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DETERMINANTS OF SUGARCANE PRODUCTION EFFICIENCY IN NAROK COUNTY, KENYA.

[1]Josiah M. Orina, **[2] Dr. Ibrahim Macharia (PhD)**, **[3]Dr. Nigat A. Bekele (PhD)**
[1]Student [2]Lecturer (Dr) [3]Lecturer (Dr)
[1]Department of Agricultural Economics
[1]Kenyatta University, Nairobi, Kenya

ABSTRACT

Sugarcane farming remains a key sub-sector in Kenya for achieving food and nutrition security as well as improving incomes both at household and national level. However, Kenya experiences a domestic production deficit of 64% of annual sugar consumption of 1.03 million metric tonnes. This trend continues despite Kenyan Government concerted effort to increase yields by expanding the area under sugarcane cultivation. Trans Mara Sub-County of Narok County was identified as one of the target areas for massive sugarcane planting to improve output, but the reality is that the total annual output is dwindling, as one cannot be fixated on expanding cultivable land while overlooking transformation of sugarcane productivity. The study aimed to assess technical (TE), allocative (AE), and economic (EE) efficiency in sugarcane production, and identify the socioeconomic factors that influencing these efficiencies in Trans Mara West, Narok County, Kenya. The study's hypothesis was that sugarcane farmers have homogeneous socioeconomic characteristics and are technically, allocatively, and economically efficient in input utilization; and that farmers' socioeconomic characteristics do not influence their level of production efficiency The study employed a multi-stage sampling technique that targeted 200 farmers randomly sampled out of 10,661; and the cross-sectional data was collected using a structured questionnaire. Using STATA, the Stochastic Frontier Production model and the Tobit regression were estimated to determine efficiency levels as well as analyze the effects of determinants on efficiency levels respectively. The estimated results revealed an average level of 90% (TE), 85% (AE), and 77% (EE). This showed that using current agricultural resources can improve the mean yield efficiency by 10%, 15%, and 23%, respectively. This further imply that farmers in the region are operating at greater levels of efficiency and that there is room for a further increase in output without raising the current level and costs of inputs. Overall, the TE, AE and EE levels observed in Trans Mara West were very higher than most sugarcane growing regions in Kenya, however, they were comparable to those found in African countries that are efficient in the sugarcane cultivation. The estimates of Cobb Douglass stochastic production frontier maximum likelihood indicated that fertilizer, seed-cane cuttings, herbicides, land size, and labour significantly determined the output of sugarcane yields. The results of stochastic cost frontier demonstrated that the cost of land, seed, fertilizer, and labor sufficiently impacted on the total cost of production. The study concluded that landownership, access to extension services, credit, and the Tropical livestock unit are significant predictors of technological efficiency. Experience, access to credit, and tropical livestock unit, on the other hand, are significant drivers of allocative efficiency. In terms of economic efficiency, the most important drivers were land ownership, access to credit, and tropical livestock unit. The study recommends policy changes that will increase farmers' contact and access to extension services by improving recruitment and incentives for extension workers to help sugarcane farmers reduce not just technical, but also allocative and economic inefficiencies. Establish a farmer-training program that promotes experience sharing, addresses optimal input usage, and enhances effective utilization including adoption of streamlined cane agronomic technologies to boost productivity. Additionally, promote accessibility of

affordable credit to assist farmers in purchasing inputs throughout the planting season. Most significantly, introduce policy initiatives that redress inequities in land ownership should be promoted.

1. INTRODUCTION

1.1. Background Information

Most Kenyans rely on crop and livestock farming to generate household income and food provision. Agriculture substantively dictates the country's economic inclination which is characterized by how residents are food secure and economically empowered (Government of the Republic of Kenya, 2018a). In Kenya, the agricultural sector remains a major driver of the national economy. It accounts for 24% directly and 27 % indirectly to the Gross Domestic Product (GDP). It is believed that growth in the agricultural sector has a positive marginal effect of 1.6 on the national GDP (Government of the Republic of Kenya, 2018a). It generates 45% of the national revenue, accounts for 60% of national employment, forms the main livelihood for 80% of the rural population (Government of Kenya, 2009). Sugar consumption in Kenya has grown steadily over the last three decades, outpacing the domestic production levels. In 2017, only 376,111 tonnes were produced domestically against the consumption of 11.03 million tonnes in the same period, resulting in a deficit of 64% (Government of the Republic of Kenya, 2018b). The persistent sugar deficit calls for concerted investment in the sugarcane sector. In Kenya, despite the continuous investment in sugar production and milling, the country is yet to attain self-sufficiency status in sugar production as several sugar mills still operate below capacity. For this reason, the country has been filling the deficit by importing sugar, predominantly Common Market for Eastern and Southern Africa (COMESA) affiliated nations.

As an effort to narrow the gap between domestic production and consumption levels, all levels of Kenyan Governments are continuously investing in initiatives that are geared towards boosting sugarcane production in terms of area coverage and productivity. One of the target counties for expansion of sugarcane production is Narok County, which exhibits a favorable agro-ecological requirement for sugarcane production To this end, the government and other stakeholders have been promoting sugarcane in Trans Mara West, Sub-county of Narok County to become a major cash crop (The Wood Foundation, 2020). However, despite the enhanced total production of the crop in the county, not all sugarcane farmers have attained the best possible output despite farming in the same agroecological zones (Onyango et al., 2018). There are currently limited studies on sugarcane production efficiency levels in the county, as well as the underlying farmer-specific socioeconomic factors that influence efficiency. Lack of this vital information created a knowledge gap, which this study sought to fill. The objective of this study was therefore to determine technical, allocative and economic efficiency and the effect of selected socioeconomic factors on these efficiencies amongst sugarcane farmers in Trans Mara Sub County.

