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The Effect of Extension Services Access on Technical Efficiency Among Smallholder Sugarcane Farmers in Kilombero Valley: Evidence from the Propensity Score Matching Approach

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Ikisiri

Utafiti huu ulitathmini athari za upatikanaji wa huduma za ugani kwenye tija kwa Wakulima Wadogo Wadogo wa Miwa (WWWM) 274 katika bonde la Kilombero, Tanzania. Mpaka wa uzalishaji wa stochastic (stochastic production frontier) na mbinu ya kulinganisha alama za uelekeo (Propensity Score Matching) zilitumika katika uchambuzi wa taarifa zilizokusanywa. Utafiti ulilinganisha utendaji wa kazi wa miundo ya mipaka ya "Cobb-Douglas" na "Translog", ambapo muundo wa Cobb-Douglas ulionekana kufaa zaidi ya ule wa Translog na hivyo kuchaguliwa kutumika katika ukadiriaji wa tija ya uzalishaji katika utafiti huu. Wastani wa tija ya uzalishaji ulikadiriwa kufikia 60%, na hivyo kuonesha kuwa bado kuna nafasi ya kuongeza tija kwa kutumia pembejeo zinazotumiwa na WWWM kwa sasa. Kwa kuzingatia mbinu ya kulinganisha alama za uelekeo (propensity score matching), uchambuzi umeonesha kuwa upatikanaji wa huduma za ugani huongeza tija katika uzalishaji kwa WWWM. Hivyo, sera zinahitajika za kuimarisha taasisi zinazotoa huduma za ugani zitazohakikisha uwepo na upatikanaji rahisi wa huduma hizi, pamoja na ubora wa huduma zenyewe. Changamoto na maeneo ya utafiti zaidi pia yameelezwa.

Abstract

This study assesses the effect of access to extension services on the Technical Efficiency (TE) of Smallholder Sugarcane Farmers (SHSCFs) in Kilombero valley, Tanzania. Based on a cross-sectional survey of 274 randomly selected SHSCFs, the study compared the Cobb-Douglas (CD) and translog frontier models and selected CD which fitted well in the dataset. The Propensity Score Matching (PSM) method was then applied to determine the effect of extension service access on TE. The estimated mean technical efficiency is 60%, suggesting that there is room for improving efficiency in the use of production inputs at the disposal of SHSCFs. Furthermore, based on the propensity score matching method, the analysis indicates that access to extension services generates a positive and significant differential effect on technical efficiency. As such, policies are needed to strengthen the institutions providing extension services in order to not only ensure availability and make them readily accessible but also improve the quality of the services provided. Limitations and avenues for further research are also highlighted.

Keywords: Smallholder Sugarcane Farmers, Propensity Score Matching, Technical Efficiency, Extension Services, Kilombero valley

1.0. Introduction

Improving efficiency and productivity of the agricultural sector especially of smallholder farmers is imperative for economic development and enhancing the livelihoods of farm households in most developing economies. In Tanzania, the agricultural sector provides foreign currency, raw materials for the growth of the industrial sector, employment opportunities for the majority of households and food for the growing population (URT, 2021). Certainly, the agricultural sector efficiency and productivity improvement are thus fundamental for the progression of Tanzania to an upper middle-income country by 2030 (Ali *et al*., 2020).

Sugarcane is among the strategic crops that form the agricultural transformation agenda of the country. The crop is produced for both export and domestic consumption in different proportions depending on the market demand variations. In light of this importance, the country has in place numerous market-based efforts to promote the agricultural sector performance in general and the sugarcane subsector in particular as reflected in the agricultural policy (URT, 2021) and implementation strategies 2015-2025 (URT, 2021). However, sugarcane production remains low, averaging 300,000 tons per year as compared to domestic demand of 350,000 tons (URT, 2021). It further observed that sugarcane productivity in Tanzania remains at an average of 37.8 tons/hectare, which is below both the national average of 70 tons/hectare and the world average of 60-70 tons/hectare (URT, 2021).

