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Smallholder Agricultural Production Efficiency of Adopters and Nonadopters of Land Conservation Technologies in Tanzania

Onesmo Selejio[1], Razack B. Lokina[1], and John K. Mduma[1]

Abstract

Promotion and supporting the adoption of land management and conservation technologies (LMCTs) among poor farming households has been considered to improve crop yields as well as production technical efficiency (TE). This article compares production efficiency between adopters and nonadopters of LMCTs in Tanzania. Using national panel data, the study applied stochastic frontier model to estimate the TE of adopters and nonadopters. The findings show that adopters of LMCTs had a relatively significantly higher TE (0.73) than their nonadopter counterparts (0.69). Therefore, promotion and supporting the adoption of LMCTs among smallholder farmers is pertinent for improving their TE as well as for increasing crop yield, thereby reducing encroachment into forest areas. There is also a need to understand how adopters and nonadopters of LMCTs are affected by different factors when designing the policies that promote the adoption of LMCTs among the smallholder farmers for sustainable increase of agricultural productivity and TE.

Keywords

agriculture, technical efficiency, land management, conservation technologies, deforestation

[1]Department of Economics, University of Dar es Salaam, Tanzania

Corresponding Author:

Razack B. Lokina, Department of Economics, University of Dar es Salaam, P. O. Box 35045, Tanzania.
Email: rlokina@udsm.ac.tz

Literature shows that the adoption of land management and conservation technologies (LMCTs) has a positive and significant impact on crop yield (Kassie et al., 2008; Kassie, Zikhali, Pender, & Kohlin, 2010; United Republic of Tanzania, 2013; Zikhali, 2008). This is an incentive for farmers to adopt or continue with the technology because the return to their efforts on investment is realized, that is, increased productivity. Even if increase of productivity and production is necessary, it is not a sufficient condition to influence all farmers to invest in the adoption of land conservation technologies given the fact that most of the technologies are expensive and risky (Alem, Bezabih, Kassie, & Zikhali, 2010; Nyangena & Juma, 2014; Shively, 1997). For example, Msuya, Hisano, and Nariu (2008) find that smallholder farmers in Tanzania who use a hand hoe (poor technology) are more efficient compared with those using an ox-plough or tractor (advanced technology). They also find that farmers who use agrochemicals are less efficient compared with farmers who do not apply the chemicals to their farms. This implies that the adoption of new and improved technology in agriculture does not automatically lead to an increase of crop yield or production efficiency as argued by Kassie et al. (2008) and Medhin and Gunnar (2011).

Production efficiency is, therefore, one of the economic aspects that may explain the importance of adoption of LMCTs as inputs of production for a sustainable productive environment. This is because low production efficiency among rural farming households in developing countries has led them to constantly clear forests to get more crop virgin lands. In so doing, they expose more areas to soil erosion and threaten productive sustainability of environment (Hepelwa, 2013; Lokina & Lwiza, 2016; Prabodh, 2005). Thus, it is imperative to understand the efficiency of production between adopters and nonadopters of LMCTs for proper addressing of the adoption of the technologies and sustainable agricultural productivity and land conservation.

Most of the previous studies have approached this problem by using a cross section (Hepelwa, 2013; Lokina & Lwiza, 2016; Msuya & Ashimogo, 2006; Msuya et al., 2008); in this study, we take the advantage of the existence of a unique national panel of data to compare the technical efficiency (TE) between adopters and nonadopters of LMCTs.[1] The study also analyses the factors that affect TE for adopters and nonadopters. We apply the stochastic frontier approach to estimate TE in agricultural production using FRONTIER 4.1. The rest of the article is structured as follows: The next section presents the relevant literature review, which is followed by the section that describes the methodology. This is followed by the section that presents and discusses the empirical results, while the last section presents the conclusions and and policy implications.

Evidence of Agricultural Production Efficiency

The empirical literature on efficiency in agricultural production is quite rich. Literature shows that there is a wide variation of production efficiency in agriculture across and within countries for same or different crops. Similarly, the factors that explain production efficiency across countries and crops also vary. For example, Obwona (2006) applies a stochastic production function to study determinants of TE among small- and medium-scale tobacco farmers in the Arua District in Uganda using cross-sectional data and finds that the TE among tobacco smallholder farming household ranges from 44.8% to 97.3% with a mean TE of 76.2%. Using balanced panel data of 660 observations in mid-western Uganda, Masindi District, Samwel (2011) found that TE ranges from 14.21% to 95.40%, with an overall mean of 52.10% in tobacco smallholder farms.

The study of Obwona (2006) further finds that family size, education, credit facilities, and extension contact improve TE, while off-farm income, hired labor, poor health of the farmer, and fragmented land reduce TE. According to Samwel (2011), the numbers of social networks, extension training, experience, and social cohesion have significant negative influence on technical inefficiency. He also finds that the area of other crops, tobacco plot size, and farm distance to baling are positive and significant in increasing technical inefficiency. Although most factors that affect TE in the two studies or areas are common, the large difference of the TE in the two areas in the same country and for the same crop is not explained. This might be attributed to specific inherent potentials of the areas such as land quality and land management, which are not captured by these studies.

Asekenye (2012) employed a Cobb–Douglas stochastic frontier production function on household survey data to analyze productivity gaps among smallholder groundnut farmers in Uganda and Kenya. The study finds that mean TE for smallholder groundnut farmer is 54.6% and 54.5% with a range of 11.7% to 77.9% and 9.8% to 92% in Uganda and Kenya, respectively. Although the mean TE among groundnut farmers was almost the same in the two countries, a higher variation is noted in Kenya. Asekenye (2012) further finds that land, seed, and seed varieties were positive and statistically significant in explaining groundnut output in both countries. However, the study shows a technological gap in production, as farmers who used improved seeds had higher output compared with those who used local seeds.

It is not always the case that high technology influences TE positively. For instance, Msuya et al. (2008) find that smallholder farmers who use the hand hoe in maize production in Tanzania were more efficient than those who use tractors. Similarly, they find that farmers who use agrochemicals are less efficient compared with farmers who do not spray the chemicals to their farms. These findings may explain the low adoption of sustainable LMCTs, which theoretically should enhance productivity and production efficiency. Nevertheless, there is scant information on the linkage of the TE variation with the land management and conservation. Such information is useful for a policy aiming at enhancing sustainable productivity and land/environment conservation.

TE in smallholder agriculture has an influence on the type of farming system and sustainability of environmental conservation. The low production efficiency may force the farmers to find an alternative production technology or farming system such as the shifting cultivation/clear and burn system. Such a system is not friendly to the environment. Using survey data in the Sigi catchment area in the Tanga region of Tanzania, Hepelwa (2013) finds that there is forest loss due to clearing to establish new farms in virgin lands that is closely linked to low mean TE of maize, which is 33%. This concurs with the finding in Yucatan area in Mexico where shifting cultivation was due to low agricultural production efficiency. However, a good number of the studies that were conducted in developing counties, particularly sub-Saharan Africa, show that TE for many crops, including maize, is below 50% with a high variation (Chiona, 2011; Chirwa, 2007; Geta, Bogale, Kassa, & Elias, 2013; Kibaara, 2005).

The low TE in production in sub-Saharan Africa implies that sustainability of environmental protection and food security is at risk. As has been noted, the low TE in agriculture production encourages smallholder farmers to seek new productive land by clearing forest (Hepelwa, 2013; Lokina & Lwiza, 2016). Thus, a policy that advocates for the provision of subsidized improved inputs and other technologies enhancing agricultural productivity and efficiency is important for sustainable land and environment management. It is, however, to be noted that although the adoption of new technologies enhances productivity without enhancing efficiency, it may also result into environmental degradation problems because of intensive use of the technologies such as modern inputs. Srivasta and Shirvastava (2002) estimated farm efficiencies due to adverse impact of environmentally detrimental inputs, positive impact of environmental recuperative inputs, and impact of basic inputs. They concluded that the best combination of all three types of inputs is likely to yield enhanced productivity and sustainability of improved agriculture in India.

