.2%) is arable land, 4 million ha is permanent meadows and pastures, 0.85 million (2%) ha is forest and the rest corresponds to areas not used for agricultural or forest purposes (FAOSTAT, 2014). Of the 3.5 million ha equipped for irrigation (FAOSTAT, 2014), approximately 1.5 million ha is estimated to be moderately salinized, while 0.5 million ha has severe levels of salinity that prevent farming. Due to soil salinity-fallow practices, and the unstable political situation, it is estimated that only 2.8–4.9 million ha is actually cultivated annually.

Soil salinity explains up to 50% of lost agricultural productivity in saline-affected areas (Soppe and Saleh, 2012; Dhehibi *et al.*, 2013). Other factors, such as outdated agricultural machinery, poor management practices and lack of fertilizers, certified seeds and pesticides have to a lesser extent negatively affected agricultural productivity growth. From the national context and in historical perspective, there is no doubt that the Iran–Iraq War (1980–1988), the Gulf War (1990–1991), the period of United Nations sanctions (1990–2003) and the Iraqi occupation (2003–2011) have meant about 30 years of conflict for the country and undermined efforts to develop the agricultural system in Iraq, including to improve agricultural productivity. These conflicts have particularly weakened the infrastructure and the whole chain and marketing system of agricultural and livestock commodities.

It is clear that salt-induced land degradation occurs in both on and off sites and affects the livelihoods inside and outside the farming communities. However, there would be a need for thinking and acting beyond the classical farm level salinity management. It is within this context that this research paper attempt to fill the gaps identified in the analysis of the impact of salinity on livelihoods by determining the extent to which it is possible to raise efficiency for salt-affected farmers with the existing resources base and available technology.

Following this Introduction, Section 2 describes the conceptual framework to measure both technical and allocative efficiency using a production and cost function framework plus the model specifications. The study area and data used are outlined in Section 3. Section 4 deals with the presentation and discussion of our empirical results. In the last section, conclusion and policy implications emerging from the results are presented.

2. Conceptual Framework: Efficiency and Frontier Production Functions

Efficiency is a very important factor of productivity growth, especially in developing agricultural economies where resources are scarce and opportunities for developing and adopting better technologies are essential. Two techniques of estimating a firm's relative position to the frontier are used in empirical studies: non-parametric approaches that involve Data Envelopment Analysis (DEA), and parametric approaches that comprise econometric models (such the Stochastic Frontier Production Function – SFPF) and index numbers. Choosing between parametric and non-parametric methods is a delicate matter as there are many controversies about the choice of the right method to estimate efficiency (Johansson, 2005).

Since the SFPF model was almost simultaneously published by Meeusen and van den Broeck (1977) and Aigner *et al.,* (1977) there has been considerable research to extend the model and explore exogenous influences on producer performance. Early empirical contributions investigating the role of exogenous variables in explaining inefficiency effects adopted a two-stage formulation, which suffered from a serious econometric problem.[1] Kumbhakar *et al.,* (1991), Reifschneider and Stevenson (1991) and Huang and Liu (1994) proposed stochastic production models that simultaneously estimate the parameters of both the stochastic frontier and the inefficiency functions. While the formulated models differ somewhat in the specification of the second error component, they all use cross-section data. Battese and Coelli (1995) formulated a stochastic frontier production model (SFPF) similar to that of Huang and Liu (1994) and specified for panel data. We adopted the model of Battese and Coelli (1995) as a general framework considering that our data were obtained in a cross-section context. The model consists of two equations, with the first specifying the SFPF and the second capturing the effects of technical inefficiency:

$$LnY_i = Ln f(x_i ; \beta) + v_i - u_i \tag{1}$$

$$u_i = \delta' z_i + \varepsilon_i \tag{2}$$

where Y_i denotes the production of the i^{th} firm; x_i is a vector of input quantities of the i^{th} firm; β is a vector of unknown parameters to be estimated; v_i represents the random errors that are assumed to be independent and identically distributed $N(0, \sigma_v^2)$, while u_i is a non-negative random component modeled as $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ with the distribution of ε_i bounded below by the truncation point $-\delta Y_i$. In equation (2), u_i is the inefficiency term, while $-\delta z_i$ is a systematic component associated with the exogenous variables and a random component ε_i.