1.2. The significance of the study

The global sugar market is growing progressively viable, which means that only those that operate at highest efficiency can remain competitive. As a result, Kenyan sugar is facing intense rivalry especially from the global market coupled with huge expenditure in imports of the commodity. Therefore, it is imperative to explore strategies to improve the technological, allocative and economic efficiency of the sugarcane farms in order to achieve optimum outputs from the limited resources. Sugarcane sector's enhanced production efficiency is critical given the value it adds to the economy, accounting for roughly 7% of agriculture's GDP. This additionally contributes to reducing poverty by promoting livelihoods and employment. Moreover, based on the fact that the sugarcane demand exceeds domestic production, it calls for a need to assess the factors that hinder its production efficiency and productivity so that the findings can be used as a basis of developing appropriate policies to boost production and reverse the withdrawal from sugarcane farming in the traditionally sugarcane-growing regions (William, 2013). The findings from the study would assist policy makers and development partners to identify the specific key areas of investment to boost sugarcane production in the country. Knowledge generated will be passed on to the major stakeholders, the sugarcane farmers, as a guide to help them enhance production efficiency for optimum yield. It will also provide baseline information for use in related future studies on sugarcane farmers in Narok County and the country at large. Overall, the research's results will help policymakers design appropriate and evidence-based policies that can transform sugarcane production; and additionally contribute to the wealth of existing studies.

1.3. Scope and delimitation of the study

The study is limited to smallholder sugarcane growers in Narok's Trans Mara sub-county, who are the majority and have not attempted to capture farmers who are operating on the bigger scale. The study measured technical, allocative, and efficiency at the farm level rather than across the sugar sub-sector's value chain. In terms of limitations, the study used a structured questionnaire, and the researcher anticipated that the projected number of respondents would be difficult to get due to low cooperation, inaccessibility, and data that is incomplete. To address the limitations, the researcher first assessed whether clients could respond to the questions without assistance by pretesting the questionnaire. Whenever it was determined that the respondents could reply with difficulty, the researcher walked them through the questionnaire so that she or he could fill in the information as required by the questions. The study was further complicated by a deficit of dependable information as it counted exclusively on the sincerity of sugarcane farmers since the vast majority of the sugar cane growers scarcely maintain farming records. However, this situation was offset by use of multiple sources of data in order to validate the findings.

1.4. Theoretical and Conceptual framework.

1.4.1. Theoretical framework

This study was based on the neoclassical production theory of the firm that describes the relationship between output level and the factors of production used in the production process (Debertin, 2002, Belotti et al., 2013). A firm is a unit that is mandated to make production decisions. Production entails the conversion of inputs into products (outputs) to create utility. A production function is employed to illustrate the technical interactions among set combination of inputs and outputs. The set combinations are depicted quantitatively. The largest quantity of output that could be generated using a specific bundle of inputs is hence the production function, which additionally symbolizes a company's technology. Technical efficiency is attained when highest potential yield is generated given the set of inputs utilized, contingent on available technology (Nchare, 2007). Whereas Economic efficiency is achieved whenever a sugarcane farmer generates a particular yield at the least cost (Wassie, 2014). In respect to this study, farmer’s sugarcane production function was modeled as;

$$\boldsymbol{Q = f(L_1, L2, L_3 \ldots L_n)} \quad (1)$$

Where the dependent variable Q is the total sugarcane yield while $L_1 \ldots . L_n$ are independent variables of physical input quantities such as farm size, the quantity of labor, and the amount of capital used to produce Q. reduction of the number of inputs to only labor and capital yields to:

$$\boldsymbol{Q = F}(\mathrm{K}, \mathrm{L}) \quad (2)$$

Q can increase in response to the increases of L and K, holding other factors constant. The sugarcane farmer's production shall always rise or decline contingent on the time frame, ranging from short to long-run. Equation (2) demonstrates the maximum yield a farmer can attain with a specific mix of labor and capital. Production inefficiency may limit yield beyond what is technically feasible (Lobo et al, 2013).

1.4.2. Conceptual Framework

In respect to this study, the level of sugarcane production and level of technical and economic efficiency are influenced by several variables that are categorized into socio-economic, institutional and technical factors of production. The usage of farm inputs determines the output level while the socio-economic and institutional factors determine the combination of factors of production, which maximize agricultural production/ output. The farmer is the decision-maker in the production process, the specific farmer and farm characteristics influence what, when, how much and for whom to produce. Therefore, the household decision-making process influences the process of producing sugarcane while considering various institutional and technical factors such as the size of the farm size and labour used.

The socio-economic and institutional factors influence the household decision-making process and consequently will influence the farmer’s sugarcane output and technical efficiency levels. Farmers' tactics for managing are influenced either partly by socioeconomic and institutional issues or entirely by the technology adopted. A case in point, a seasoned producer, is presumed to be more efficient over an inadequately experienced producer. In the event that cost of inputs escalate significantly, the sugarcane producer is bound to use lesser inputs, leading to decreased yield. Technical efficiency is closely related to farm managerial technique. The realization of technical efficiency leads to enhanced farmer's income including welfare, and eventually to sustainable likelihoods.

2. MATERIALS AND METHODS

2.1. Description of study area

The study was conducted in Trans Mara West sub-county of Narok County, Kenya which is the main sugarcane producing sub-county in Narok County. Trans Mara West is located in Kenya's South-Western part of the Rift Valley and its latitudinal boundaries lie between 0° 50' and 1° 50' South and longitudinal boundaries being 34° 35' and 35° 14'. The sub-county is majorly inhabited by the Maasai community who are culturally pastoralists, but due to in-migration and urbanization other tribes such as Kisiis, Kipsigis and Kikuyu have settled within the sub-county. The major economic activities in the area are livestock rearing, crop farming, and trade. the major crops cultivated in the area being maize, beans, and sugarcane. The county has approximately 12,500 Ha under sugarcane farming, undertaken by 10,661 farmers according to County Government of Narok (2018).

2.2. Research design

The study included a mix of descriptive and correlational research designs. Descriptive research design seeks to methodically collect and collate quantitative and qualitative data in order to describe a phenomena, situation, or population under inquiry. The descriptive research design was employed to analyze production factors and socio-economic factors influencing technical, allocative and economic efficiency. A correlational design investigates the association between two or more variables while not interfering with the process. The analyst may identify intrinsic correlations between variables applying a correlational approach. As a result, data becomes a better reflection of events in reality. Correlation design was applied when estimating the empirical associations of the variables earmarked for Stochastic Frontier Production. Stochastic Cost Frontier and Tobit regression.

2.3. Sampling design

A multistage sampling technique was used in sample selection where the first stage involved purposive selection of the sub-county (Transmara West) which is the sole producer of sugarcane out of the six sub-counties that make up the county. The second stage was purposeful selection of three wards of the sub-county, which produce sugarcane. The third stage involved systematic random sampling of farmers (respondents) from each of the three wards to cumulatively get 200 farmers/ respondents who were subsequently interviewed for this study.