Analytical Framework

There are two distinct approaches for estimating efficiency in production: (a) an econometric or stochastic frontier and (b) data envelopment analysis (DEA), which uses mathematical programming method (Greene, 2008). The stochastic frontier approach was proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), later modified by Jandrow, Lovell, Materov, and Schmidt (1982). The potential for the misspecification of functional form resulting in biased estimates of technical inefficiency is considered to be a weakness of the stochastic frontier approach relative to nonparametric approaches such as DEA. Another disadvantage of stochastic frontier is that the selection of a distributional form for the inefficiency effects may be arbitrary (Coelli, 1995). However, the disadvantages of DEA relative to stochastic frontier modeling are that it is not stochastic, and hence, it is not possible to isolate TE from random noise (Lovell, 1993). Given the inherent stochasticity involved in agricultural production, such as bad weather, unreliability of the rainfall pattern, pests, and diseases, the stochastic frontier approach appears to offer the best method for assessing the efficiency of individual farms (Kirkley, Squires, & Strand, 1995; see also Campbell & Hand, 1998). The stochastic approach assumes that farmers may deviate from the frontier not only because of measurement errors, statistical noise, and nonsystemic influence but also because of technical inefficiency caused partly by farmers' failure to undertake proper land management and conservation practices.

Specification of the Stochastic Frontier

Therefore, the TE analysis in this study is conducted within the framework of a production frontier function for panel data as proposed by Battese and Coelli (1995) in accordance with the original framework of Aigner et al. (1977) and Meeusen and van den Broeck (1977). This is represented as

$$Y_{it} = f\left(X_{it;}\beta\right) \exp \varepsilon_{it} \tag{1}$$

where Y_{it} denotes vector of output, X_{it} is the vector of conventional input, β is a vector of parameters to be estimated, and ε_{it} is a composite error term. All firms or farms are indexed with a subscript i, and all years are indexed with a subscript t. The composite error term can be further specified as

$$\varepsilon_{it} = v_{it} - u_{it} \tag{2}$$

where u_{it} is a nonnegative random error term, independently and identically distributed as $N\ (u, \delta_u^2)$, which captures the farm-specific technical inefficiency in production; v_{it} is the conventional stochastic error term, which represents the random variations in production due to observation and data measurement errors, uncontrolled factors, and so forth. The conventional stochastic error term (v_{it}) is assumed to be an independently and identically distributed normal random variables with mean zero and constant variance $(0, \delta_v^2)$.

Using Equations 1 and 2, the TE of production of the i^{th} farm, given the level of inputs, can be defined as

$$TE_{it} = \frac{f(X_{it};\ \beta)\exp(\varepsilon_{it})}{f(X_{it};\ \beta)\exp(v_{it})} = \frac{f(X_{it};\ \beta)\exp(v_{it} - u)}{f(X_{it};\ \beta)\exp(v_{it})} = \exp(-u) \tag{3}$$

where $u_i \leq 0$ and $0 \leq \exp(-u_i) \leq 1$.

It is necessary to separate technical inefficiency from statistical noise in the composite error term from Equation 3. The estimator of TE is as defined by

Battese and Coelli (1988, 1992)

$$TE_i = E\left(\frac{\exp(u_i)}{\varepsilon_{it}}\right) = \left(\frac{1 - \Phi[\sigma. - (\gamma\varepsilon_i/\sigma.)]}{1 - \Phi(\gamma\varepsilon_i/\sigma.}\right) \exp((\gamma\varepsilon_i/\sigma^2/2) \quad (4)$$

where $\Phi(.)$ is the distribution function of a standard normal random variable, $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$ and $\sigma. = \gamma(1-\gamma)[\sigma^2 + \sigma_v^2]$. The technical inefficiency score is computed as minus the natural log of the TE via $E(\mathrm{u}^{it}/_{\varepsilon_{it}})$. Furthermore, γ is the ratio of smallholder farmers' output deviation due to technical inefficiency to overall deviations. It ranges from 0 to 1; when $\gamma = 0$, it implies that all output deviations are caused by factors outside the control of farmers; when $\gamma = 1$, it shows that all output deviations are due to technical inefficiency.

Note that in the second part, the stochastic frontier estimation involves the estimation of the function that relates the inefficiency measurement obtained in the first stage with set of explanatory variables, which are farm and farmer-specific characteristics. From Equation 2, the inefficiency function can be defined as

$$u_{it} = z_{it}\delta + w_{it} \quad (5)$$

where z_{it} is a vector of variables representing the technical inefficiency of the ith observation (farm) at time t, δ corresponds to a parameters vector, and w_{it} represents the error term. Equation 5 captures the effects of technical inefficiency and has a systemic component, $z_{it}\delta$, associated with the exogenous variables and a random component, w_{it}, The distributional assumption on w_{it} is consistent with the distributional assumption on u_{it}.

Thus, combining Equations 3 and 5, the TE of production for the ith observation at time t can be defined as

$$TE = \exp(-u_{it}) = \exp(-z_{it}\delta - w_{it}) \quad (6)$$

Empirical Model Specification

The empirical model to estimate TE can take either the Cobb–Douglas production function (CDPF) or the translog production function (TLPF; Cobb & Douglas, 1928; Sharma & Leung, 2000). The TLPF assumes the existence of a nonlinear relationship between output and inputs. In TLPF, the production elasticities are not constant. Therefore, the TLPF is adopted in this study because of this flexibility and has mostly been preferred and used in TE studies (Battese & Coelli, 1988, 1995; Tchale, 2009). The specification of the stochastic frontier model for assessment of the TE is made based on four factors of production as follows

$$\begin{aligned} lnY_{it} = {} & \beta_{0+}\beta_1 lnX_{1it} + \beta_2 lnX_{2it} + \beta_3 lnX_{3it} + \beta_4 lnX_{4it} + \beta_5 lnX_{1it}^2 + \beta_6 lnX_{2it}^2 + \beta_7 lnX_{3it}^2 \\ & + \beta_8 lnX_{4it}^2 + \beta_9 lnX_{1it} lnX_{2it} + \beta_{10} lnX_{1it} lnX_{3it} + \beta_{11} lnX_{1it} lnX_{4it} \\ & + \beta_{12} lnX_{2it} lnX_{3it} + \beta_{13} lnX_{2it} lnX_{4it} + \beta_{14} lnX_{3it} lnX_{4it} + v_{it-}u_{it} \end{aligned} \quad (7)$$

where Y_{it} is quantity of harvest (kg; *yield*) of *i*th farm or household at time *t* ($i = 1, 2,\ldots,1{,}287$ for first wave and 610 for second wave); X_{1it} is the total area planted/harvested (acres; *araeharv*); X_{2it} is family labor (man-days; *tflabor*); X_{3it} represents amount of wage paid to hired labor (Tshs; *tpayhl*); X_{4it} represents the expenditure on intermediate materials (fertilizer, seeds, agrochemicals; *expmater*); β_0, β_1, $\beta_2,\ldots, \beta_{14}$ are parameters to be estimated; v_{it} is the random error; and u_{it} is the error term that reflects the technical inefficiency.

The factors of production in Equation 7 have an impact on TE in different ways. Theoretically, the total land planted or harvested, family labor, and hired labor are expected to influence the TE within the optimal range of the inputs positively. They may influence the TE negatively beyond certain limits because of diseconomies of scale (Peterson, 1997). For example, it becomes very difficult to manage and supply all necessary inputs by a smallholder farmer to a large planted area. Msuya et al. (2008) also argue that a lack of opportunities among smallholder farmers may force large number of family members to work in a small plot of land, which leads to low productivity per labor.