Low productivity in the sugarcane subsector is attributable to several factors including limited input use, a limited understanding of production technology and land management practices (Ambetsa *et al*., 2020; Asghar *et al*., 2022; Kosim, Aji, and Hapsari, 2021). Similarly, in Kilombero farmers are characterized with limited input use, a limited understanding of production technology and land management practices. These factors have caused low productivity in sugarcane production in the country, and have highlighted the importance of transferring advanced knowledge to Smallholder Sugarcane Farmers (SHSCFs). Governments' participation in agricultural knowledge diffusion has been caused by the public-good nature of agricultural information, coupled with the increasing gap between SHSCFs and private estate plantation productivities (Maulu *et al*., 2021; Chune *et al*., 2022).

In Tanzania, the central government, as well as agricultural stakeholders, continue to invest funds in agricultural extension through employment of agricultural extension officers. Kilombero valley, which contributes about 45%of the sugar produced in Tanzania, has the country's highest agricultural extension expenditure at district level (URT, 2021). Extension services are provided intwo ways, through conducting training and seminars, as well as by conducting farm visits to SHSCFs. Agricultural extension officers are organizing training and seminars at farmer organizations offices on how to use available inputs extensively. Also, extension officers conduct farm visits to SHSCFs and teach them improved technology and good land management practices. It was reported that between 2020 and 2021, around 12 training and 23 farm visits were conducted as well as 500 million was spent on agricultural extension and advisory services with an estimated 50% increase by the end of 2022 (URT, 2021).

However, despite the fact that the government of Tanzania employs and stations extension officers in each village but, most SHSCFs have not only limited knowledge of these technologies but also limited ability to practice good land management practices. In this regard, understanding the effect of extension services on productivity by SHSCFs is of the utmost importance. Extension services can be used for the dissemination of newly developed technology to SHSCFs (Emmanuel *et al*., 2021; Midamba, 2022) hence, acting as a source of knowledge of up-to-date technologies and good agricultural practices for farmers which when adopted can improve production efficiency and productivity.

Earlier studies examining the effect of extension services on agricultural productivity have produced different findings. For instance, Ambetsa *et al*. (2020), Biswas *et al*. (2021), Gatheru *et al*. (2021) and Kosim, Aji and Hapsari, (2021) found that access to extension services has no effect on agricultural productivity; whereas Agboola (2018) Atukunda, Atekyereza and Walakira, (2022), Maulu *et al*. (2021), Midamba, (2022) and Nagar, Nauriyal, and Singh, (2021) found it to have a significant effect on technical efficiency. While a plethora of earlier studies have examined the effect of extension services across the globe, a lacuna of knowledge still exists in two main fronts that form the basis of this study. First, a few studies have tested and compared the performances of the Cobb-Douglas and Translog stochastic frontier models and then adopt the most appropriate model. Earlier studies (e.g., Lema, Masresha and Neway, 2022) have shown that the two models tend to produce significantly different findings. Hence, the study used the likelihood ratio test to select the appropriate model in a given crop context. Second, the effect of extension service access on TE has been widely studied globally, producing inconsistent findings. This is mostly attributable to weak methodology. As such the current study aims to contribute on two fronts. First, this study used the likelihood ratio test to select the appropriate stochastic frontier model which was used to analyze TE among SHSCFs in Kilombero valley. The study selected the Kilombero valley because it produces a great proportion of sugarcane in the country i.e., about 45% of the sugar produced in Tanzania comes from the Kilombero valley (URT, 2021). Second, the study assesses the effect of extension services access on TE using the Propensity Score Matching (PSM) method. To the best of our knowledge, this method has scantly been used in the analysis of TE. An advantage to using propensity score matching in this context is that, the model discards those who did not access extension services who are dissimilar to those who access extension services. The model retains only controls who are similar to those who access extension services.

The rest of the paper is organized as follows. Section 2 presents the theoretical and empirical literature informing the study. This is followed by the description of the methodology in Section three. The results and discussions of the main findings are presented in Section four. The study's conclusions and implications are presented in Section five.

2.0. Literature Review

2.1. Theoretical perspectives

Technical efficiency is the farmer's ability to produce the maximum quantity of output from a given set of minimum quantity of input (Birhanu, Tsehay, and Bimerew, 2022). Cobb-Douglas and Translog models have been prominently used widely in the analysis of the technical efficiency of a production unit. The Cobb-Douglas production function assumes that there are constant returns to scale (Ngango and Hong, 2021). This implies that if inputs used in the production process are doubled, the total output automatically doubles. The assumption of constant return to scale in the Cobb-Douglas production function has been widely criticized (Meeusen and Van-den-Broeck, 1977). This is largely because it is not possible to change all inputs to bring a proportionate change in the outputs of all the industries given that some inputs are scarce and hence, cannot be increased in the same proportion as the abundant ones.