2.4. Determination of the Sample size

The number of respondents (sample size) for the study was determined through the following equation (Israel, 1992) as cited by (Adam, 2021)

$$n = \frac{N}{1+N(e^2)} \qquad (3)$$

Thus in the study $n = \frac{10,661}{1+10,661\,(0.07^2)} = 200$

Whereby; n represent the targeted sample size (No. of respondents), N - Stands for the population of sugarcane farmers in the targeted Wards (10,661), and e - Level of precision expressed as a decimal (0.07)

2.5. Method of data collection

The study used primary and secondary data. The primary data was collected from the sugarcane farmers by using structured questionnaires while the secondary data was collected from sugar millers' records, farmers' records, reports from Kenya Sugar Board, Journals, research publications, theses, internet, newspapers, and government publication.

2.6. Data analysis Methods

The data collected was analyzed using descriptive statistics and inferential statistics. Multiple regression models were used to determine the research objectives and to analyze the relationships between the dependent and independent variables. Stochastic Frontier Approach was used to estimate the sugarcane production efficiencies while Tobit regression was used to determine the demographic and social-economic variables impacting technical, allocative and economic inefficiencies.

2.7. Analytical framework

2.7.1: Technical, allocative and economic efficiency computations

Models commonly used for estimating production efficiency are generally grouped into parametric models (models that take a specified function form to explain the relationship between the dependent variable and the independent variables) and non-parametric models (models that do not take any specified function form to explain the relationship between the variables. In the context of the reviewed literature, the Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA) are the most widely and commonly used approaches in estimating the level of production efficiencies. The DEA is a non-parametric linear programming approach with no functional form and does not consider the random error component of the model. Contrary to DEA, the SFA is a parametric methodology used in the estimation of a stochastic production frontier, and eventual computation of technical, allocative, and economic efficiency scores. Under the SFA, the production output is modeled to relate to a given combination of factors of production (inputs), inefficiency component and the random error. Since the SFA approach measures/ estimates both the random error and inefficiency it becomes more relevant in the agricultural sector compared to DEA. Therefore the SFM approach looks realistic and superior to the DEA since farmers always operate under uncertainty in real-life situations (Ali & Jan 2017). Notably, in the stochastic frontier analysis, the effects of both the errors due to measurement and other noise in the data are taken care of in the model. Generally, Data Envelopment Analysis (DEA) is anchored on mathematical programming estimation whereas the Stochastic Frontier Analysis is based on econometric estimation.

Usage of SFM is advantageous over the OLS in the sense that the latter gives estimates based on the average firm, while on the other hand the estimates of the SFM are largely influenced by the best/ highest producing farms/ firms and therefore reflecting the technology being used. According to Battese, (1991) and Perez et al., 2017, a frontier function represent a best practice technology against which the efficiency of firms within an industry can be evaluated. The key aim of carrying out technical efficiency analysis is to understand those factors of production that cause an upward shift in the production function. The SFM can be fitted to either a production or cost function in a variety of functional forms, most notably Cobb-Douglas (C-D) or translog, which have been estimated in most empirical SFM and efficiency estimates works. Okello et al., 2019; Wai & Hong, 2020). In this study, the Cobb-Douglas production function is specified to estimate sugarcane production efficiency due to its simplicity and wide application in similar studies.

The C-D production is expressed as follows:

The Cobb-Douglas model based on SFM model was log-transformed for easy interpretation of the parameters. It is therefore presented as below,

$$lnY_i = \beta_0 + \beta_1 lnLAND + \beta_2 lnLAB + \beta_3 lnCAP + \beta_4 lnSEED + \beta_5 lnFERT + \beta_6 lnHERB + V_i - U_i \qquad (3)$$

Where ln denotes natural logarithm, Y_i denotes dependent variable (Quantity of sugarcane produced in Tonnes), β_0, represents intercept, LAND (size of land under sugarcane measured in Acres), LAB (The amount of labour measured in man-days), CAP(If one owns draught animal used in farming activities), SEED (Amount of Seeds used in Tonnes), FERT (amount of both Basal and Top dressing fertilizer applied measured in Kgs), and HERB (amount of herbicides applied in Liters), $(V_i - U_i)$ is equivalent to a composite error term ε_i where V_i denotes statistical noise component or disturbance term dealing with unobserved factors while U_i denotes non-negative random variable taking care of inefficiency and its distribution is half normal $u|N(0, \sigma_u^2|$.

The associated cost function was also expressed as:

$$lnC_i = \alpha_0 + \alpha_1 lnPLand + \alpha_2 lnPLAB + \alpha_3 lnPCAP + \alpha_4 lnPSEED + \alpha_5 lnPFERT + \alpha_6 lnPHERB + \alpha_1 lnY + V_i + U_i \qquad (4)$$

Where C equals the total cost of sugarcane production, Y denotes the output of sugarcane (in tonnes); $\alpha_0 - \alpha_6$ are parameters to be estimated; P are the unit prices of the factors of production.

Derivation of the technical, cost and allocation efficient scores are derived by reparameterization of the stochastic Cost frontier function. So given the vector of input prices for the i^{th} farm is (P_{ij}), parameter estimates of the stochastic frontier production function in $\hat{\beta}$ and the input oriented adjusted output level in Y_i^* in equation (4), the following Cobb-Douglas dual cost frontier is generated and present as follows:

$$lnC_i = b_0 + \sum_{i=1}^{m} b_j lnP_{ji} + \phi lnY_i^* \quad (5)$$

By introducing Shephard's Lemma, the cost minimizing rather (economically efficient) input vector, X_i^C, is derived by substituting the firm's input prices and adjusted output quantity into the system of demand equations which is presented as below:

$$\frac{\partial C_i}{\partial P_i} = b_j P_j^{-1} C_i = X_i^C \quad (6)$$

For a given level of output, the corresponding technical efficient, cost efficient and actual costs of production are equal to, PX_i^T, $P_iX_i^C$, and P_iX_i, respectively. These three cost measures are then used as the basis for calculating the technical and cost efficiency scores for the th farm as follows:

$$TE_i = \frac{P_iX_i^T}{P_iX_i} \quad (7)$$

$$CE_i = \frac{P_iX_i^C}{P_iX_i} \quad (8)$$

The allocative efficiency can be calculated based on Farrell's methodology which states that the cost efficiency (CE) is divided by the technical efficiency (TE) to get allocative efficiency:

$$AE_i = \frac{P_iX_i^C}{P_iX_i^T} \quad (9)$$

However, Stata program estimates the cost efficiency (CE), which, conversely, corresponds to the allocative efficiency index $\left[CE = \frac{C}{C^*}\right]$, and the AE index of the individual farmer is shown in the following relationship: $\left[AE = \frac{1}{CE}\right]$. Technical efficiency scores, allocative and cost efficiency scores were generated using a program that was written and implemented in STATA version 15.0. However, this study employed a two-stage estimation approach of efficiencies, which entails estimating SFM to generate efficiency indices first, and then regressing the efficiency indices on demographic and social economic variables employing a two-limit Tobit regression. This technique was selected due to its capacity for the assessment of allocative, economic as well as technical efficiencies of sugar cane yields (Beshir et al., 2012; Wana & Sori, 2018).