The presence of land management and conservation practices on a plot is expected to influence TE positively. However, the cost of investment in these technologies may affect the TE of production if they are high. Shively (1997) and Nyangena (2005) argue that investment in land conservation is costly and risky, and therefore, the return from this investment may not be always justifiable by the cost of investment. The inefficiency model is estimated based on 20 variables that reflect technical inefficiency measures and specified as

$$u_{it=\delta_0} + \sum_{k=1}^{20} \delta_k z_{ikt} + w_{it} \tag{8}$$

where u_{it} is technical inefficiency of i^{th} plot or household at time *t*; δ_0, $\delta_1, \delta_2,\ldots,\delta_{20}$ are inefficiency parameters to be estimated; $z_{i1t}\ldots z_{i4t}$ are input variables; z_{i5t} is the *Age* of the farming household head; z_{i6t} represents the *Gender* of the head of the household (1 = male, 0 = female); z_{i7t} stands for *Hhsize*, which is the household size (number of persons in the house who provide labor in farming); z_{i8t} stands for *Edu*, which is the education level attained by the head of household (number of years in school); z_{i9t} is *Ownland*, which shows whether the household owned the cultivated land (1 = yes, 0 = otherwise); z_{i10t} represents *Offinc*, which stands for the household with income sources out of farming (1 = yes, 0 = otherwise); z_{i11t} is farm size owned by household in acres (*Fsize*); z_{i12t} represents the distance to farm from home in kilometers (*Fdist*); z_{i13t} is *eros*, which represents the presence of soil erosion on a plot (1 if yes, 0 otherwise); z_{i14t} is *pltgood*, which represents the soil quality of a plot (Value 1 if good quality, 0 otherwise); z_{i15t} represents the soil quality of a plot (Value 1 if average quality, 0 otherwise), while bad quality is treated as a reference to avoid dummy variable trap; z_{i16t} is *fltbot*, which represents the slope of a plot (Value 1 if flat bottom, 0 otherwise); z_{i17t} is *flttop*re, representing the slope of a plot (Value 1 if flat top, 0 otherwise); z_{i18t} is *slgsloptt*, representing the slope of a plot (Value 1 if slightly sloped, 0 otherwise), while steep slope variable is treated as a reference point to avoid dummy variable trap; z_{i19t} is *Conserv*, which stands for any management and conservation of the plot (1 = yes/presence LMCTs on plot,[2] 0 = otherwise); z_{i20t} represents time period; first wave and second wave (Value 0 for first wave and 1 for second wave). Last, w_{it} is the error term in the technical inefficiency model.

Model Specification Test

The stochastic frontier model can take either the CDPF or the TLPF. The model can also be specified as production function, which has either neutral technical inefficiency effects or nonneutral technical inefficiency effects, depending on the nature of the data used. In this regard, the study conducts model specification tests to examine which model may be appropriately used in the analysis. Tests are performed by using the generalized likelihood ratio (LR) statistics, which is given by

$$LR = -2\left[ln\left\{L(H_0)\right\} - ln\left\{L(H_1)\right\}\right] \tag{9}$$

where $L(H_0)$ and $L(H_1)$ are values of likelihood functions under the null (H_0) and alternative (H_1) hypotheses, respectively; $ln\left\{L(H_0)\right\}$ and $ln\left\{L(H_1)\right\}$ are log-likelihood functions that are straightforwardly given from the FRONTIER 4.1 results. The generalized LR statistics has approximately a chi-square/mixed chi-square distribution; thus, the calculated LR statistics is then compared with the critical chi-square value from the chi-square table, corresponding to the degree of freedom that is equal to the number of parameters assumed to be zero in null hypothesis.

Elasticity and Returns to Scale

The individual input coefficients estimated in translog frontier production model in Equation 7 do not have straightforward interpretation. This is due to the fact that for a TLPF, the output elasticities with respect to the inputs are functions of the first-order and second-order coefficients with the level of inputs. In addition to that, the study includes input variables in both the stochastic frontier model (Equation 7) and inefficiency model (Equation 8), implying that the output elasticity with respect to inputs is the function of the value of the input in both the frontier and the inefficiency model. Thus, it is appropriate to estimate output elasticity for each of the inputs, as the individual impact of each input on output is clearly observed from output elasticity. The elasticity of mean output is decomposed into the frontier and TE elasticities as proposed by Battese and Broca (1997).

The elasticity of mean frontier output with respect to the *j*th input variable comprises two components: (a) elasticity of frontier output with respect to *j*th input, given by the estimated β_j parameters, and (b) elasticity of TE with respect to *j*th input given by estimated δ_j parameter. In this case, the elasticity of mean output with respect to the input variables (area harvested, family labor, hired labor, and material inputs) is estimated by using the following equation

$$\frac{\partial lnE(Y_{it})}{\partial lnX_{jit}} = \left\{ \beta_j + \beta_{jj} lnX_{jit} + \sum_{j \neq k} \beta_{jkt} lnX_{kit} \right\} + C_i \left\{ \frac{\partial \mu_{it}}{\partial X_{jit}} \right\} \tag{10}$$

where

$$C_i = 1 - {}^{1}/_{\sigma} \left\{ \frac{\emptyset\left({}^{\mu}i/_{\sigma} - \sigma\right)}{\Phi\left({}^{\mu}i/_{\sigma} - \sigma\right)} - \frac{\emptyset\left({}^{\mu}i/_{\sigma}\right)}{\Phi\left({}^{\mu}i/_{\sigma}\right)} \right\} \tag{11}$$

μ_i is defined by model (5.8); ($\emptyset$) and (Φ) are density and distribution functions of the standard normal variables, respectively. The first component of the model (10) is referred to the elasticities of frontier output, and second part is called elasticity of TE. The sum total of the output elasticity is the estimated scale elasticity (ε).

Data

This study has used national panel survey data collected in 2008/2009 and 2010/2011 by the National Bureau of Statistics. It is a national representative sample because it was drawn from all regions of Tanzania. Given the objective of this study, the data used are based on a sample drawn from agricultural data set for plots/households that meet the sampling criteria (adopters and nonadopters of LMCTs with maize-growing plots). Maize crop was sampled among other crops because it was a main crop grown widely due to its importance in the country in terms of food security. The matching was done at both the household and the plot level. The matching led to 1,897 plots that were used for analysis, including all (1,287) first-year/wave (2008) plots and 610 plots from the second year/wave (2010) that successfully matched with the first wave.

Empirical Results and Discussion

Descriptive Statistics

The descriptive statistics are presented in Table 1. The descriptive statistics indicate that the household harvested an average of 514 kg of maize on about 1.5 acres of cultivated/harvested area.

Table 1. Descriptive Statistics.

Variable	Description	Obs	*M*	*SD*	Min	Max
Quantity harvested	Total quantity of output harvested by the household (kg)	1,837	513.53	790.72	9	10,800
Area harvested	Total plot area harvested (acres)	1,857	1.50	1.60	0.05	20
Family labor	Family labor (man-days)	1,897	56.57	69.78	0	741
Hired labor	Amount of wage paid to hired labor (Tshs)	366	50941.82	86524.76	400	1,050,000
Material inputs	Total expenditure on intermediate (input) materials (Tshs)	821	27834.38	72213.51	50	1,163,000
Age	Age of the farming household head (years)	1,893	47.77	15.29	19	90
Gender	Gender of the household head (Value 1 for male, 0 for female)	1,897	0.75	0.43	0	1
Household size	The number of persons in the household	1,897	5.46	3.03	1	46
Education	Education level attained by the household head (years)	1,387	6.32	2.37	0	19
Plot ownership	The ownership of the cultivated plot (Value 1 if the household own a plot, 0 otherwise)	1,620	0.88	0.32	0	1
Off-farm income	Off-farm income (Value 1 if the household receive off-farm income, 0 otherwise)	1,529	0.12	0.32	0	1
Plot size	Total plot area owned by the household (number)	1,883	6.19	10.78	0.25	300
Plot distance	The distance of the plot from home (km)	1,618	2.89	5.59	0	65
Erosion	Presence of soil erosion on a plot (Value 1 if there is soil erosion 0 otherwise)	1,620	0.14	0.35	0	1

(continued)

Table 1. Continued

Variable	Description	Obs	*M*	*SD*	Min	Max
Plot good	The soil quality of a plot (Value 1 if good quality, 0 otherwise)	1,897	0.42	0.49	0	1
Plot average	The soil quality of a plot (Value 1 if average quality, 0 otherwise)	1,897	0.39	0.49	0	1
Flat bottom	The slope of a plot (Value 1 if flat bottom, 0 otherwise)	1,679	0.27	0.44	0	1
Flat top	The slope of a plot (Value 1 if flat top, 0 otherwise)	1,679	0.26	0.44	0	1
Slightly sloped	The slope of a plot (Value 1 if slightly sloped, 0 otherwise)	1,679	0.12	0.33	0	1
Conservation	Adoption of LMCTs on a plot (Value 1 if LMCTs was adopted, 0 otherwise)	1,620	0.39	0.49	0	1
Time	Waves used in analysis (Value 0 for the first wave, 1 for second wave)	1,897	0.32	0.47	0	1

Source. Authors' computations based on 2008/2009 and 2010/2011 panel data.
Note. LMCTs = land management and conservation technologies.