The translog production function is mainly used to identify a specific functional form for a production function that embodies all of the assumptions and results of the production minimization model (Lema, Masresha and Neway, 2022). In the Translog production function, the number of parameters practically explodes as the number of considered production factors increases (Ndubueze-ogaraku, Adeyoola and Akuchinyere, 2021). This may lead to the problem of collinearity. Both models are relevant in explaining the technical efficiency of the SHSCFs. However, to determine which model is more appropriate, the two models are tested empirically.

2.2. Empirical Review

Empirically, earlier studies have examined technical efficiency using the Cobb-Douglas and translog models. For example, Ambetsa *et al*. (2020) revealed that the average level of technical efficiency of SHSCFs in Kenya was 29.31% which is technically low. Using the Cobb-Douglas production function for 200 smallholder farmers, Midamba, (2022) revealed that the level of technical efficiency of smallholder farmers in Uganda is 46%. Other studies revealed that levels of technical efficiency in Ethiopia and Nigeria are 53%, 48%, respectively (Birhanu, Tsehay and Bimerew, 2022; Chune *et al*., 2022). A few studies (e.g., Chune *et al*., 2022; Lema, Masresha and Neway, 2022; Mesfin, Bamlaku and Admasu, 2021) applied the Translog production function in the analysis of technical efficiency and found that results differed significantly. Despite many studies using the Cobb-Douglas production function, the performance of the two models has rarely been tested and compared.

Similarly, studies on the effects of extension services on technical efficiency are scanty. Some of them include Atukunda, Atekyereza and Walakira, (2022), Carrer, *et al*., (2022), Maulu *et al*., (2021) and Midamba, (2022) who found a significantly different level of technical efficiency between extension service programme participants and non-participants in Ethiopia. In addition, Agboola (2018), Nagar, Nauriyal, and Singh, (2021) and Ragasa and Mazunda (2019) revealed a significant relationship between technical efficiency and extension services. Whereas Biswas *et al*., (2021), Gatheru *et al*., (2021) and Kosim, Aji and Hapsari, (2021) and found that access to extension services has no effect on agricultural productivity. However, these studies are limited in terms of differences in findings, geographical, crop, and methodological contexts and hence are not generalizable. The current study is an attempt to address this lacuna of knowledge on two fronts: first, it examines the technical efficiency of SHSCFs and compares the performance of the Cobb-Douglas and Translog models. Second, the study examines the effect of extension services on sugarcane technical efficiency based on the PSM approach, which is one of the rigorous quasi-experimental methods.

3.0. Methodology

The study was conducted in Kilombero valley in June 2021. The valley is located in Kilombero and Kilosa districts in the Morogoro region. The Kilombero valley was purposively selected as 97% of the SHSCFs in Tanzania are found in this area and contributing about 45% to Tanzania's total sugarcane production (URT, 2021).

Out of the fifteen farmer organizations exist in Kilombero valley, the study purposively selected two: the farmer organizations of Ruhembe Cane Growers Association (RCGA) from Kilosa district and the Kilombero Cane Growers Association (KCGA) from Kilombero district. The selected associations have registered more than 50% of all SHSCFs in Tanzania, and they are also the oldest (more than 30 years) and biggest farmer organisations in Tanzania (KCGA has 3500 members and RCGA has 3507 members) (URT, 2021).

A total of 358 SHSCFs were sampled using stratified sampling technique, of which 178 SHSCFs were randomly selected (from member's register by using SPSS random number generator) from KCGA and 180 SHSCFs from RCGA. A structured questionnaire was distributed to the selected respondents. The survey questionnaire was pre-tested with 20 SHSCFs prior to the commencement of the full-scale survey. The pre-testing exercise was important for enhancing the content and face validity of the measuring instrument. During the data collection, the self-administered questionnaire was distributed to the 274 SHSCFs (of which 159 were from KCGA and 115 were from RCGA) who were assembled in the respective farmer organization offices. This method was appropriate for enhancing the response rate, which stood at about 77%. Certainly, this response rate is reasonably high for a cross-sectional survey.