2.7.2: Determinants of technical, allocative and economic efficiencies

The two-limit Tobit regression, rather than OLS, was used to examine the sources of inefficiencies. This is due to the fact that the efficiency scores employed as dependent variables are typically truncated and censored, and thus OLS regression cannot yield consistent estimates., in view of this the maximum likelihood-based Tobit approach is a preferable option for estimating regression with a censored response variable, (Maddala, 1999). Thus, the model by J. Tobin (1958) was used to show the relationship between efficiency level (explained variable) and socio-economic factors (independent variables). Tobit depicts a relationship between a non-negative dependent variable y_t and a set of explanatory variables x_t in the form;

$$y_t^* = x_t^* \beta + \mu_t \quad (10)$$

Applying a censored observed response variable as Y_i, the Tobit model is expressed

$$Y_i = \begin{cases} 1 & if \quad Y_i^* \geq 1 \\ Y_i^* & if \quad 0 < Y_i^* < 1 \\ 0 & if \quad Y_i^* \leq 0 \end{cases}$$

where Yi^* is a latent variable denoting efficiency index of the ith farmer, X_{ij} s are vectors of social economic regressors influencing (TE, AE, EE) for farmer i, β_{ij}s denotes parameters to be estimated, and $\mu_i$is an error term, which is $u|N(0, \sigma_u^2|$.

Using Tobit equation (10) above, the explained (TE, AE, EE indices) and the explanatory variables (socio-economic factors) were taken to be mathematically related as in equation (11);

$$U_i = \delta_0 + \delta_1 N_1 + \delta_2 N_2 + \delta_3 N_3 + \delta_4 N_4 + \cdots \ldots \ldots + \delta_n N_n + \varepsilon_i \quad (11)$$

Where U_i is level of technical efficiency, Allocative efficiency, and Economic efficiency; δ represents the parameters to be estimated in the model; N is the Socio-economic variables e.g., years of experience, education level, gender, credit access, etc., ε_i is the two-sided error term. The parameters were estimated using the Maximum Likelihood Estimate techniques.

3. RESULTS AND DISCUSSIONS

3.1. Introduction

This chapter presents the research findings on analysis of the determinants of sugarcane production efficiency in Narok County, Kenya. The data set generated from survey was analysed guided by the research methodology and was used to develop a descriptive analysis involving production, cost and socioeconomic variables under study. The descriptive analysis provided relative frequencies, which have been summarised and presented in form tables and narratives. To determine levels of efficiencies Cobb Douglas Stochastic Production and Cost frontier were independently estimated, and the efficient scores were generated accordingly. The sources of inefficiencies were determined by Tobit regression model. The results of descriptive analysis and Stochastic frontiers are presented accordingly. Furthermore, the results are discussed in terms of their relation to the research objectives and questions. The data was analyzed using Stata version 15.

3.2. Sample and Response Rate

The survey retained 200 completed useable questionnaires generating a 100% response rate. This implies that study had a appropriate size for most behavioural research and multivariate regression analysis, (Sekaran, 2003). Therefore, the sample size was deemed acceptable for the purpose of this study.

Table 1: Response rate of farmers across three-sampled (sugarcane growing) wards.

No	Name of Ward	No. of sugarcane farmers	Number of Respondents	Response Rate (%)
1	Keiyan	5,801	109	54.5
2	Kilgoris Central	3,518	66	33
3	Shankoe	1,322	25	12.5
	Total	**10,661**	**200**	**100%**

Source: Survey data, (2022)

3.3. Descriptive statistics results for the sampled sugarcane farmers in Trans Mara West

3.3.1. Descriptive outputs of the demographic and socioeconomic characteristics of the sampled sugarcane farming households on Trans Mara west

Table 2 depicts descriptive outputs of the demographic and socioeconomic characteristics of the sampled sugarcane farming households on Trans Mara west. According to the survey, household sizes in the research area ranged from one to 22, with a mean of nearly 7, which is relatively large in comparison to the country's average household size of 3.9 (KNBS, 2019) indicating the potential for excess labor supply in sugarcane cultivation. According to (Effiong et al., 2018), a significantly larger household size improves the availability of labor; however, larger household sizes do not ensure improved productivity though since family labor, which consists primarily of pupils, is always in school. The finding revealed that smallholder farmers had an average of 14 years of farming experience ranging from 2 to 50 years, this meant that many sugarcane growers had substantial agricultural experience, meaning that they could supply accurate facts as well as an excellent grasp of sugar cane cultivation. Approximately 65% (130 farmers) had more than 5 years' experience of farming. The tropical livestock unit (TLU), which is a measure of the number of animals owned by a household, averaged 28.23 units, which is significantly larger than many smallholder sugarcane growers in

Kenya because they are predominantly agro pastoralists. The survey analysis indicated that 94% of farmers (187) experienced frequent visits from extension workers, with an average of nearly 10 visits per growing season. This means that modern sugarcane-growing technology is being evenly diffused to many farmers as required.