The average age of the household head was 48 years. About 75% of the households were headed by male, while 25% by female, with an average household size of five persons per household. The average time spent in school by the household head was 6 years. Concerning land ownership, the majority of the households owned the land they cultivated (about 88%) with an average farm size of 6 acres. The results also show that only 12% of the households earned their income out of farming activities. About 14% of plots cultivated by households experienced soil erosion, whereas 40% of the households adopted LMCTs.

Model Specification Test

The study conducted model specification tests to examine which model may appropriately represent the data. As described in the methodology section, tests are performed by using the generalized LR statistics. The log-likelihood functions that are used to estimate LR are straightforwardly given from the FRONTIER 4.1. Table 2 summarizes the test results, which were performed separately under neutral and nonneutral model specification.

We find that all the formulated null hypotheses are rejected at 5% level of significance in both neutral and nonneutral specifications. The first hypothesis in both forms of specification was to test the absence of technical inefficiency effects, which was strongly rejected in both neutral and nonneutral model specifications, suggesting the presence of a one-sided error component in the model, thus implying the use of ordinary least squares may not be appropriate (i.e., $H_0 : \gamma = 0$ rejected). The second hypothesis tests whether the CDPF is suitable model for the analysis. The null hypothesis ($H_0 : \beta_i = 0,\ i = 5 \ldots. = 14$) was rejected in both neutral and nonneutral model specification, suggesting that the TLPF is adequate in representing the data. The third hypothesis tests the absence of inefficiency function; that is, all parameters in the inefficiency function are equal to zero; that is, $H_0 = \delta_j = 0,\ j = 1 \ldots\ldots = 20$. This was strongly rejected irrespective of whether neutral or nonneutral model specification is used, implying that all parameters included in the inefficiency model are significantly different from zero.

Table 2. Model Specification Tests.

Test	Null hypothesis	Log-likelihood	LR statistics	Critical x^2	Decision
	Neutral model specification				
1	$H_0 : \gamma = 0$	−1598.94	885.31	Mixed $x^2_{2,0.95} = 5.14$	Reject H_0
2	$H_0 : \beta_i = 0,\ i = 5 \ldots. = 14$ (Cobb–Douglas frontier)				
		−1212.88	113.20	$x^2_{10.0.95} = 18.31$	Reject H_0
3	$H_0 = \delta_j = 0,\ j = 5 \ldots\ldots = 20$ (No tech inefficiency function)				
		−1502.66	692.75	$x^2_{16,0.95} = 26.30$	Reject H_0
	Nonneutral model specification				
1	$H_0 : \gamma = 0$	−1598.94	915.92	Mixed $x^2_{2,0.95} = 5.14$	Reject H_0
2	$H_0 : \beta_i = 0,\ i = 5 \ldots. = 14$ (Cobb–Douglas frontier)				
		−1195.54	109.11	$x^2_{10,0.95} = 18.31$	Reject H_0
3	$H_0 = \delta_j = 0,\ j = 1 \ldots\ldots = 20$ (No tech inefficiency function)				
		−1502.66	723.35	$x^2_{20,0.95} = 31.41$	Reject H_0
	Neutral versus nonneutral model				
1	$H_0 = \delta_j = 0,\ j = 1 \ldots\ldots = 4$ (Neutral translog model)				
		−1156.28	30.60	$x^2_{4,0.95} = 9.49$	Reject H_0

Source. Author's estimations based on 2008/2009 and 2010/2011 panel data.
Note. Mixed x^2 values are taken from Kodde and Palm (1986; Table 1, p. 1246); x^2 values are taken from the chi-square table.
LR = likelihood ratio.

The last hypothesis tests whether neutral model specification should be used instead of nonneutral model, and because the preceding tests (in both neutral and nonneutral) reject Cobb–Douglas production model in favor of translog production model, then the last hypothesis compares neutral versus nonneutral translog production models. This hypothesis $\left(H_0 = \delta_j = 0, j = 1 \ldots\ldots = 4\right)$ was strongly rejected as well, suggesting that input usage has an impact on farming efficiency; thus, more general nonneutral translog production frontier is appropriate for the used data. Therefore, interpretation of the study results is based on the results of nonneutral TLPF as described in the following sections.

The study examined the TE between adopters and nonadopters as one of the objectives of this study. Figure 1 presents the distribution of TE among adopters and nonadopters of LMCTs for 2-year panel data. The ranges of TE were almost the same for both adopters and nonadopters with the same minimum value but the highest maximum value for nonadopters. The results in Figure 1 further indicate that, for lower TE classes, percentage of adopter households is less than nonadopter households. On one hand, households who have TE less than 0.50 were 9% and 14% for adopter and nonadopters, respectively. On the other hand, we found that about 72% of the adopters have efficient scores above 60% but less than 90%, and about 68% of nonadopters have efficient score above 60% but less than 90%. Furthermore, about 9% of the adopters and 6% of the nonadopters have efficient scores above 90%.

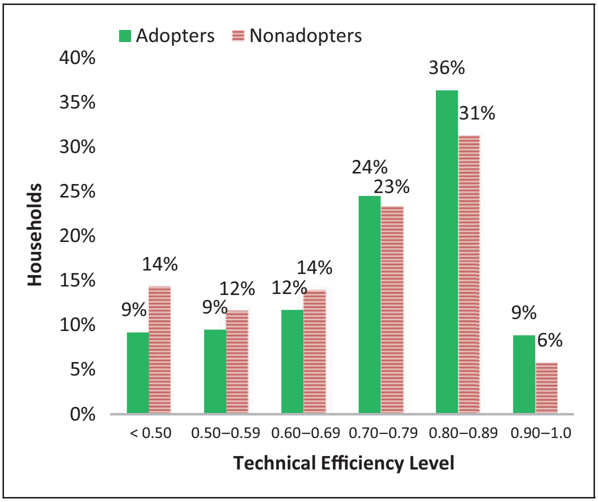

Figure 1. Comparison of distribution of technical efficiency among adopters and nonadopters.

From the preceded analysis, we note that the TE difference between adopters and nonadopters is 0.04 (the TE for adopters is 0.73 while that of nonadopters is 0.69), which is not large as one would have expected. The independent t test was further performed to establish any significant difference of TE between adopters and nonadopters of LMCTs. The results of independent t test for each type of conservation or LMCT adopted are presented in Table 3. The results show that the adopters had statistically significantly higher TE (0.73 ± 0.007) and (0.74 ± 0.010) compared with nonadopters (0.69 ± 0.006) and (0.70 ± 0.005) at 1% level of significance for overall conservation and organic fertilizers, respectively. The results also show that there was no statistically significant difference of TE means between adopters and nonadopters of Soil Water Conservation and Erosion Control (SWCEC) and inorganic fertilizers, implying that the null hypothesis of no significant difference could not be rejected.

The higher TE of adopters than nonadopters of organic fertilizers from 2-year panel data was expected because the use organic fertilizers (manure, composite) a has long time effect in soil unlike inorganic fertilizers (Hao & Chang, 2002; Kassie, Jaleta, Shiferaw, Mmbando, & Mekuria, 2013; Marenya & Barret, 2007). The acceptance of the null hypothesis of no significant difference between adopters and nonadopters of inorganic fertilizers is probably due to the fact that most of households do not apply expensive inorganic fertilizers on highly degraded and very poor soils. In addition to that, very few farmers can afford to apply the required amount of fertilizers in a given area. To ascertain the facts of these arguments, the independent t test was further performed to establish any significant difference of TE between adopters and nonadopters of inorganic

Table 3. Mean TE Differences Between Adopters and Nonadopters of LMCTs.