3.1. Technical Efficiency and its Measurement

Technical efficiency is analyzed as a two-stage procedure. First, it involves measuring the level of technical efficiency and second, it involves estimating the effect of socioeconomic and institutional factors such as extension service access on technical efficiency. Studies have used two methods for measuring technical efficiency namely, Stochastic Frontier Analysis (SFA) and Data Environment

Analysis (DEA). The current study adopted Stochastic Frontier Analysis (SFA) whose production function separates random noise from inefficiency errors. Similarly, SFA is suitable for large samples.

SFA permits the testing of three major assumptions. First, the appropriateness of the specified model in estimating the stochastic frontier model. Second, the presence of inefficiency. Third, the significance of farm, farmer and institution characteristics in explaining inefficiency.

In the SFA, the most used production functions are Cobb-Douglas production function and Translog production function. The Cobb-Douglas production function can be expressed as :

$$lny_i = \beta_0 + \sum_i^3 =_1 \beta_i lnx_i + (v_i + u_i) \qquad (1)$$

The Translog production function can be expressed as;

$$n\, y_i = \beta_0 + \sum_i^3 =_1 \beta_1 lnx_1 + \frac{1}{2}\sum_i^3 =_1 \beta_{ii} lnx_i^2 + \sum_i^3 =_1 \sum_j^3 -_1 \beta_{ij} lnx_i lnx_j + (v_i + u_i) \qquad (2)$$

Where;

yi = the quantity of output β0 = the constant

βi, βii, βij = the production function parameters to be estimated for each input.

The Cobb-Douglas production function is a special case of the translog production function where all bi, k = 0 and composed error (εi) representing vi and ui. It should be noted that, there are two error terms in the equation, the first error, υi, assumed to be normally distributed with a mean of 0 and variance σ2υi, that is to say, υi˷ N (0, σ2υ) captures the impacts of random shocks (like weather changes,) on output. The second error, μi, captures the disturbances that cause technical efficiency losses i.e., the systematic difference between observed outputs and the production frontier.

The two error components, vi and ui are also assumed to be independent of each other. The variance parameters are estimated using the maximum likelihood approach which provide the estimates of β and the gamma γ. The gamma explains the variations of the total output from the frontier output and it can be expressed as:

$$\sigma_s^2 = \sigma_v^2 + \sigma_u^2 ; \gamma = \frac{\sigma_u^2}{\sigma_s^2} \; and \; 0 \le \gamma \le 1 \qquad (3)$$

The closer the value of the gamma γ is to one, the more the deviation of the observed output to the deterministic output. It simply suggests that there is inefficiency. A gamma value closer to zero, suggests that the deviation may be caused by random factors (Farrell, 1957).

The stochastic frontier model can be used to test two hypotheses namely: testing the presence of inefficiency and testing the significance of the explanatory variables that determine inefficiency. The hypotheses can be presented as:

H0: γ = δ0 = δ1 = ……. δn = 0

There are no inefficiency effects among SHSCFs

H0: γ = δ0 = δ1 = ……. δn = 0

To test the above hypotheses, the study used the generalized likelihood ratio test and it was presented as;

$$LR(\lambda) = -2[\{lnL(H_0)\} - \{lnL(H_1)\}] \quad (4)$$

Where;
ln(H0) = the null hypothesis
ln(H1) = the alternative hypothesis

The selection of either to use Cobb-Douglas production function or the Translog production function to represent data depends on the functional form test. The study used the likelihood ratio test to select the appropriate model between the Cobb-Douglas production function and the Translog production function.

The hypothesis for empirical testing can be stated as; H0: Translog production function is not appropriate while H1: Translog production function is appropriate

The study formulated a stochastic frontier model based on the Cobb-Douglas production function and it was presented as follows:

$$\ln\acute{y}_{in} = \beta_0 + \beta_1 lnL + \beta_2 lnHL + \beta_3 lnC + \beta_4 lnS + \beta_5 lnF + \beta_6 lnP + £ \quad (5)$$

Whereby; Ln = denotes logarithms to base e, Y = the maximum attainable output for a given level of all inputs, (ton), L = land, (acres), Hl = Hired labour, (unit cost per fam), C = capital (hired tractor) (in TZS), S = seeds (in kg), F = fertilizer (in kg), P = pesticides (in kg), £ = an error term that follows a half normal distribution.