The survey results showed that the male-headed households comprised of 83.5% of the sugar cane farmers, while female-headed household made up 16.5%, suggesting that sugarcane cultivation, while crucial for both genders, is predominantly done by male. This, however, indicates that not only do men make up a larger share of sugarcane planters, but that sugarcane production decisions are often made by men who are household heads. Due to limited access to agricultural resources, this may imply that women are primarily engaged in sugarcane producing operations, often as part timers and never as landowners (Fonjong & Athanasia, 2007). The average years of education was found to be 10.45, implying most farmers had attained secondary education. Further analysis illustrated that only 7% did not attain formal education; and approximately 68 percent had done either secondary or tertiary education, and the percentage of farmers with secondary education was higher than the national average of 24.5 percent (KNBS, 2019). This means that the research area appears to be rich in literate farmers, who are thought to be more open to new farming practices and capable of increasing productivity through rapid adoption of farming innovations, (Okunlola et al., 2011). The mean age was 41 with a range of 24-76, suggesting that sugarcane cultivation is actively practiced by both younger and older generations, with 88% constituting the most productive age segment (24-55) years. Farmers (13%) over the age of 55 are more likely to be sluggish in meeting the demands of menial sugarcane labor.

Table 2: Descriptive statistics of the Demographic and Socio-Economic characteristics of the sampled households

Variables	Mean	Std.Dev	Min	Max
Household size (HHS)	7.37	3.89	1	22
Farming experience	14.35	10.09	2	50
TLU	28.23	22.90	0	132.50
Extension visits	9.71	7.00	0	37
Age in Years	41.15	11.18	24	76
Years Education	10.45	4.16	0	17

Variables	Categories	Dummy	Frequency	Percent	χ^2-Test
Gender	Female	0	33	16.5	
	Male	1	167	83.5	0.000
Land Ownership	Leased	0	41	20.5	
	Own	1	129	64.5	
	Own & leased	2	30	15.0	0.000
Access to Credit	No access	0	77	38.5	
	Access	1	123	61.5	0.001
Group Membership	Non-member	0	107	53.5	
	Member	1	93	46.5	0.396
Off-farm income	No	0	4	2	
	Yes	1	196	98	0.000

Source: Results from sample survey data (2022).

The study also established that (65%) of the sugarcane farmers owned land, while 32% leased the land. Owned land can be used as collateral for accessing credit easily. While 62% of the farmers managed to access credit for sugarcane production, 38% could not access any credit to support production processes. This suggests that the large bulk of farmers could buy inputs, implying that shortage of financial resources is not a constraint for such greater part of sugarcane farmers. The study also revealed that 98% of sugarcane farmers also participated in non-farming activities to supplement their income: this significant number of sugarcane farmers participating in non-farming activities demonstrates that farmers must work until the end of the growing season to earn income. Farmers typically participate in a wide range of activities in order to diversify one‘s income and food sources, as well as to reduce risks. Furthermore, as a risk-mitigation strategy, farmers can sometimes participate in a mixture of agricultural enterprises (Debertin, 2012). The study results reported that 107 farmers, approximately 54%, did not belong to any group membership, even though Group membership has been actively promoted as an agricultural development policy initiative to assist smallholder farmers in dealing with various production constraints and marketing limitations. Farmer groups are crucial in disseminating agricultural knowledge to farmers and facilitating access to extension services and credit.

The nonparametric Chi-Square test was applied to all categorical variables based on a 2 by 1 contingency table analysis, which is an equivalent test against the Null hypothesis that there is no variation in percentages within each group. Except for group membership, the categorical variables of gender, land ownership, access to credit, and off-farm income all had p-values ($0.01<0.05$), indicating that there was a 1% chance that we could have made this observation based on random error if the null hypothesis was true at 5% alpha; thus, the null hypothesis was rejected.

3.3.2. Descriptive statistics for the Stochastic Production Model variables

Table 3 shows the statistical results for the variables utilized in estimating the Cobb-Douglas stochastic frontier and technical efficiency scores. Under this research work, both stochastic production frontier and technical efficiency were evaluated by employing five varieties of inputs: fertilizer (FERT), labor (LAB), land (LAND), herbicides (HERB), and seed (SEED) i.e. Sugarcane cuttings. According to the statistics in Table 3, sugarcane farmers produced approximately 61 tonnes per acre on average, a spectacular 151% increase above the national average yield of roughly 24.28 tonnes per acre (Sugar Directorate, 2018). This signifies that farmers in the study area are producing above national performance. The average Basal fertilizer (BFERT), Top dressing fertilizer (TFERT), herbicides, labor, and seed-cane values per acre are provided as follows: 74.86 kg, 72.38 kg, 1.00 liters, 54.54 man-days, and 5.21 tonnes, respectively.

Table 1: Summary statistics for the Stochastic Production Model variables

Variable	Mean	Std. dev	Minimum	Maximum	Mean/acre
Sugarcane yield (tonnes)	246.37	157.21	45	760	60.97
Land (acres)	4.04	3.23	1	30	
Seed (tonnes)	21.07	15.07	4	136	5.21
Basal fertilizer (Kgs)	302.53	181.63	50	1000	74.86
Top fertilizer (Kgs)	292.50	171.42	50	1000	72.38
Basal+Top fertilizer (Kgs)	595.03	348.84	100	2000	147.25
Herbicides (liters)	4.04	2.97	1	25	1.00
Labour (man-days)	220.4	206.93	21	1487	54.54

Source: Survey data (2022)

The average land size dedicated to sugarcane cultivation was 4.04 acres; the findings are in tandem with the (World Bank, 2021) estimations that smallholder farmers on average operate on farm size of between 0.2 and 3 hectares or (0.494 and 7.41 acres). This indicates that sugarcane in Transmara West is typically grown on smaller farms. The study failed to generate significant responses on whether the farmers applied manure or Pesticides; hence, the two variables were dropped in the analysis.

3.3.3. Descriptive statistics of the variables of Stochastic Cost Frontier Model

The descriptive statistics for all the variables in the sugarcane stochastic cost frontier model are summarised in Table 4. On average, the total cost of sugarcane production ranged from KES 66,665 to KES 1, 313,007 with an average cost of KES 68,712.77 per acre. Since there is such a wide range in total costs, it is evident that there is also a wide range scale of sugarcane farming.