	M of TE				
Conservation status/ Type of LMCTs	Nonadopters of LMCTs	Adopters of LMCTs	t	$\Pr(\lvert T\rvert > \lvert t\rvert)$	df
Overall conservation	0.6938501 (0.005918)	0.7297946 (0.0069049)	−3.8944	0.0001	1618
SWCEC	0.7049223 (0.0049732)	0.7228253 (0.0108428)	−1.4735	0.1408	1618
Organic fertilizers	0.7006135 (0.0050113)	0.7442857 (0.0101512)	−3.5897	0.0003	1617
Inorganic fertilizers	0.7050896 (0.0050172)	0.7207527 (0.0104091)	−1.3077	0.1912	1617

Source. Author's computations based on 2008/2009 and 2010/2011 panel data.
Note. The numbers in parentheses are standard errors. TE = technical efficiency; LMCTs = land management and conservation technologies; SWCEC = Soil Water Conservation and Erosion Control.

fertilizers and SWCEC, taking into account of the perception of households on fertility of soil (Table 4).

The results from Table 4 reveal that the null hypothesis of no significant difference between adopters and nonadopters of inorganic fertilizers and SWCEC is rejected with $t = -1.88$ and $t = -2.13$ in good fertile and poor fertile soils at 10% and 5% level of significance, respectively. The adopters of inorganic fertilizers in good fertile soils had higher TE (0.74 ± 0.015) than did nonadopters (0.71 ± 0.007). In case of SWCEC, the adopters in poor fertile soils had higher TE (0.73 ± 0.013) than did nonadopters (0.70 ± 0.007). We also note that there was no significant difference between the adopters and nonadopters of inorganic fertilizers and SWCEC in poor and good fertile soils, respectively. Thus, these results suggest that inorganic fertilizers work well in moderately good fertile and not/less degraded soils, while the reverse is true for soil water conservation and erosion control practices.

Nonneutral TLPF (Results)

Table 5 presents the diagnostic statistic of the model which indicates that the sigma-square (σ^2) coefficient is 4.56 for all farmers in aggregate, which further support that the assumption of distribution of composite error term was correctly specified. Similarly, the sigma-square (σ^2) coefficient is 2.69 and 2.45 for adopters and nonadopters of LMCTs, respectively. The sigma-square (σ^2)

Table 4. Mean TE Differences Between Adopters and Nonadopters of Inorganic Fertilizers and SWCEC in Different Soil Fertility Types.

	M of TE				
Conservation status/ Type of LMCTs	Nonadopters of LMCTs	Adopters of LMCTs	t	$\Pr(\lvert T\rvert > \lvert t\rvert)$	*df*
inorg _ plot not good	0.70474 (0.006951)	0.7065 (0.014439)	−0.1116	0.9111	812
inorg _ plot good	0.705423 (0.007225)	0.739916 (0.014674)	−1.8752	0.0611	803
SWCEC _ plot not good	0.698973 (0.007038)	0.734014 (0.013154)	−2.1286	0.0336	812
SWCEC _ plot good	0.71081 (0.007027)	0.710315 (0.01763)	0.0276	0.9780	804

Source. Author's computations based on 2008/2009 and 2010/2011 panel data.
Note. The numbers in parentheses are standard errors. TE = technical efficiency; LMCTs = land management and conservation technologies; SWCEC = Soil Water Conservation and Erosion Control.

Table 5. Frontier Model for Nonneutral Translog Specification Results.

		All households in aggregate		Adopters		Nonadopters	
Variable	Parameters	Coefficient	*t* ratio	Coefficient	*t* ratio	Coefficient	*t* ratio
Constant	β_0	2.59***	80.54	2.64***	16.88	2.62***	27.31
Area harvested	β_1	0.97***	17.22	1.08***	7.09	1.17***	9.07
Family labor	β_2	0.07	1.45	0.09	0.53	0.01	0.10
Hired labor	β_3	0.06	1.08	0.04	0.59	0.04	0.58
Material inputs	β_4	−0.17***	−6.75	−0.17***	−3.49	−0.09*	−1.56
Area harv × Area harv	β_5	0.20***	4.72	0.15*	1.67	0.27***	4.16
Flabor × Flabor	β_6	0.01	0.47	0.01	0.31	0.01	0.33
Hlabor × Hlabor	β_7	0.00	−0.42	−0.02	−1.25	0.00	0.23
Materinp × Materinp	β_8	0.05***	9.30	0.06***	6.84	0.04***	2.68
Area harv × Flabor	β_9	−0.10***	−2.93	−0.18**	−2.04	−0.20***	−2.76
Area harv × Hlabor	β_{10}	0.02	1.10	0.01	0.35	0.03	1.25
Area harv × Materinp	β_{11}	−0.01	−1.09	−0.02	−0.79	0.00	−0.03
Flabor × Hlabor	β_{12}	−0.01	−0.88	0.02	1.31	−0.02	−1.22
Flabor × Materinp	β_{13}	−0.01	−1.81	−0.05***	−2.75	−0.01	−0.53
Hlabor × Materinp	β_{14}	0.00	−1.39	0.00	0.89	−0.01	−1.41
Sigma-squared	σ^2	4.56***	8.89	2.69***	4.70	2.45***	5.71
Gamma	γ	0.99***	557.54	0.98***	180.48	0.97***	196.64
Mean efficiency		0.70		0.73		0.690	
Number of observations		1897		633		987	
Constant	δ_0			−2.54*	−1.88	−6.39***	−3.56
Area harvested	δ_1			1.44***	3.20	3.27***	4.29
Family labor	δ_2			0.53	1.50	−0.82***	−2.66
Hired labor	δ_3			−0.48***	−3.95	0.01	0.11
Material inputs	δ_4			−0.05	−1.01	0.35***	4.20
Age	δ_5			0.08***	3.84	0.08***	4.71
Gender	δ_6			−0.73	−1.49	−0.03	−0.10
Household size	δ_7			−0.28***	−4.06	−0.14***	−3.64
Education	δ_8			0.15***	3.19	0.14***	3.28
Plot ownership	δ_9			−2.04***	−3.64	1.43***	2.81
Off-farm income	δ_{10}			−0.88	−1.13	−0.55	−1.02
Plot size	δ_{11}			−0.01	−1.49	0.01	0.68
Plot distance	δ_{12}			0.00	−0.19	−0.04**	−2.19
Erosion	δ_{13}			1.20***	3.30	0.49	0.74
Plot good	δ_{14}			−3.42***	−3.91	−2.37***	−3.83
Plot average	δ_{15}			−3.34***	−3.73	−2.18***	−3.68
Flat bottom	δ_{16}			−1.55**	−2.45	−1.80***	−3.36

(continued)

Table 5. Continued

Variable	Parameters	All households in aggregate		Adopters		Nonadopters	
		Coefficient	t ratio	Coefficient	t ratio	Coefficient	t ratio
Flat top	δ_{17}			−2.58***	−3.48	−1.01***	−2.97
Slightly sloped	δ_{18}			1.01	1.43	−2.56***	−3.75
Conservation	δ_{19}						
Time	δ_{20}			−1.51**	−2.27	1.94***	3.60
Mean efficiency				0.73		0.69	
Number of observations				633		987	

Source. Results from FRONTIER 4.1.
***Significant at 1%, **significant at 5%, *significant at 10%.

coefficients for all farmers in aggregate, adopters, and nonadopters, were significant at 1% level.

In addition, the gamma (γ) coefficient is 0.99, 0.98, and 0.97 for all farmers in aggregate, adopters, and nonadopters, respectively, and is statistically significant at 1% in all models. The value is very close to 1 in all models, assuring the stochastic nature of production function. It implies that about 99%, 98%, and 97% of output variation of maize farmers in Tanzania is attributed to technical inefficiency effects.

Concerning the input variables (area harvested, family labor, hired labor, and material inputs), the results indicate that area harvested has positive sign and is significant at 1% level for all farmers in aggregate, adopters, and nonadopters, implying a positive influence of area harvested on quantity harvested. The positive significant relationship between the harvested quantity and the harvested area is obvious and was expected; that is, the harvest increases as the harvested area increases.

Expenditure on material inputs has a negative sign in all situations, implying a negative impact of this farming input on the level of output. Family labor and hired labor are shown to have positive influence on the output level, though not significant. However, individual input coefficients estimated in the translog frontier production model presented in Table 5 do not have straightforward interpretation. Thus, the estimation of output elasticity for each input used is suggested for better and meaningful interpretation.