The parameters of the SFPF in equation (1) and the model for technical inefficiency effects in equation (2) can be simultaneously estimated by the maximum likelihood method. The technical efficiency of production for the i^{th} farm in the t^{th} period of time

[1] In the first stage of this formulation, the stochastic frontier model is estimated and the residuals are decomposed using the Jondrow *et al.,* (1982) technique. The estimated inefficiency scores are then regressed, in a second stage, against the exogenous variables contradicting the assumption of identically distributed inefficiency of the first stage.

can be defined as follows (Battese and Coelli, 1995):

$$TE_i = \exp(-u_i) = \exp(-\delta' z_i - \varepsilon_i) \tag{3}$$

Thus technical efficiency (*TE*) is allowed to change over time. This model does not impose any firm specific effects, which means that it does not account for possible heterogeneity between farms in the sample. The maximum likelihood estimation of equation (1) provides estimates of β and the variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma_u^2}$. Thus, the mean technical efficiency is redefined as:

$$TE_i = E(\exp(-U_i) \tag{4}$$

A predictor for which is provided by its conditional expectation[2]:

$$E\left[\exp\left\{-u_i\right\} \middle| (v_i - u_i)\right] = \left[\exp\left\{-\mu_{*i} + \frac{1}{2}\sigma_*^2\right\}\right] \cdot \left[\frac{\Phi\left[(\mu_{*i}/\sigma_*) - \sigma_*\right]}{\Phi(\mu_{*i}/\sigma_*)}\right] \tag{4a}$$

Where,

$$\mu_{*i} = \frac{\sigma_v^2(\delta' z_i) - \sigma_u^2(\varepsilon_i)}{\sigma_v^2 + \sigma_u^2} \tag{4b}$$

$$\sigma_*^2 = \frac{\sigma_v^2 \, \sigma_u^2}{\sigma_v^2 + \sigma_u^2} \tag{4c}$$

Bravo-Ureta and Rieger (1991) and Sharma *et al.,* (1999) used the cost decomposition procedure, developed by Kopp and Diwert (1982), to measure economic and allocative efficiencies. Therefore, technical and economic efficiencies can be combined to yield a measure of allocative efficiency using Farrel decomposition (Farrel, 1957).

When applying different approaches to estimate efficiency, it is customary to use yields of a given commodity (normally expressed in kg/ha) as the dependent variable, and production factors (such as fertilizers, irrigation, machinery usage and seeds) as the independent variables. The issue with using yields is that this normally does not reflect the potential yield of the whole spectrum of products produced at farm level. Farmers cultivate a range of crops for the market, household consumption and animal feed.

Instead of yields we use the annual maximum NDVI – an advantage of using NDVI as a proxy for yields is that it accounts for all vegetation conditions of a given area based on differences in the amount of near-infrared and red light reflected from plants on the Earth's surface. Thus NDVI not only gives an indication of the natural potential production at farm level, but is also a measure of plant health, density and productivity. NDVI is hence considered as a market indicator given that it can be estimated as a function of production and/or cost that reflect the preferences of the market and the relative cost that farmers have to pay for inputs. Yields of commodities only reflect the market preferences, but do not reflect the natural potential that different soils will yield in re-

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2 For the derivation of the likelihood function, its partial derivatives with respect to the parameters of the model and an expression for the predictor of technical efficiency see Battese and Coelli (1995).

sponse to different intensities of production factors. Thus, we use an approach that uses annual maximum NDVI as a proxy for yields, which can be particularly useful in cases where markets do not work properly and generate unclear opportunity costs for the estimation of significant parameters of production factors. We apply NDVI as a proxy to estimate annual land productivity in farms experiencing different degrees of salinization. NDVI can provide better estimations of those production factors that are very important to improving production and productivity. However, using NDVI demands spatial information (i.e. latitude and longitude coordinates) and extraction of its value for each pixel of the observed farm in which plant health, density and productivity were measured.