Table 2: Summary statistics of variables in the Stochastic Cost Frontier Model (KES/acre

Variable	Mean	Std. Dev.	Min	Max	Mean Cost /Acre
Total cost (TC)	277,599.60	185,084.40	66,664	1,313,007	68,712.77
Land cost (PLAND)	34,208	29,685.32	6,500	260,000	8,467.33
Seed cost (PSEED)	78,558.02	54,521.08	3,900	460,000	19,445.05
Herbicides cost (PHERB)	3,064.88	2,607.83	300	18,000	758.63
Labour cost (PLAB)	49,693.50	32,740.87	5,250	175,500	12,300.37
Fertilizer cost (PFERT)	35,332.50	23,382.80	4,600	138,800	8,745.67

Source: Survey data (2022)

Some farmers opt not to cultivate more land due to the higher upfront outlay and the increased labor requirements. Sugarcane cuttings (seed price) had the biggest share of total cost amongst the inputs and the cost averaged 19,445.05 per acre. This was attributable to higher seed costs and improved planting procedures, which required more seed cuttings per acre, and Trans Mara averaged 5.21 tonnes per acre versus 2.27 tonnes per acre nationwide (Francis et al., 2020).

The labor cost to total cost was the second largest at KES12, 300.37 per acre, and this is because sugarcane cultivation takes a longer period (14 to 18 months), requiring a significant quantity of menial labor such as tillage, weeding, fertilizer application, herbicide spraying, and harvesting. Sugarcane cultivation involves applying various fertilizers at various stages of sugarcane growth. As a result, the cost fertilizer treatment per acre was KES 8,745.67; however, this represented the cost of both Top and Basal dressing. On average, farmers spent KES 758.63 per acre on herbicides (PHERB), and it has the least input cost share to the total cost. It should be mentioned that most the farm households in the study area do not use tractors in the cultivation of their fields, instead they use drought animals, which is captured as capital (PCAP); thus, the cost of hiring drought animals to prepare an acre of land was nearly KES 5,441. However, the variable was dropped, as many sugarcane farmers did not use the drought animal.

3.4. Estimation of the level of Technical, Allocative and Economic efficiencies of sugarcane production among farmers in Narok County.

3.4.1 Determinants of sugarcane output in Trans Mara West using Maximum Likelihood Estimation of the Cobb-Douglas Stochastic Production Function

Table 5 reports the results of the maximum likelihood (ML) estimates of the stochastic frontier production (SFP) that were identified to determine the factors influencing sugarcane productivity in Trans Mara. The results show that all the five variables incorporated into the SFP were significant determinants of the sugarcane yields amongst farmers (Appendix 4.4). These include land allocated for sugarcane (LLAND), sugarcane cuttings (LSEED), and fertilizer application (LFERT), herbicides (LHERB), and labour (LLAB). However, from the sampled farmers almost none used pesticides and manure; and most of the applied basal fertilizer (LBFERT), top fertilizer (LTFERT) shared similar quantities, and separate incorporation of these two variables into the SFP introduces Multicollinearity, which could result into bias estimates: hence, a new variable (LFERT) was generated from the combination of the two. Except for labor, all five input coefficients exhibited positive coefficients (production elasticities) as expected, with significant levels ranging from 10% to 1%: suggesting that inputs have a significant effect on the yields.

Table 3: Maximum likelihood Estimation of the Stochastic Production Frontier

LYIELD	Coefficients	Robust std-errors	Z	P>|Z|
LLAND	0.7159854***	.0786196	9.11	0.000
LSEED	0.1721253***	.0637056	2.70	0.007
LHERB	0.0802762**	.0397469	2.02	0.043
LFERT	0.1055223***	.0350317	3.01	0.003
LLAB	-0.0358153*	.0216366	-1.66	0.098
Const.	3.546567	.1759991	20.15	0.000

Parameters are significant at * p<0.1, ** p<0.05, *** p<0.01

Diagnostic statistics	
Log likelihood	104.22
Sigma square ($\sigma_s^2 = \sigma_u^2 + \sigma_v^2$)	17.39***
Gamma $\gamma = (\sigma_u^2/\sigma_s^2)$	0.9994
Lambda	41.58

Source: Own computations from survey data (2022)

The higher land coefficient in Table 5 reveals a high elasticity of output to land (0.716), implying that sugar cane production is considerably sensitive to land area as the main contributor to the production of small-scale sugarcane growers. Thus, a 1% increase in the land area cultivated resulted in a 0.72% increase in the sugar cane output, ceteris paribus. At 1% alpha levels, the seed and fertilizer coefficients were both positive and significant, implying that a 1% increase in seed and fertilizer will boost sugarcane yields by 0.17% and 0.11%, respectively. These results agree with those of Ambetsa et al., (2020); Thabethe, et al., (2014); and Zulu et al., (2019). The coefficient of log liters of herbicides (LHERB) applied was positive and significant at 10% alpha levels, according to the results in Table 4.5. This, however, revealed that a 1% increase in herbicide treatment would improve sugarcane yields by 0.08%, all else being equal. At 5% alpha levels, labor (LLAB) had a negative and significant effect on the sugarcane yields: implying that 1% increase in Man-days is likely to decrease output by 0.04%, ceteris paribus. The inverse relationship between labor and sugarcane yields could be credited to failure to properly account for optimal labor quantity that might be required per planted area. Additionally, the results are consistent with economic theory of production according to Cobb-Douglas. The sum of the partial elasticities with respect to every input estimated by the maximum likelihood estimator of the CD-SFP is 1.04; $[0.72 + 0.17 + 0.08 + 0.11 + (-0.04)]$, indicating increasing returns to scale, that is, any additional input may result in greater than a proportional variation in output, demonstrating the possibility for sugarcane farmers to enhance output.

The results in Table 5 also reports the parameter (λ) lambda value of 41.58 indicating that a 41.6 percent difference between observed and potential yield is due to inefficiency amongst survey participants. Lambda is the ratio of the standard deviation of the inefficiency component over the standard deviation of the idiosyncratic component, thus $\lambda = [\sigma_u/\sigma_v]$. The parameter gamma (γ) value (variance ratio) is 0.999, which is very close to one, is typically connected with both error terms of stochastic frontier production model (Battese & Coelli, 1995). This parameter accounts for the variance of the output as from the frontier resulting from the effect of technical inefficiency, and it is represented as $\left[\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)\right]$; whereas σ_u^2 denotes the variance due to technical inefficiency and σ_v^2 denotes statistical noise. The values therefore indicated that 99.9% variations in the composite error terms was caused by inefficiency effects. Moreover, the null hypothesis of no technical inefficiencies in our model was rejected since the computed LR, which was 37.3, was found to be greater than the critical values 16.047 derived from the mixed distribution of Kodde and Palm (1986). This therefore implies that the stochastic Frontier production is appropriately specified for this analysis. This therefore confirms the presence of technical inefficiency in the model. Furthermore, the estimated value of sigma squared $(\sigma_s^2 = \sigma_u^2 + \sigma_v^2)$ is 17.39 at $(p < 0.01)$ and the log likelihood statistic 104.22 at $(p < 0.01)$ demonstrates the model's appropriateness.