The TE Results

The results in Table 5 shows that the mean farming TE of small-scale maize farmers in aggregate in Tanzania is 0.70, indicating that farmers still have room to improve TE by 0.30 or 30%. The mean TE for adopters and nonadopters of LMCTs is 0.73 and 0.69, respectively. We note that the adopters had higher TE than their nonadopter counterparts and all farmers in aggregate, implying that adopters of LMCTs are more efficient in maize production than nonadopters. This suggests that the promotion and supporting the investment in land management and conservation practices increases smallholders' farm TE. The estimated technical efficiencies for maize production in this study for all farmers in aggregate, adopters, and nonadopters are higher than that estimated by Msuya et al. (2008), who got the same mean TE of 0.61 for maize production.[3] This difference might be attributed to different data types used by the studies. The current study has used national panel data, while other studies used cross-sectional data that covered small areas: The study of Msuya et al. (2008) covered only two districts, namely, Mbozi and Kiteto, while that of Miho (2017) used two representative regions (Ruvuma and Tabora) from agricultural sample census survey data. In addition to that, the panel data used for this study were collected when Agricultural Input Voucher System program was in place, which might have led to increase of the number of smallholder farmers applying inorganic fertilizers, which increases maize production.

Determinants of the TE

This section discusses the determinants or factors influencing the TE of maize smallholder farmers in Tanzania. Specifically, it discusses how different factors affect the TE between adopters and nonadopters of LMCTs. The determinants are the key variables that should be considered when addressing the adoption issues of LMCTs. We have noted that there is an opportunity to increase TE, thereby increasing productivity through the adoption of LMCTs and reducing the expansion of cropland. Table 5 (lower panel) presents an inefficiency model for adopters and nonadopters of LMCTs in Tanzania.

The parameters in the inefficiency model are interpreted as change in inefficiency with respect to change in the explanatory variable. Therefore, whenever there is a negative coefficient, it indicates that a variable has a negative (positive) influence on farming inefficiency (efficiency). The significant negative relationship between inefficiency and most of the variables implies the presence of the opportunity to increase the TE.

Results from Table 5 show that the usage of all farming input variables have an influence on farming efficiency among farmers in Tanzania for both adopters and nonadopters, supporting the nonneutrality of the translog production model. The input variables have found to influence TE of adopters and nonadopters differently with exception of area planted that affected both adopters and nonadopters in the same way. The results show that the coefficient of the area harvested is positive and statistically significant at 1% in all models (adopters and nonadopters), implying that farming efficiency reduced as the area harvested increases. This is consistent with the results of other authors (Lokina & Lwiza, 2016; Peterson, 1997; Samwel, 2011) who found that the increase of farm size reduces TE, implying diseconomies of scale as farm size increases.

The results further indicate that hired labor is an important factor that influences significantly positively the TE of adopters, while it has no effect on TE among the nonadopters. The reverse is true for family labor whereby it is significantly positively related to TE among nonadopters, but it has insignificant effect among the adopters. The positive effect of the hired labor on TE was expected because the farm or firm normally hires the most efficient labor. The results reveal the real behavior or normal conduct of the smallholder farmers in Tanzania and other developing countries. As noted earlier, the majority of households that afford to adopt LMCTs have a relatively higher income than do nonadopters. Therefore, they (adopters) can pay for the hired labor for farm operations including the application/use of LMCTs. On the other hand, the majority of nonadopters are poor and depend much more on family labor in the production process. The present results are different from that of Obwona (2006), Msuya et al. (2008), and Chirwa (2007) in Uganda, Tanzania, and Malawi, respectively, who found that labor force affected negatively the TE in maize production. However, in their studies, the labor force combined both the family and the hired labor in one variable unlike current study that included them in a model separately. The use of material inputs (improved seed, pesticides) had significant negative influence on TE among only nonadopters, implying that efficiency decreases with the rise in spending on material inputs among nonadopters. Therefore, the use of improved inputs efficiently should be completed with the adoption of other land management and conservation practices. These findings are consistent to that of Msuya et al. (2008), who found that use of pesticides had inverse relationship with TE in maize production.

The results show that the age coefficient has positive sign and is statistically significant at 1% in all models (adopters and nonadopters), indicating that as the age of the household head increases, farming efficiency declines. The possible reason for this is that farming production depends more on labor energy than on farm implements (capital), and farmers become weak and lose energy as they become old; thus, this leads to efficiency decline. Another reason is that, aged household heads normally use traditional farming methods, and most of them are inferior, and the adoption of new farming and land technology is easily done by young household heads.

The results further indicate that the size of the household significantly influences farming activities efficiency in all. The negative sign of household size coefficient indicates that the size of the household is negatively (positively) influencing farming inefficiency (efficiency) in all models. This directly supports the previously mentioned positive influence of family labor on TE among the nonadopters as poor smallholder farming households depends on family labor or household members. Therefore, the larger the household size, the larger the number of household/family members available for agricultural production.

Education level of the household head significantly affects farming efficiency of the household. The coefficient of education is positive and significant at 1% level consistently among adopters and nonadopters, indicating that as the household head spends more years in schooling, the farming efficiency level declines. The possible reason is that education enables the household head to engage in other income-generating activities apart from agriculture; as a result depends less on agriculture and concentrates much on other activities. These results are consistent to those of Msuya et al. (2008), who found that households with a secondary education had a positive impact on TE compared with households with a lower education level.

The distance of the farm from home tended to affect the farming efficiency. Unexpectedly, the coefficient of the distance is negative and statistically significant at 5% level of significance for nonadopters, implying that farming efficiency increases as the plot becomes farther from home. The distance had no significant effect on TE for adopters. These results are different from other previous studies (see Asekenye, 2012; Obwona, 2006; Samwel, 2011) that found distance to affect negatively the farm TE. However, there is a possibility of the distant farm to be efficient. A smallholder farm decides to have a distant farm near the forest because it has special comparative advantages to nearby home farms in terms of fertility and production potentials, especially for nonadopters. Msuya et al. (2008) also find that distance was not statistically significant influenced by TE.

As expected, the results show that the presence of soil erosion adversely affects farming efficiency for pooled sample and adopters. The coefficient of erosion is positive and statistically significant at 1% for the two models, implying that the presence of soil erosion on a plot reduces farming efficiency. Soil erosion involves the removal of the most productive layer (top layer), which is enriched with soil nutrients, and as a result leaves the plot with low-quality soil and thus affects the productive capacity of the farmland.

The study shows that soil quality affects farming efficiency. The coefficients of good and average quality plot are negative and statistically significant at 1% level of significance for all models as was expected. This implies that efficiency significantly improves when farmers grow crops in plots with good and fertile soils as they get high yields. This may support the earlier results of the small differences of TE between adopters and nonadopters. Therefore, farmers with degraded and infertile land will constantly seek good and high crop-yielding areas to raise output as well as TE if there are no initiatives to rehabilitate the degraded land and conserve/manage the land under continuous cultivation.

The last and most interesting result here is the reverse impact of time on farming efficiency for adopters and nonadopters. The results show that farming efficiency increases with time for adopters of LMCTs. The possible reason is that land conservation improves and preserves soil fertility, and this leads to efficiency improvement with time. On the other hand, for nonadopters, efficiency decreases with time.

Normally, farmland loses fertility the more is utilized, and if none of any of LMCTs is done, the productivity and efficiency of plots decrease over time.

Input Elasticity and Returns to Scale

As described in methodology section, we estimated elasticities of mean output with respect to input variables (area harvested, family labor, hired labor, and materials inputs). Table 6 summarizes the results of input elasticities and returns to scale.

The elasticities, as shown in Table 6, are generally low and always below unity, suggesting the low responses of harvests to the scale of farming inputs. The low input elasticities for other inputs suggest that there is low response of maize harvest to the scale of those farming inputs. The key message here is that if smallholder farmers continue to apply the current inputs, it would result in a smaller increase in crop output. Therefore, there is a need of introducing and adopting new inputs to supplement or complement the currently used inputs. We found that the elasticity of area harvested is consistently higher in both frontier output and TE efficiency. The elasticity of family labor and hired labor is significant and negative for both frontier out and in TE, respectively, which suggests that the mean farm may be subject to input congestion and operates in Stage III of the production function where the isoquant has a positive slope. Farmers may be using excessive labor in their small for social reasons or may not have adjusted to the given plot level.