In the literature, different methods have been developed to predict crop yields using remotely sensed data, and the most common approach is, by generating regression model, to develop direct empirical relationships between the NDVI measurements and the crop yield. These approaches assume that measures of the photosynthetic capacity from spectral-vegetation indices are directly related to crop yield. This assumption is used because many of the conditions that affect crop growth, development and ultimately yield could be captured through spectra measurements such as the NDVI. A summary of these approaches and methods could be found in Jingfeng *et al.,* (2013).

3. Study Area and Data Analysis

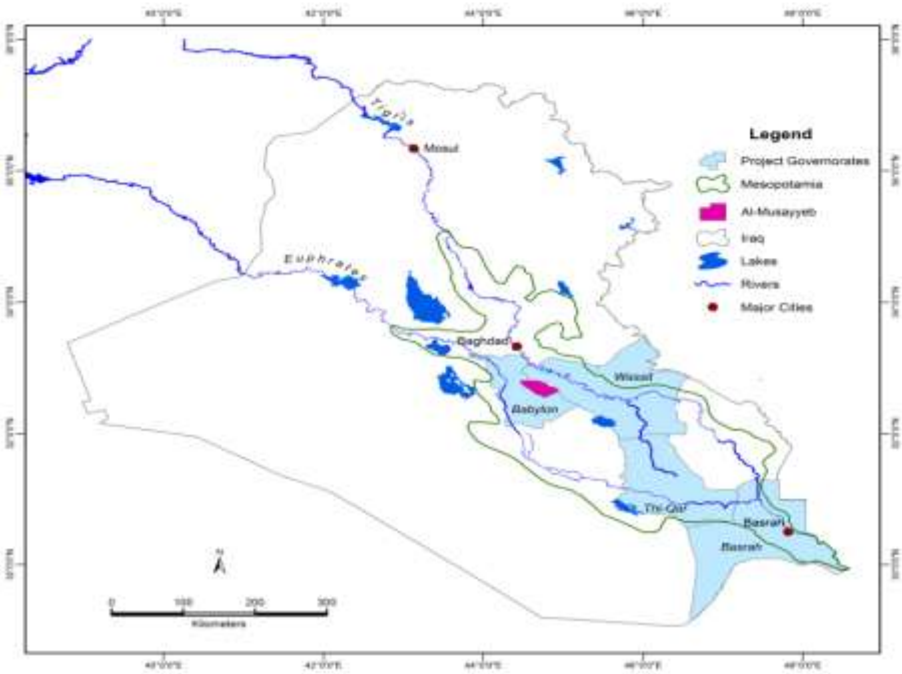
3.1. Study area

The Al-Musayyeb district, one of four main districts of the Babylon Governorate, is one of the most important agricultural areas in ‘central and southern Iraq’ (Fig. 1). The total area is 80,000 ha, of which about 45,000 ha is cultivable. The total population is around 150,000 with an average family size of 7 persons. The total number of farmers is estimated at 3745 that hold three types of farms: private, leased and rented. They are relatively smallholding farmers with an average farm size of 8 ha. Geo-morphologically, the district is a part of the Mesopotamian alluvial plain where soils are mainly silty loam or loamy silts subject to different levels of salinity (Wu *et al.,* 2014a and 2014b).

The climate is characterized by hot summers and warm winters with absolute mean minimum and maximum temperature of 1°C in January and 46.7°C in July–August, respectively, and annual rainfall was 110 mm in the past 30 years. Due to aridity, irrigation is essential for agricultural production in Al-Musayyeb. A wide range of crops are cultivated in this district, including fruit trees (e.g. date palm, citrus, figs, apricot, olives and grapes), cereal crops (e.g. barley and wheat), vegetables and forages. Some vegetables are grown in about 135 greenhouses. In addition, hundreds of sheep, goats, buffalo and cows are owned by Al-Musayyeb farmers.

3.2. Data collection and descriptive analysis

The data used in this study was obtained from a cross-sectional survey including 220 farmers randomly selected from 10 villages of Al-Musayyeb district. A summary of statistics of variables used for the stochastic production and cost function analyses is presented in Table 1. The average age of interviewed farmers with farm management



Source: Wu *et al.*, (2014a).