The empirical model for the inefficiency is expressed as follows:

$$U_I = \delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + +\delta_5 Z_5 + \delta_6 Z_6 + \delta_7 Z_7 + \delta_8 Z_8 + W_i \quad (6)$$

Whereby; Z_1 = Education level (Primary School [yes], Secondary School [yes], Certificate/Diploma [yes]), Z_2 = Age [years], Z_3 = Income [TZS], Z_4 = Distance [kilometer], Z_5 = Extension services [Yes/No], Z_6 = Membership [years], Z_7 = Family size[number], Z_8 = Access to credit [Yes/No], W_i = An error term

3.2. Propensity Score Matching Approach

The current paper used the Propensity Score Matching (PSM) method to assess the effect of access to extension services on sugarcane technical efficiency among SHSCFs. The PSM method was introduced by Paul Rosenbaum and Donald Rubin in 1983. The PSM method was selected due to its ability to estimate valid and reliable results that explain the effects of access to extension services as adopted (Kaliba *et al*., 2021). The advantage of propensity score in comparison to the Ordinary Least Square (OLS) method, Instrument Variables (IV) or Difference in Difference (DiD) is the separation of confounding factor adjustment and analysis of the treatment effect steps.

PSM involves two estimation stages. In the first stage of this analysis, propensity scores were estimated using the probit model to estimate the probability of receiving extension services. The second stage involved matching the scores where SHSCF who receive extension services were matched with SHSCFs who do not receive extension services based on the closeness of their propensity scores that reflect the probability of receiving extension services subject to different farm characteristics, farmer characteristics, and institutional characteristics. Different matching algorithms, such as nearest neighbour matching, radius caliper matching, kernel matching is normally used in literature (Atube *et al.*, 2021). This study used radius caliper matching.

In the PSM approach, the propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics as follows;

$$P(X) = Pr\{g_i = 1 \mid X\} = E\{g_i \mid X\}, P(X) = F(X) \tag{7}$$

Where;

$g_i =$ The values of 1,0 and if $g_i = 1$ then it indicates receive extension services, referred to as 'treatment', and the propensity score, $g_i = 0$ then indicates do not receive extension services

$P(X) =$ The probability of receiving the treatment given X

$F(X) =$ Normal or logistic cumulative distribution

To estimate the average treatment effect based on the propensity scores, two assumptions were met. The first assumption was the Conditional Independence Assumption (CIA) which states that for a given set of covariates, participation is independent of potential outcomes (Asghar *et al.*, 2022). The second assumption ensured that the average treatment effect for the treated (ATT) was defined within the region of common support. For this case, it implies that SHSCFs with the same characteristics have a positive probability of being in a group of SHSCFs who receive extension services and those who do not receive extension services (Agboola, 2018). Therefore, following Ragasa and Mazunda (2019), once the propensity scores are computed, the ATT effect can be calculated as follows;

$$ATT = E(\Delta_i \mid g_i = 1) \tag{8}$$

$$ATT = E[E\{Y_{1i} \mid g_i = 1, P(X)\}] - E[E\{Y_{0i} \mid g_i = 0, P(X)\}g = 1) \tag{9}$$

In addition, the study used Nearest Neighbour Matching (NNM), radius matching (R.), and Kernel-Based Matching (KBM) to match the scores to obtain the ATT as procedure to get valid results. The common support was imposed to estimate the matching estimates thus, treatment observations with weak common support were dropped, since inferences about causality can be made only in the area of common support (Houessou, Mugonola and Odongo, 2020). Also, the study applied the Rosenbaum bounds sensitivity test of the sensitivity of the estimated effects of extension services to hidden bias. The test can determine how strongly an unobservable variable must influence the selection process to undermine or reverse the findings based on matching on observables (Atsbeha and Gebre, 2021).

4.0. Results and Discussions

4.1. Results of Descriptive Analysis

Table 1 shows the results of the descriptive statistical analysis. It has been observed that SHSCFs who receive extension services and those who do not receive extension services differ significantly in some factors such as sugarcane output, and land size. Furthermore, the study indicates that, on average, SHSCFs who receive extension services apply more improved seeds and pesticides compared to those who did not receive extension services.