Furthermore, elasticity of maize harvests with respect to area harvested, hired labor, and material inputs have positive signs, consistent with production function theory. However, only elasticity of the area harvested is found to be higher and statistically significant, at 1% level. It implies that as area harvested increases by 1%, quantity harvests increases by 0.8%. Coefficients in TE elasticity are statistically significant at 1% level (except for family labor), implying that the average quantity of maize harvests is relatively more sensitive to the elasticity of TE with respect to the input usage.

Table 6. Elasticity Parameter Estimates With Respect to All Inputs.

Variable	Frontier output elasticity		Technical efficiency elasticity	
Area harvested	0.844	(0.158)	3.135	(0.312)
Family labor	−0.031	(0.117)	0.182	(0.175)
Hired labor	0.006	(1.119)	−0.136	(0.041)
Material inputs	0.019	(0.053)	0.145	(0.037)
Returns to scale	0.838	(1.447)	3.325	(0.565)

Source. Author's computations based on 2008/2009 and 2010/2011 panel data.
Note. The numbers in parentheses are standard errors.

Specifically, the coefficients of area harvested and expenditure on input materials were found to be positive and statistically significant for TE elasticity, with area harvested coefficient having the highest elasticity. As noted earlier, this implies that farm TE decreases with the increase in plot size cultivated and input materials. The positive sign of the area harvested is attributed to the poor management of the farm as the plot/farm size increases due to smallholders' low farming technology (hand hoe, local seeds) and poverty that constrain them from accessing improved agricultural inputs (improved seeds, inorganic fertilizers, pesticides) and implements. We also note that the increase of the use of materials such as inorganic fertilizers, pesticides, and improved seeds decreases efficiency, which is contrary to production theory. This situation could possibly be attributed to the inappropriate usage of the input materials and using materials in a severely degraded land without prior initiatives of rehabilitating/conserving the land. Similar results have been also reported by Baffes (2002) and Msuya et al. (2008) that the use of agrochemicals had negative impact on production efficiency and productivity of maize, possibly due to inappropriate usage of chemicals in terms of time, quality, and right ratios of chemicals.

The coefficient of hired labor for TE elasticity is negative and statistically significant at 1%, which implies that farming efficiency increases with the increase in payment to hired labor. This suggests that payment to hired labor is made to efficient workers, implying that smallholder farmers can efficiently adopt land conservation technologies if they can use hired labor.

Furthermore, the results in Table 6 indicate that the return to scale elasticity (ε) is 3.3 for TE elasticity and is statistically significant, increasing returns to scale. There is room for increasing the inputs to realize more maize output.

Conclusion and Policy Implications

The objective of this article was basically to examine the difference in the production efficiency between adopters and nonadopters of land management technologies such as organic manure, use of inorganic fertilizers, soil erosion control, and water conservation measures. The analysis has used 1,897 matched plots constituting all (1,287) first-year/wave (2008) plots and 610 plots from the second year/wave (2010). The matching was done at both the household and the plot level. The analysis of data used FRONTIER 4.1 program that estimate simultaneously the stochastic frontier and technical inefficiency models.

The study findings have shown that the TE for the pooled sample of adopter was 0.70, implying that there is a room to improve efficiency by 0.30. Furthermore, the results show that adopters had higher TE than did their nonadopter counterparts. Adopters had TE of 0.73 with a range of 0.03 to 0.94, while nonadopters had TE of 0.69 with a range of 0.03 to 0.95. The majority of nonadopters were found to fall in lower classes of TE and vice versa for adopters of LMCTs. Although the difference of TE means between adopters and nonadopters of LMCTs was statistically significantly different, the difference was small in magnitude as one would expect, implying that nonadopters of LMCTs have land with good qualities to produce efficiently close to the conserved plots. The descriptive statistics supported this argument because 65.2% and 66.7% of households with good fertile soils and located at flat bottom, respectively, did not adopt LMCTs.

Furthermore, a good number of factors were identified to affect the TE differently of the adopters and nonadopters, for example, the expenditure on input materials, family labor, hired labor, plot ownership, and time. Therefore, there is also a need to understand how adopters and nonadopter of LMCTs are affected by different factors when designing the policies that promote the adoption of LMCTs among the smallholder farmers for sustainable increase of agricultural productivity and TE.

The findings have also shown that the efficiency decrease with the rise in spending on farm material inputs, implying inappropriate use of inputs. Similarly, the results revealed that there was the decreasing return to scale in frontier output elasticity. Therefore, to increase crop production, there is a need to introduce other inputs or complement the existing ones as well as improving the land management and conservation before using other improved inputs. Provision of extension services is important to increase the farmers' skills to apply the inputs and agronomic practices appropriately.

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Notes

1. Schmidt and Sickles (1984) argue that there is quite a large potential gain from using panel data to measure TE compared with using cross-sectional data. They point out that there are difficulties concerning maximum likelihood estimation methods and the consistency of estimates from using cross-sectional data. The difficulties include the estimation of TE of a particular firm that is not consistent, requirement of distributional assumptions about TE to estimate the model and separate technical inefficiency from statistical noise, and an assumption that efficiency is independent of regressors that may be incorrect.
2. Presence of LMCTs on the plot include the use of organic fertilizer or use of inorganic fertilizer or presence of soil erosion control and water conservation practices.

3. Msuya et al. (2008) used field survey data from two districts (Kiteto and Mbozi), while Miho (2017) used National Sample Census of Agriculture 2007/2008 (specifically for Tabora Region).

References

Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*, 21–37.

Alem, Y., Bezabih, M., Kassie, M., & Zikhali, P. (2010). Does fertilizer use respond to rainfall variability? Panel data evidence from Ethiopia. *Agricultural Economics*, *41*, 165–175.

Asekenye, C. (2012). *An analysis of productivity gaps among smallholder groundnut farmers in Uganda and Kenya* (Master's thesis, Paper 323, pp. 37–63). University of Connecticut, Storrs, CT.

Baffes, J. (2002, December). *Tanzania's cotton sector: Constraints and challenges in a global environment* (Africa Region Working Paper Series No. 42). Washington, DC: The World Bank.

Battese, G. E., & Broca, S. S. (1997). Functional forms of stochastic frontier production functions and models for technical inefficiency effects: A comparative study for wheat farmers in Pakistan. *Journal of Productivity Analysis*, *8*, 395–414.

Battese, G. E., & Coelli, T. J. (1988). Prediction of technical efficiencies with a generalized frontier production and panel data. *Journal of Econometrics*, *38*, 387–399.

Battese, G. E., & Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Production Analysis*, *3*(3), 153–169.

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

Campbell, H. F., & Hand, A. J. (1998). Joint ventures and technological transfer: The Solomon Islands pole-and-line fishery. *Journal of Development Economics*, *57*, 421–442.

Chiona, S. (2011). *Technical and allocative efficiency of smallholder maize farmers in Zambia* (Master's thesis, pp. 1–49). University of Zambia, Lusaka, Zambia.

Chirwa, E. W. (2007). *Sources of technical efficiency among smallholder maize farmers in southern Malawi* (Research Paper No. 172, pp. 9–14). Nairobi, Kenya: African Economic Research Consortium.

Cobb, C. W., & Douglas, P. H. (1928). A theory of production. *The American Economic Review*, *18*(1), 139–165.

Coelli, T. J. (1995). Estimators and hypothesis tests for a stochastic frontier function: A Monte Carlo analysis. *Journal of Productivity Analysis*, *6*, 247–268.

Geta, E., Bogale, A., Kassa, B., & Elias, E. (2013). Productivity and efficiency analysis of smallholder maize producers in southern Ethiopia. *Journal of Human Ecology*, *41*(1), 67–74.

Greene, W. H. (2008). The econometric approach to efficiency analysis. In H. O. Fried, C. A. K. Lovell, & S. S. Schmidt (Eds.), *The measurement of efficiency* (Chapter 2, pp. 3–25). New York, NY: Oxford University Press.

Hao, X., & Chang, C. (2002). Effect of 25 annual cattle manure applications on soluble and exchangeable cations in soil. *Soil Science Journal*, *167*, 126–134.

Hepelwa, A. S. (2013). Technical efficiency as a sustainability indicator in continuum of integrated natural resources management. *Resources and Environment*, *3*(6), 194–203.

Jandrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function. *Journal of Econometrics*, *19*, 233–238.

Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., & Mekuria, M. (2013). Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania. *Technological Forecasting & Social Change*, *80*, 525–540.