Fig. 1 *Location of the study area, Al Musayyeb (Babylon Governorate), in Mesopotamia, Iraq*

responsibility was 57 years. Average family household is about 13 persons, with about six of them working in agriculture. Of the households, 68% have a moderate level of education, and the remaining 32% are illiterate. Of the group with some level of education 23.3, 22.3, 21.9 and 0.9% of the households completed primary, secondary and university levels, respectively.

The average total gross margin per farmer per annum was 4,032,592 Iraqi Dinars (ID – about US$3430) with large variability of 4,921,351.000 ID (US$ 4180), implying a large disparity in gross margins among sampled farmers. Farm size was in the range of 1–97.75 ha with average size of 13.1 ha. The average cost of labor shows that Al-Musayyeb farms use relatively small amount of labor, with a mean cost of 13,966 ID (US$12)/ha. This is because farmers in the study area depend heavily on family labor for most farming operations as reflected in the percentage of family labor used – 94% of the total labor force. If family labor is monetized, then the labor cost will be more than US$100/ha. In addition, analysis of the variables reveals that the cost percentage share of machinery, seeds, fertilizer, irrigation, chemicals and other costs account for 20.55, 10.03, 16.66, 9.81, 10.47 and 31.20% of the total variable production cost, respectively. The results indicate that farming is the main source of household income in Al-Musayyeb (67.2%), off-farm income represents only 3.4%, while livestock contributes 29%. Finally, the NDVI range of 0.13–0.64 with an average of 0.43, implies that there is large variability in vegetation cover and biomass, and consequently in yields among sampled farmers. The analysis of a soil salinity indicator (electrical conductivity – EC) indicates that 20% of farms have a high salinity level (EC $>$ 8 dS/m) and the remaining 80% have low soil salinity (EC $<$ 8 dS/m).

Table 1 *Summary statistics of variables for stochastic production and cost function analyses*

Notation	Variables	Mean	Standard Deviation	Min	Max
S	Area (ha)	13.1	14.3	1	97.75
TGMC	Total Gross Margin (ID/ha)	4,032,592	4,921,351	53,000	26,666,667
TVC	Total Variable Cost (ID/ha)	652,379	832,210	77,599	8,619,933
L	Cost of Labor (ID/ha)	13,966	77,406	0	720,000
M	Cost of Machinery (ID/ha)	229,318	306,548	0	2,140,000
SE	Cost of Seeds (ID/ha)	111,991	150,153	0	1,565,467
F	Cost of Fertilizer (ID/ha)	185,888	408,542	0	4,666,667
IC	Cost of Irrigation (ID/ha)	109,542	226,146	0	2,116,667
CC	Cost of Chemical (ID/ha)	116,828	448,491	0	3,500,000
OC	Other Costs (ID/ha)	348,180	1,238,386	800	10,000,031
NDVI	*Normalized Difference Vegetation Index*	0.43	0.10	0.13	0.64
EC	Electrical Conductivity (dS/m)	8.92	10.55	5.46	75.67
OFI	Off-Farm Income (%)	3.4	8.7	0	50
AGE	Farmer Age (years)	56.39	11.83	24	100
EL	Education Level (*Dummy variable: 1 secondary to high; 0 otherwise)*	0.23	0.42	0	1
LT	Land Tenure (*Dummy variable: 1 private ownership; 0 otherwise*)	0.21	0.41	0	1
FSL	Income From Livestock Sector (%)	29	16	0	75
FLTL	Family Labor with Respect to Total Labor (%)	94	21	0	100

Note: ID – Iraqi Dinars (1000 ID = US$0.8 - Average in 2013).

Source: Own elaboration based on our field survey data (2013).