Similarly, the analysis shows that, on average, SHSCFs who receive extension services have a higher income and live closer to the factory than those who did not receive extension services. Lastly, SHSCFs who did not receive extension services were on average less likely to get access to credit than those who received extension service

Table 1: Descriptive Statistics

Variables	All	Extension Access	No extension Access	P-values
Sugarcane output [Ton per hectare]	129.453	143.843	122.529	0.020
Land size [hectare]	5.851	6.618	5.481	0.013
Labour cost [TZS]	2846259	3073315	2737027	0.363
Equipment cost [TZS]	496861.3	470112.4	509729.7	0.377
Improved seeds [kilogram]	24.460	27.842	22.832	0.015
Fertilizer [kilogram]	4964.891	4130.056	5366.514	0.376
Pesticide [litre]	12.070	13.483	11.389	0.017
Age of SHSCFs [years]	47.974	46.270	48.795	0.057
Family size [number]	5.697	6.157	5.476	0.101
Income of SHSCFs [TZS]	6544422	7681583	5997355	0.022
Distance to the factory [kilometer]	16.763	16	18.348	0.028
Membership experience [years]	11.942	12.079	11.876	0.426
Education level				0.016
Primary School [yes]	0.833	0.719	0.778	
Secondary School [yes]	0.235	0.202	0.173	
Certificate/Diploma [yes]	0.091	0.079	0.049	
Get credit access				0.032
Yes	0.317	0.416	0.249	
No	0.809	0.584	0.751	
Observations	274	89	185	

4.2. Estimated Results of Cobb-Douglas and Translog Stochastic Frontier Models

Table 2 shows the results of the Cobb-Douglas and Translog stochastic frontier models. The results of the Cobb-Douglas stochastic frontier models show that land size, labour cost, improved seeds, equipment cost as well as amount of pesticide are significant at 5% and 10%. The finding is consistent with Ambetsa *et al*. (2020), Lema, Masresha and Neway, (2022) who indicated that land size and improved seeds statistically influential factors in sugarcane output. Also, Birhanu, Tsehay and Bimerew, (2022), Midamba, (2022) and Ndubueze-ogaraku, Adeyoola, and Akuchinyere, (2021) found that labour cost, equipment cost and amount of pesticide are statistically influencing sugarcane output.

The monotonicity condition is confirmed for the Cobb-Douglas model, but not for the Translog stochastic frontier model. As Table 2 shows, the estimated coefficients are positive for the Cobb-Douglas model, whereas those for Translog stochastic frontier model are both positive and negative. The elasticity of scale is 2.272, suggesting that if a farmer increases all input quantities by 1%, technical efficiency will increase by 2.3%. Based on this result, it is reasonable to conclude that sugarcane farmers in the study area are operating under the increasing returns to scale (elasticity of scale > 1). The estimated gamma coefficients are 0.376 and 0.861 for the translog and Cobb-Douglas stochastic frontier models, respectively. This means the deviations from the production frontier models are explained by both inefficiency and statistical noise but the inefficiency term is more important than the statistical noise term. It also means that about 37% and 86% of the variation in technical efficiency is due to technical inefficiency. The mean technical efficiency for the Cobb-Douglas and the Translog stochastic frontier models are 0.60 and 0.55, respectively. This suggests that there is scope for increasing technical efficiency by 40% and by 45 % through efficient use of existing inputs and technology.

Table 2: Results of Maximum Likelihood Estimates of Cobb-Douglas and Translog Stochastic Frontier Models