3.4.2 Maximum-Likelihood parameters of the Stochastic Cost Frontier Cobb-Douglas Estimation

Table 6 below presents the results of a dual cost function derived systematically from the SCF, as well as the elasticities of cost of inputs to the total cost value of sugarcane. The log of land cost (LPLAND), log seed cost (LPSEED), log fertilizer cost (LPFERT), the log cost of labour (LPLAB), and the log of Yield (LYEILD) were positively significant, and the implication is that the cost of production significantly depends on the cost of inputs ($p < 0.01$). According to the results: 1% increase in the cost of Land would likely increase total production cost by approximately by 0.13%; and likewise, 1% increase in the of cost of seed will increase total production cost by 0.23%; and 1 % increase in the cost of fertilizer will increase the cost of total cost by 0.24%. The cost of labour and yield significantly ($p < 0.01$) influenced cost of production as by 0.14% and 0.18% respectively.

Table 4: Maximum-likelihood Estimation of the Parameters of Stochastic Cost Function

LTC	Coefficients	Std-errors	Z	P> $\|Z\|$
LPLAND	.1271288***	.0323509	3.93	0.000
LPSEED	.2332681***	.0749026	3.11	0.002
LPFERT	.2362566***	.0327033	7.22	0.000
LPHERB	-.0081856	.0347724	-0.24	0.814
LPLAB	.1444171***	.0301411	4.79	0.000
LYIELD	.1834421***	.0759088	2.42	0.016
Const.	3.43938	.5339556	6.44	0.000
Diagnostic statistics				
Log likelihood	45.87			
Sigma square $(\sigma_s^2 = \sigma_u^2 + \sigma_v^2)$	44.78***			
Gamma $\gamma = (\sigma_u^2/\sigma_s^2)$	0.999			
Lambda	60.77			

Source: Own computations from survey data (2022)

The cost of herbicides (PHERB) was not statistically significant. However, all the significant parameters are positive; suggesting that the cost function increases input prices monotonically. The estimate of the composite error rather the total error variance denoted as sigma squared $[\sigma_s^2 = \sigma_v^2 + \sigma_u^2]$ is 44.78, and it is much above zero. The estimated gamma parameter $[(\gamma = (\sigma_u^2/\sigma_s^2))]$ of the SCF is 0.999, almost closer to one, and it is decidedly significant at 1% alpha level of the measurement error and other random disturbance thus, signifying that 99 percent of the variation in the total cost is influenced by cost inefficiencies, which was attributed to the cost of inputs.

The presence of cost inefficiency was validated by the LR statistic of 37.16 following estimation of $-2[ln\{L(H0)\} - ln\{L(H1)\}]$, which was greater than critical value 11.911 at $p < 0.05$) given by Kodde & Palm table (1986), implying that the typical response function (OLS) is not a sufficient representation of the data.

3.4.3 Summary efficiency scores of sugarcane production in Trans Mara West

Sugarcane production was technically and economically inefficient on every farm, implying that their levels of productivity were less than 100%, as the means for Technical Efficiency (TE), Allocative efficiency (AE), and Economic efficiency (EE) were 90%, 85%, and 77%, respectively (Table 4.7). The Technical efficiency (TE) values range from 33.1% to 97.7 % —the broad range in technical inefficiency demonstrates that many sugarcane growers are inefficiently employing their resources in the sugarcane farms. Similar findings were confirmed by Ambetsa et al., (2020) and (Nyanjong et al., (2012).

Table 5: Summary statistics of Efficiency Scores

	Frequency			Percentage		
Score distribution (%)	TE	AE	EE	TE	AE	EE
91-100	118	74	6	59.0	37.0	3.0
81-90	65	83	89	32.5	41.5	44.5
71-80	11	21	61	5.5	10.5	30.5
61-70	5	8	17	2.5	4.0	8.5
51-60	0	5	12	-	2.5	6.0
41-50	0	9	12	-	4.5	6.0
31-40	1	0	2	0.5	-	1.0
21-30	0	0	1	-	-	0.5
Total	200	200	200	100	100	100
Farmers below mean	65	59	72	32.5	29.5	36.0
Farmers above mean	135	141	128	67.5	70.5	64.0
Mean (%)	89.9	85.0	76.5			
Std Deviation (%)	7.57	11.9	12.9			
Minimum (%)	33.4	43.1	21.9			
Maximum (%)	97.6	98.1	93.0			

Source: Survey data (2022)

Furthermore, this suggests that if sugarcane grower was to operate on the frontier, they will save 10% $(100\% - 89.9\%)$ on their costs; in contrast, if the average sugarcane planter was to achieve the technical efficiency level of its most efficient neighbor, the average small-scale sugarcane planter might save 8% $[1 - (89.9\%/97.6\%)]$. Similarly, the least technically efficient sugarcane grower saves 66% $[1 - (33.4\%/97.6\%)]$. However, none of the growers attained 100% (89.9%<100%) technical efficiency, showing that with existing technology and resource availability, there is a substantial amount of room for improvement in sugarcane production in Narok County.

The mean allocative efficiency (AE) was 85.0% and ranged from 43.1% to 98.1%. Going by the mean value, it indicates that on average farmers can reduce their cost of production by 11.9% if they are to function on the frontier. Furthermore, if the average sugarcane planter wanted to attain the allocative efficiency of their most efficient neighbor, the average grower could save 13% $\left[1 - \left(\frac{85.0}{98.1}\right)\right]$, while the least efficient grower could save 56% $\left[1 - \left(\frac{43.1}{98.1}\right)\right]$. In a similar vein, none of the sugarcane growers had an allocative efficiency of 100 percent. This means that the sugarcane farmer could allocate resources to the optimum alternative uses and prices; enabling them to carry out their allocative functions through input utilization.