3.3. Empirical Model

The model proposed for analysis of farm-level data involves a SFPF, in which the parameters of the production function are specified. According to Kopp and Smith (1980), functional forms have a limited effect on empirical efficiency measurement. A Cobb-Douglas (CD) form has been used in many empirical studies, particularly in those relating to developing agriculture (Battese, 1992). The CD functional form also meets the requirement of being self-dual, allowing an examination of economic efficiency. In this study, the following CD functional form was selected to model Al-Musayyeb farms' production technology:

$$\text{Log } Y_i = \beta_0 + \beta_1 \log X_1 + \beta_2 \log X_2 + \beta_3 \log X_3 + \beta_4 \log X_4 + \beta_5 \log X_5 + \\ + \beta_6 \log X_6 + \beta_7 \log X_7 + \beta_8 \log X_8 + (v_i - u_i) \quad (5)$$

where Y_i is the total output approximated by the NDVI indicator; β_0 is the intercept; and X_1 represents land area, X_2 labor cost, X_3 mechanization cost, X_3 seed cost, X_5 fertilizer cost, X_6 irrigation cost, X_7 chemical costs and X_8 other costs. All *X* and *Y* are measured in ID/ha. The β are parameters to be estimated, v_i represents a random variable for farm *i*, and u_i represents the specific technical efficiency factor for farm *i*.

The CD cost frontier function for Al-Musayyeb farms in the study area is formulated as follows:

$$\text{Log } TVC_i = \alpha_0+\alpha_1 \log W_1+ \alpha_2 \log W_2+\alpha_3 \log W_3+\alpha_4 \log W_4+\alpha_5 \log W_5+ +\alpha_6 \log W_6+\alpha_7 \log W_7+ (V_i - U_i) \quad (6)$$

Where TVC_I is total variable production cost; α_0 is the intercept; and W_1 represents labor cost, W_2 mechanization cost, W_3 seed cost, W_4 fertilizer cost, W_5 irrigation cost, W_6 chemical costs and W_7 other costs. All W and TVC are measured in ID/ha; the α are parameters to be estimated, V_i is a random variable for farm *i*, and U_i is the specific allocative efficiency factor for farm *i*.

The technical, allocative and economic inefficiencies are explained by:

$$\mu_i =\delta_0+\delta_1 Z_{1i}+\delta_2 Z_{2i}+\delta_3 Z_{3i}+\delta_4 Z_{4i}+\delta_5 Z_{5i}+\delta_6 Z_{6i}+\delta_7 Z_{7i} \quad (7)$$

where μ_i represents inefficiency effects; δ_0 the intercept; Z_{1i} percentage of source income generated by livestock production; Z_{2i} percentage of off-farm income; Z_{3i} age of farmers (years); Z_{4i} farmers' education level (1 if education level is secondary, high school, university and higher, and 0 otherwise); Z_{5i} percentage of family labor with respect to the total farm labor; Z_{6i} land tenure (1 for private ownership; 0 otherwise) and Z_{7i} is EC level (in dS/m). The frontier functions (production and cost) were estimated through maximum likelihood methods. In addition, the computer program FRONTIER version 4.1 (Coelli, 1996) was used to estimate the allocative efficiency (AE) computed originally as the inverse of the farm-level economic efficiency (EE).

4. Results and Discussion

Maximum Likelihood Estimates of the Production and Cost Production Functions

The maximum likelihood parameters of the CD production and cost frontier models (equations 5 and 6) were estimated using the computer package FRONTIER version 4.1. Parameter estimates along with the standard errors of the Maximum Likelihood (ML) estimators of Al-Musayyeb producing farms' production and cost frontier models are presented in Table 2. These parameters represent percentage changes in the dependent variable as a result of percentage changes in the independent variables, showing the relative importance of these variables to agriculture output/total variable costs in the Al-Musayyeb district.

The ratio of farm specific variability to total variability (γ) is positive (significant at 5% level), implying that farm specific technical efficiency is important in explaining the total variability of agricultural output produced.