	Translog			Cobb-Douglas		
lnTons	**Coef.**	**Std. Err.**	**P>|z|**	**Coef.**	**Std. Err.**	**P>|z|**
lnLand	-12.435	10.389	0.231	0.297	0.420	0.040
lnLabour	4.634	4.880	0.342	0.246	0.241	0.008
lnEquipment_Cost	7.526	4.354	0.084	0.044	0.043	0.013
lnFertilizer	-0.619	3.478	0.859	0.017	0.038	0.726
lnPestcide	25.846	15.208	0.089	0.033	0.187	0.016
lnSeeds	-23.788	15.474	0.124	0.154	0.220	0.043
lnLandLabour	0.108	0.533	0.838			
lnLandEquipment	1.355	0.669	0.043			
lnLandFertilizer	-0.103	0.436	0.812			
lnLandSeeds	-3.373	1.666	0.043			
lnLandPestcide	1.916	1.970	0.331			
lnLabourEquipment	-0.553	0.354	0.118			
lnLabourFertilizer	0.112	0.269	0.676			
lnLabourPestcide	-2.189	1.183	0.064			
lnLabourSeeds	2.149	1.278	0.093			
lnEquipmentFertilizer	-0.068	0.054	0.207			
lnEquipmentPestcide	-0.031	0.365	0.932			
lnEquipmentSeeds	-0.378	0.317	0.233			
lnFertilizerPestcide	-0.068	0.208	0.744			
lnFertilizerSeeds	0.068	0.245	0.780			
lnPestcideSeeds	1.280	0.924	0.166			
_cons	-59.032	59.510	0.321	0.174	3.033	0.954
Sigma-squared	0.431					
Lambda	0.749			1.935		
Gamma	0.376			0.861		
Mean Efficiency	0.55			0.60		
Elasticity of Scale				2.272		
Number of Obs. = 274			Wald chi2(6) = 425.04			
Log likelihood = -249.98779			Prob > chi2 = 0.0000			

Table 3 shows the results of the likelihood test of the appropriate functional form, with a p-value of 0.107. This suggests that the Cobb-Douglas production function is more appropriate than the Translog production function.

Table 3: Test suitability of functional form

Hypotheses	Test Statistics	P-value	Decision Rule
Functional form test	52.56	0.107	Accept H0: Cobb-Douglas is appropriate
Inefficiency effects are stochastic	29.45	0.001	Reject H0: Presence of inefficiency
Effects of farm and institutional characteristics	17.75	0.000	Reject H0: farm and institutional characteristics exert significant effect

In addition, Table 4 presents the summary statistics of technical efficiency of SHSCFs in Kilombero valley.

Table 4: Summary statistics of the technical efficiency

Technical Efficiency Level	Frequency	Percent
0.00-0.20	7	2.55
0.21-0.40	28	10.22
0.41-0.60	71	25.91
0.61-0.80	155	56.57
0.81-0.99	13	4.74
Total	274	100.00
Mean	0.6029374	
Std. Dev.	0.161439	
Minimum	0.0771554	
Maximum	0.9206747	

Table 5 shows the results of the analysis of the determinants of technical inefficiency. Results show that, the coefficient of extension services is negative (-0.321) and statistically significant from zero (p=0.008), suggesting that access to extension services reduces the technical inefficiency of SHSCF by -0.321. This finding is consistent with Carrer *et al.* (2022). Further analysis of the effect of extension services on technical efficiency is shown in Table 6. Results further reveal that, education level, income of SHSCFs and distance from the farm to the factory have a statistical significance different from zero in affecting technical inefficiency among SHSCFs.

Table 5: Determinants of technical inefficiency

Variables	Coefficient	Std. Err.	Z	P>|z|
Education Level	-0.001	0.225	-3.80	0.000***
Age	0.612	0.489	1.25	0.210
Income	-0.238	0.147	-2.21	0.027*
Distance	0.981	0.258	3.80	0.000***
Extension services	-0.321	0.264	-3.34	0.008*
Membership	0.426	0.198	0.43	0.541
Family Size	0.581	0.311	0.36	0.551
Credit Access	-0.636	0.311	-1.25	0.193
_cons	-1.812	2.821	-0.64	0.521

Notes: * implies at 10%, ** implies 5% and *** implies 1%

4.3. Effects of Extension Services on Technical Efficiency

Results in Table 6 show that, education level is positive and significant at 5%; implying that the probability of SHSCF accessing extension services is higher by 0.099 (9.9%) among smallholder sugarcane farmers who spent more years in school. This result happened because of the skills, knowledge and awareness that farmers benefit from as they advance their studies. Moreover, education improves reasoning ability, which in turn increases farmers' eagerness to access agricultural extension services. This result is in line with Nagar, Nauriyal, and Singh, (2021) and Ragasa and Mazunda (2019) who observed that, size of land matters for access to extension services.