Kassie, M., Pender, J., Yesuf, M., Kohlin, G., Bluffstone, R., & Mulugeta, E. (2008). Estimating returns to soil conservation adoption in the northern Ethiopian highlands. *Journal of Agricultural Economics*, *38*, 213–232.

Kassie, M., Zikhali, P., Pender, J., & Kohlin, G. (2010). The economics of sustainable land management practices in the Ethiopian highlands. *Journal of Agricultural Economics*, *61*(3), 605–627.

Kibaara, B. W. (2005). *Technical efficiency in Kenyan's maize production: An application of the stochastic frontier approach* (Master's thesis, p. 10). Colorado State University, Fort Collins, CO.

Kirkley, J. E., Squires, D., & Strand, I. (1995). Assessing technical efficiency in commercial fisheries: The Mid-Atlantic sea scallop fishery. *American Journal of Agricultural Economics*, *27*, 686–697.

Kodde, D., & Palm, F. (1986). Wald criteria for jointly testing equality and inequality restrictions. *Econometrica*, *54*, 1243–1248.

Lokina, R., & Lwiza, S. (2016). Technical efficiency in agriculture and its implication on forest conservation in Tanzania: The case study of Kilosa District (Morogoro). *Tanzania Economic Review*, *5*(1), 2016.

Lovell, C. A. (1993). Production frontiers and productive efficiency. In H. O. Fried, C. A. Lovell, & S. S. Schmidt (Eds.), *The measurement of productivity efficiency: Techniques and applications* (pp. 3–67). New York, NY: Oxford University Press.

Marenya, P. P., & Barrett, C. B. (2007). Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food Policy*, *32*, 515–536.

Medhin, H., & Gunnar, K. (2011). Soil conservation and small-scale food production in highland Ethiopia: A stochastic metafrontier approach. In R. Bluffstone & G. Kohlin (Eds.), *Agricultural investment and productivity: Building sustainability in East Africa*. New York, NY: RFF Press.

Meeusen, W., & Van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production function with composed error. *International Economic Review*, *18*, 435–444.

Miho, A. (2017). Comparing technical efficiency of maize smallholder farmers in tabora and ruvuma regions of tanzania: a frontier production approach. *Asian Journal of Agriculture and Rural Development, 7*(9), 180–197.

Msuya, E. E., & Ashimogo, G. C. (2006). An estimation of technical efficiency in Tanzanian sugarcane production: A case study of Mtibwa Sugar Company Outgrower's Scheme. *Journal of Economic Development*, *1*(1), 28–46.

Msuya, E. E., Hisano, S., & Nariu, T. (2008). *Explaining productivity variation among smallholder maize farmers in Tanzania*. Paper presented at the XII World Congress of Rural Sociology of the International Rural Sociology Association, Goyang, Korea (MPRA Paper No.14626, pp. 7–24). Retrieved from http://mpra.ub.uni-muenchen.de/14626/

Nyangena, W. (2005). Social determinants of soil and water conservation in rural Kenya. *Environment Development and Sustainability*, *10*(6), 745–767.

Nyangena, W., & Juma, O. M. (2014, January). *Impact of improved farm technologies on yields, the case of improved maize varieties and inorganic fertilizer in Kenya* (Environment for Development Discussion Paper, EfD DP 14-02, p. 23). Nairobi, Kenya: Environment for Development.

Obwona, M. (2006). *Determinants of technical efficiency differentials amongst small- and medium-scale farmers in Uganda: A case of tobacco growers* (Research Paper No. 152, pp. 5–13). Nairobi, Kenya: African Economic Research Consortium.

Peterson, W. L. (1997). *Are large farms more efficient?* Minneapolis, MN: University of Minnesota. Retrieved from http://ideas.repec.org/p/wop/minnas/9702.html

Prabodh, I. (2005, October). *Technical efficiency in agriculture and dependency on forest resources: An economic analysis of rural households and the conservation of natural forests in Sri Lanka* (Doctoral dissertation). University of Hawai'i, USA.

Samwel, T. (2011). *Analysis of production efficiency of tobacco smallholder farms in mid-western Uganda: Understanding its implications for rural livelihood policy* (Master's thesis). Ghent University, Ghent, Belgium.

Schmidt, P., & Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business and Economic Statistics*, *2*, 367–374.

Sharma, K. R., & Leung, P. (2000). Technical efficiency of carp pond culture in South Asia: An application of a stochastic meta-production frontier model. *Aquaculture Economics & Management*, *4*(3–4), 169.

Shively, G. E. (1997). Consumption risk, farm characteristics, and soil conservation adoption among low-income farmers in the Philippines. *Agricultural Economics*, *17*, 165–177.

Srivastava, A., & Shrivastava, R. S. (2002, December). *Methodology for measuring environmental efficiency*. Paper presented at the Ninth International Conference of Forum for Interdisciplinary Mathematics on Statistics Combinatorics and Related Areas, University of Allahabad, India.

Tchale, H. (2009). The efficiency of smallholder agriculture in Malawi. *AFJARE*, *3*, 101–121.

United Republic of Tanzania. (2013). *Ministry of Agriculture, Food Security and Cooperatives: National agriculture policy* (pp. 1–30), Dar es Salaam, Tanzania.

Zikhali, P. (2008). *Fast-track land reform and agricultural productivity in Zimbabwe* (Working Papers in Economics, No. 322). Gothenburg, Sweden: University of Gothenburg, Department of Economics.

Author Biographies

Onesmo Selejio is a lecturer in the Department of Economics, University of Dar es Salaam and research fellow at the Environment for Development (EfD), Tanzania. He holds PhD in economics from University of Dar es Salaam and BSc and MSc (Agricultural Economics) from Sokoine University of Agriculture (SUA), Tanzania. He has researched and published in areas of agriculture, microfinance and development, and natural resources and environment. He has been involved in several consultancies in the same areas for local (private and public) and international organizations such as UNDP, UNEP,

ILO, EfD/SIDA, French Development Agency (AFD), and Belgium Technical Cooperation (BTC). He is one of the editors of the book *How Can Tanzania Move from Poverty to Prosperity* (DUP 2015).

Razack B. Lokina is an associate professor of the Department of Economics of the University of Dar es Salaam. He holds a doctorate degree in economics from the University of Gothenburg in Sweden. His main research interest is in the area of environment and natural resource economics, particularly application of valuation techniques in the environmental issues, forestry, fisheries, and wildlife. Courses that Razack teaches at the Department of Economics are Mathematics for Economists for graduate students, Environmental and Resource Economics (PhD and MA classes), and Applied Econometrics and Quantitative Methods for undergraduate students. He has supervised a larger number of MA and PhD students writing on environment and natural resource issues. He has served as a consultant to the different government departments including Division of Environment-Office of the President, National Environment Management Council (NEMC). He was also involved with a team of experts in conducting a study on *Integrated Ecosystem Assessment*, which is a global initiative to protect the mountain ecosystem. He was also the lead consultant for the production of the second Tanzania state of the Coast Report.

John K. Mduma is a senior lecturer and economist at the University of Dar es Salaam. He holds a PhD in Agricultural Economics (2006) from University of Bonn, Germany, and master degree (1999) and a bachelor degree (1997) in economics, both from the University of Dar es Salaam. His research area of interest includes poverty and inequality analysis. He authored a book *Rural Off-Farm Employment and its Effects on Adoption of Labour Intensive Soil Conserving* (Peter Lang, 2006) and is one of the editors of the book *How Can Tanzania Move from Poverty to Prosperity* (DUP 2015). His other research work has been published in *African Study Quarterly*, *the Journal of Applied Sciences*, *the Journal of Agronomy*, *Econometric Methods for Analysing Economic Development*, and *Fuel Taxes and the Poor: The Distributional Effects of Gasoline Taxation and Their Implications for Climate Policy*. He has also worked in short-term assignments with organizations such as the WHO/Ministry of Health in the preparation of Health Sector Strategic Plan (III), REPOA/DFDI, World Bank, ARTUMAS Groups Inc. (in Gas and Electricity Project in Tanzania), and so forth. He is a senior fellow of the Environment for Development (EfD) initiative (www.efdinitiative.org). Since February 2018, he serves as Director General and Commissioner of the Fair Competition Commission of Tanzania.