The estimates of the parameters of the stochastic frontier production model (equation 5) revealed that all the estimated coefficients of the variables of the production function were positive except those of fertilizers and chemicals. All variables in the model with positive coefficients indicate that any variable increase would lead to an increase in output crop production. A negative sign implies that as input utilization grows with no limit, output production reduces. Mechanization and farm size have the highest coeffi-

***Table 2** Maximum likelihood estimates of the stochastic frontier production and cost functions in Al-Musayyeb producing farms*

Production Function Estimates			Cost Function Estimates		
Variables	*Parameters*	*Coefficients*	*Variables*	*Parame-ters*	*Coeffi-cients*
	Stochastic Frontier Model				
Dependent Variable: NDVI (Proxy of Total Yield)			*Dependent Variable: TVC (Total Variable Cost)*		
Intercept	β_0	–0.27** (0.013)	Intercept	α_0	–0.43*** (0.09)
Ln(LA)	β_1	0.039* (0.026)	Ln(L)	α_1	–0.32* (0.18)
Ln(L)	β_2	0.011 (0.032)	Ln(M)	α_2	0.70*** (0.08)
Ln(M)	β_3	0.045** (0.021)	Ln(SE)	α_3	0.15** (0.06)
Ln(SE)	β_4	0.002 (0.015)	Ln(F)	α_4	0.21*** (0.04)
Ln(F)	β_5	–0.022** (0.011)	Ln(IC)	α_5	0.11* (0.07)
Ln(IC)	β_6	0.016 (0.002)	Ln(CC)	α_6	0.09** (0.03)
Ln(CC)	β_7	–0.007 (0.01)	Ln(OC)	α_7	0.037 (0.04)
Ln(OC)	β_8	0.008 (0.015)	-	-	-
	Partial Production / Cost Elasticities				
$E_{Y/LA}$	β_1	0.039	$E_{TVC/L}$	α_1	–0.32
$E_{Y/L}$	β_2	0.011	$E_{TVC/M}$	α_2	0.7
$E_{Y/M}$	β_3	0.045	$E_{TVC/SE}$	α_3	0.15
$E_{Y/SE}$	β_4	0.002	$E_{TVC/F}$	α_4	0.21
$E_{Y/F}$	β_5	–0.022	$E_{TVC/IC}$	α_5	0.11
$E_{Y/IC}$	β_6	0.016	$E_{TVC/CC}$	α_6	0.09
$E_{Y/CC}$	β_7	–0.007	$E_{TVC/OC}$	α_7	0.037
$E_{Y/OC}$	β_8	0.008	-	-	-
Returns to Scale	*RTS*	*0.092*	*Returns to Scale*	*RTS*	*0.97*
	Inefficiency Effects Model				
Intercept	δ_0	–0.014 (0.01)	Intercept	δ_0	0.86* (0.48)
Age	δ_1	0.009* (0.005)	Age	δ_1	0.004 (0.008)
EL	δ_2	0.11 (0.09)	EL	δ_2	0.085 (0.3)
FLTL	δ_3	–1.35* (0.103)	FLTL	δ_3	–1.93*** (0.46)
OFI	δ_4	–3.41* (2.42)	OFI	δ_4	0.58 (1.06)
LT	δ_5	–1.92** (0.096)	LT	δ_5	–1.22* (1.06)
EC	δ_6	0.02** (0.009)	EC	δ_6	0.01** (0.006)
	Variance Parameters				
Sigma-squared	σ^2	0.11* (0.06)	Sigma-squared	σ^2	0.14** (0.068)
Gamma	γ	0.97*** (0.015)	Gamma	γ	0.42* (0.33)
Log-Likelihood	*LL*	203.94	Log-Likelihood	*LL*	–45.34
N (# farms)		220	N (# farms)		220

Notes: *** Significant at 1% level; ** Significant at 5% level;
* Significant at 10% level. Standard error is in parenthesis.

Source: Own elaboration based on survey data (2013).

cients, indicating that they are the most important variables in the production system in Al-Musayyeb. Expansion in production depends mainly on increased cultivated areas, but not through increased agricultural productivity, reflecting a low level of adoption of improved technologies. Farmers in Iraq are accustomed to substantial government support in the form of subsidized inputs (mainly seeds and fertilizers), which are used by farmers in a traditional way to cultivate their land or put additional land into production. Our results show a positive relationship between expansion in cultivated areas and production. The results show a lack of availability of machines and equipment to farmers, so considerable agricultural operations depend on human labor, mostly family labor but with some hired also. Poor agricultural development and the need for security-related jobs are driving migration to urban areas, which affects the availability of agricultural labor. A 2009 National Youth Survey (Government of Iraq and the UN Population Fund, 2009) showed that rural youth unemployment is 23% of males and 21% of females aged 15–24, which has prompted migration to urban centers where they find limited employment prospects.