The results of analysis indicate that the variable age is negative and significant at the 1% level. This implies that the probability of SHSCFs of accessing extension services is lower by 0.333 (33.3%) among older people. The negative association between access to extension services and farmers' age can be attributed to the fact that farmers tend to be less active and productive as their age increases. Alternatively, younger farmers are active, implying that they can more easily access extension services than older farmers. The finding contrasts with that of Gatheru *et al*. (2021) who found that age, a proxy for experience, had a positive and significant influence on farmers' access to extension services.

The variable distance is negative and significant at the 1% level, suggesting that the distance from the farm to the factory has a lower probability (by 0.105 or 10.5%) of accessing extension services. This was attributed to the fact that farms that were near the factory could access the services more easily and timely than farms that were located far away. This happened because factories were located in urban areas where extension officers residing. This finding is consistent with Emmanuel *et al*. (2021) and Maulu *et al*. (2021) who revealed that the higher the distance from the farm to the factory, the lower the probability of SHSCFs accessing extension services.

Table 6: Probit Model of the Determinants of access to Extension Services

Variables	Coefficient	Std. Err.	Z	Marginal Effects	P>|z|
Land	0.023	0.155	0.15	0.326	0.881
Education Level	0.097	0.297	3.97	0.099	0.003**
Age	-0.633	0.357	-4.02	-0.333	0.000***
Income	-0.045	0.102	-0.44	-0.155	0.659
Distance	-0.194	0.152	-3.97	-0.105	0.003**
Family Size	0.258	0.449	0.38	0.239	0.561
Membership	0.041	0.612	0.82	0.053	0.341
Credit access	0.243	0.381	0.56	0.032	0.745
_cons	0.004	0.180	1.11	0.077	0.265
LR chi2 (12) = 23.5	Log likelihood = -160.985	Outcomes correctly predicted = 75.63			
Prob > chi2 = 0.0007	Pseudo R2 = 0.681				

Notes: * implies at 10%, ** implies 5% and *** implies 1%

4.4. Average Treatment Effect of extension services on technical efficiency

Table 7 shows the results of the analysis of the Average Treatment Effects of the Treated (ATT). The results show that access to extension services has a statistically significant effect on technical efficiency ($p<0.05$). This implies that, there is a difference in technical efficiency (0.216) between SHSCFs who receive extension services and who do not. This result supports Atukunda, Atekyereza and Walakira, (2022), Carrer, *et al*. (2022), Maulu *et al*. (2021), Midamba, (2022) and Ragasa and Mazunda (2019) which indicate that extension services affect TE among smallholder farmers. Generally, extension services are a conduit for knowledge and technology transfer, that assist farmers in solving agricultural production problems. Extension services hence, bridge the gap between agriculture educational discoveries developed by extension providers and the degree of dissemination of newly developed technology to SHSCFs.

Table 7: Average treatment effects: propensity score matching

Outcome Variable	Matching Algorithm	Receive Extension Services	Not Receive Extension Services	ATT	t-statistics
Tons	RMM	89	185	0.216	2.083

5.0. Conclusions and Implications

The current study analyzed technical efficiency by comparing the performance of the Cobb-Douglas and Translog stochastic frontier models as well as the effect of extension service access on technical efficiency (TE) using propensity score matching. The estimated TE score was 60%, suggesting that SHSCFs can improve efficiency in the use of the available inputs (land size, labour cost, equipment cost, amount of pesticides and seeds) by 40%. When comparing the Cobb-Douglas stochastic production frontier models, the study found the Cobb-

Douglas production frontier model to fit better in the empirical data set. Similarly, access to those extension services was found to be statistically significant, suggesting that the existing inefficiency in input use among SHSCFs in Kilombero valley can be minimized inter alia through access to extension services.

Based on the above, policy efforts for enhancing access and use of extension services should be promoted to improve the technical efficiency among SHSCFs. This is especially critical now that the Tanzanian government through the Ministry of Agriculture has increased spending in among other things the provision of agricultural input subsidies. It implies that public spending on input subsidies coupled with provision of extension services expects to generate higher returns. As such, given the shortage of agricultural extension officers in the country, recruitment of extension officers should be a priority for the government and other sugarcane stakeholders. However, these findings should be cautiously interpreted in light of the limitations of the cross-sectional design, based on which we cannot claim with certitude that the observed relationship is causal. In this vein, a longitudinal study may offer a better option for causal-effect analysis.

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