The elasticities of production were positive but inelastic (< 1), indicating that output increases in smaller proportion to production factor use, and hence reflecting inefficiency in the use of production factors. Specifically, empirical results show that, on average, the mechanization impact factor is greater than the fertilizer, seed, irrigation and agrochemical input factors. The values for elasticities of mechanization, fertilizers, seeds, irrigation costs and agro-chemicals were estimated at 0.70, 0.21, 0.15, 0.11 and 0.09, respectively. These results indicated that mechanization has contributed most to the agricultural production, followed by fertilizers and seeds. The return to scale (RTS) of 0.092 (Table 2) implies that the cost advantages that farms normally obtain due to greater farm size, more input use and larger scale of operations, do not reduce the cost per unit of output, and hence increasing scale does not lead to lower variable costs. In the context of a disrupted economy this result is no surprise.

The estimates of the stochastic frontier cost function (Table 2) revealed that, as expected, the coefficients of all independent variables (costs of mechanization, seeds, fertilizers, irrigation and agro-chemicals) were positive, meaning that as they increase, total production cost also increases but in different proportions. The t-tests show that all these positive variables are significantly different from zero at 5% level. Hence, these variables are important determinants of agricultural production in the study area. The negative and significant coefficient of labor (mainly family labor representing about 94% of total labor) confirms that agricultural production in Al-Musayyeb uses family labor intensively.

Analysis of Productive Efficiency

Technical Efficiency Analysis

The presence of technical inefficiency effects in Al-Musayyeb production farms are confirmed by $\gamma = 0.97$, significant at 5% level (Table 2). This value implies that about 97% variation in the output of Al-Musayyeb production farmers is due to differences in their technical efficiencies – TEs – (e.g. differences in input use, proportions, technologies and management). The predicted TEs were in the range of 0.57–0.98 with mean of 0.89 (Table 3), meaning that if an average farmer in the sample achieved the TE level of his most efficient counterpart, this would be a 9.18% cost-saving [i.e. 1 – (89.0/98.0) × 100]. A similar calculation for the most technically inefficient farmer reveals a potential cost-saving of 41.8% [i.e. 1 – (57.0/98.0) × 100]. The frequencies of occurrences of the predicted technical efficiencies in decile range indicate that the highest number of farmers have technical efficiencies of 0.90–0.99 (Table 3). The sample frequency distribution indicates a clustering of technical efficiencies (range 0.90–0.99) representing 62.72% of the respondents. This implies that there is room (about 37%) to achieve maximum output production given inputs and resources available.

Economic Efficiency Analysis

The economic efficiency analysis of Al-Musayyeb farmers reveals cost inefficiency effects in agricultural production as confirmed by $\gamma = 0.42$, significant at 5% level (Table 3). This implies that costs can be reduced up to 42% if efficiency is improved and that the variation in the total production cost is due to differences in their cost efficiencies. The predicted EEs as inverses of the cost of efficiencies differ substantially among the farmers, with range 0.32–0.94 and mean of 0.52. Thus, if the average farmer could reach the EE level of the most efficient farmer in the sample, this would achieve a cost-saving of 38.1% [i.e. 1 – (52.0/84.0) × 100]. The same computation for the most economically inefficient farmer suggests a gain in EE of 61.9% [i.e. 1 – (32.0/84.0) × 100]. A frequency distribution of the predicted EEs (Table 3) provides a better indication of the distribution of the EEs. The frequencies of occurrence of the predicted economic efficiencies in decile range indicate that the highest number of farmers have EEs of 0.50–0.59, representing about 68.2% of respondents. There are 7.7% with EE ≥ 0.60,

Table 3 *Decile ranges of frequency distribution of technical, allocative and economic efficiency in Al-Musayyeb producing farms*

Efficiency Level (%)	Technical Efficiency		Allocative Efficiency		Economic Efficiency	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
0.10–0.20	0.00	0.00	0.00	0.00	0.00	0.00
0.20–0.29	0.00	0.00	0.00	0.00	0.00	0.00
0.30–0.39	0.00	0.00	0.00	0.00	9.00	4.1
0.40–0.49	0.00	0.00	0.00	0.00	44	20
0.50–0.59	2.00	0.91	187	85	150	68.2
0.60–0.69	6.00	2.72	22	10	10.0	4.6
0.70–0.79	18	8.18	1.00	0.45	3.00	1.3
0.80–0.89	56	25.45	8.00	3.63	4.00	1.8
0.90–0.99	138	62.72	2.00	0.91	0.00	0.00
N	220	100	220	100	220	100
Mean Efficiency	0.89		0.59		0.52	
Std. Deviation	0.082		0.068		0.074	
Min.	0.57		0.56		0.32	
Max.	0.98		0.94		0.84	

Source: Elaborated based on our field survey data (2013).

indicating that farmers are very efficient in production at a given level of output using cost minimizing input ratios, which reflect the farmer's tendency to minimize resource wastage associated with production process from a cost perspective.

Allocative Efficiency Analysis

The predicted allocative efficiencies (AEs) also differ substantially among farmers, with range of 0.56–0.94 with mean of 0.59. Thus, if the average farmer was to achieve the AE level of the most efficient farmer in the sample, this would be a 37.23% cost-saving [i.e. 1 – (59.0/94.0) × 100]. A similar calculation for the most allocative inefficient farmer reveals a cost-saving of 40.42% [i.e. 1 – (56.0/94.0) × 100]. The frequency of occurrence of the predicted AEs in decile ranges indicates a certain clustering of AEs at the level of 0.50–0.59 (Table 3). So farmers are rather efficient in production at the given level of input, among which about 15% of the respondents have AE ≥ 0.60. The implication of these findings (TEs, EEs and AEs) is that given the production resources at the disposal of the farmers, mainly small-scale and resource poor, are fairly efficient in their use of resources mainly from the technical point of view. The predicted efficiencies (Table 3) indicate that variation in EEs largely results from differences in AEs.

5. Concluding Remarks and Policy Implications

This paper provides a comprehensive analysis of the agricultural production system affected by salinity in the Al-Musayyeb area from an agro-economic view. In this study area of Iraq, soil salinity has emerged as a problem, which has not only reduced the agricultural productivity but also had far-reaching impacts on the livelihood strategies of small farmers. The problem is large, which has made it very difficult for farmers to cope with the situation. The temporary solutions adopted by farmers such as irrigating with salty water to overcome lack of fresh water or abandoning salt-affected land seem to have long-term adverse effects. These will not only put more pressure on small farmers who are already on the margins but also degrade the soil and ultimately the whole production base.

Stochastic production and cost frontier models reveal an average level of technical, allocative and economic efficiency of 89, 59 and 52%, respectively. Thus, improving technical efficiency will significantly increase farmers' profits. The results of this study are consistent with 'Shultz's poor-but-efficient hypothesis' that peasant farmers in traditional agricultural settings are efficient in their resource allocation behavior despite their operational circumstances (Shultz, 1964). The results also illustrate the importance of examining not only TE, but also AE and EE when measuring productivity.

An important conclusion stemming from the analysis is that overall economic efficiency (EE) of Al-Musayyeb production farms could be substantially improved and that AE constitutes a more serious problem than technical inefficiency. Hence, despite the role of higher efficiency level in output, productivity gains due to technological innovations in agriculture remain critical in the economy of the Al-Musayyeb district. Therefore, efforts directed to generating new technologies should not be neglected – especially concerning agronomic practices, drainage and water management in areas affected by soil salinity. Technical solutions to fight further land degradation due to salinity should be backed with adequate institutional and policy support. The consequences of salinity build-up might be tolerable given a technical solution; however, these put pressure on farmers and negatively impact their livelihoods. A certain threshold of irreversible changes might pass the point of being tolerable with technical or economical solutions, and should be avoided through proper planning strategies at short and long term as the time horizon for reversing and restoring the salt affected degraded lands may take considerable investments and several years.

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