Table 7 also reports results on the distribution of economic efficiency (EE) scores. The economic efficiency (EE) scores across sugar cane farmers range from 21.9% to 93.0% with a mean score of 77%; and on average, a sugarcane grower will save approximately 23% if they operate on the most economically efficient frontier. This further implies that the average sugarcane growers could gain economic efficiency of 19% $\left[1 - \left(\frac{75.6}{93.0}\right)\right]$ if they operated on frontier. In addition, the least efficient farmer can gain economic efficiency of 77%

$\left[1-\left(\frac{21.9}{93.0}\right)\right]$, suggesting availability of incentives for sugar cane growers in Trans Mara to improve productivity and profitability.

3.5. Determination of socioeconomic and institutional factors affecting Technical, Allocative and Economic efficiencies

The impact of previously identified farm-specific variables on indices of efficiencies was evaluated employing a regression analysis. A two-limit Tobit model was further estimated to determine the sources of inefficiencies between the technical, allocative, economic efficiency scores and the vector of nominated socioeconomic and institutional variables. The Tobit results are reported in Table 8. According to the results, seven of the variables investigated account for a significant proportion of the variation in TE, AE and EE. These include Age (AGE), farming experience (EXP), access to extension services (EXT), access to credit (CRED), and Tropical Livestock unit (TLU). However, the estimated parameters for gender (GEND), Education (EDUC), household size (HHS), Land ownership (LOWN), and off farm employment (OFIN), were insignificant across the three efficiency scenarios.

Table 6: Tobit Model results on the factors affecting TE, AE and EE

Variables	Tobit (TE)	Tobit (AE)	Tobit (EE)
Age	-0.000514	-0.000398	-0.000543
	(-0.77)	(-0.39)	(-0.49)
Gender	-0.00332	0.00823	-0.00952
	(-0.23)	(-0.37)	(-0.12)
Years of education	-0.00226	0.00231	0.00221
	(-0.15)	(1.00)	(0.91)
Household size	-0.00213	0.000735	-0.00104
	(-1.16)	(0.26)	(-0.34)
Group membership	-0.00675	-0.00432	-0.00844
	(-0.61)	(-0.25)	(-0.46)
Experience	0.00000246	0.00203*	0.00175
	(0.00)	(1.81)	(1.45)
Land ownership	-0.0182*	-0.0169	-0.0283*
	(-1.94)	(-1.17)	(-1.82)
Access to extension	0.00309***	-0.00113	0.00144
	(3.65)	(-0.87)	(1.03)
Access to credit	-0.0329**	-0.0434**	-0.0658***
	(-2.71)	(-2.32)	(-3.28)
Tropical livestock unit	0.000516*	-0.00170***	-0.00124***
	(1.65)	(-4.13)	(-2.83)
Off-farm income	-0.00446	-0.00251	-0.0253
	(-0.12)	(-0.44)	(-0.42)
_cons	0.945***	0.943***	0.871***
	(19.19)	(12.44)	(10.69)

t statistics in parentheses * p<0.1, ** p<0.05, *** p<0.01

Source: Own computations from survey data (2022)

Table 8 reports results of the socioeconomic factors influencing technical, allocative and economic efficiencies estimated by a two-limit Tobit model. According to the findings, five of the ten investigated variables account for a significant proportion of the variation in TE, AE, and EE. These included farming experience, land ownership, access to extension, access to credit, and Tropical livestock unit. As a priori expectation, experience is found to have positive and significant effect on the Allocative Efficiency (AE) of the sugarcane growers, and it is significant at 10%. The positive experience parameter on Allocative Efficiency implies that a 1% increase in years of sugarcane farming experience would increase allocative efficiency by 0.20% or could result to decline in allocative inefficiency by 0.20. This finding is similar to that of Thabethe et al., (2014). Farmers with more sugarcane cultivation experience are more efficient, are familiar with agronomic practices and agroecological conditions for the crop, and ultimately, have a deeper awareness of how to allocate resources efficiently to accomplish the optimal yield. Overall, increased experience in sugarcane cultivation aids to explain scale efficiency. In their studies, Ochi et al., (2015) and Berhan, (2015) established that agricultural experience is favorably and significantly associated to farmer efficiency.

The landownership coefficients with respect to technical and economic coefficients were negative and significant. This inverse significant relationship implied 1% increase in land ownership would lead to decline in TE and EE by 1.82% and 2.83%, respectively. This implied that sugarcane farmers who leased land for sugarcane cultivation were inefficient both technically and economically. This is because farmers who lease land must incur additional costs besides the costs of other inputs. It is nearly unattainable to be economically efficient, whenever smallholder farmers are faced with the scenarios of fixed costs aggravated by the inequality of landownership.

Farmers who had access to extension services were also less inefficient, as predicted. At a 1% significance level, the coefficients were positively and significantly associated with Technical efficiency. According to the findings, utilizing extension services enhances farmers' technical efficiency in sugarcane production, which is consistent with expected prediction. The favorable effect of extension on technical efficiency might well be attributed to the expertise gained by sugarcane growers, which supplements training. This result confirms the findings of Ambetsa (2020) and Simonyan, (2012).

The study further demonstrates that access to credit (CRED) had negative and significant impact in explaining technical, allocative, and economic efficiencies at 5%, 5%, and 1% alpha levels, respectively: suggesting that every 1 % increase in the use of credit leads to the decline of TE, AE and EE by 3.29%, 4.43%, and 6.58%, respectively. This inverse relationship imply that even though credit relaxes farmers' liquidity constraints (Ike & Inoni, 2006), the fact is that financial credit attracts a cost, which, although a deterrent, might result in higher operating costs. Furthermore, credit may be infinitely divisible to other demands unrelated to sugarcane production. Tafesse et al. (2021) reported comparable results, as did Chiona et al., (2014). This finding, however, contradicts the findings of Ambetsa et al. (2020); and (Obwona, 2006), who separately observed that self-funded farmers became less efficient than those who accessed credit.

At the 10%, 5%, and 1% alpha levels, Livestock tropical unit's (TLU) demonstrated a negative and significant effect on technical, allocative and economic efficiencies; this demonstrates that farmers with much fewer livestock seem to be more technically, allocatively and economically efficient compared to those who had more livestock. Similarly, the inverse relationship may show that keeping numerous animals increases technical, allocative and economic inefficiencies of sugarcane production as animal care may compete for the same limited resources as sugarcane production. The result corroborates findings reported by Tafesse et al. (2021) and Bizuayehu, (2015).

4. CONCLUSION AND RECOMMENDATIONS

This study aimed at evaluating the factors that affect efficiency in sugarcane production in Trans Mara West using sample data generated from 200 smallholder farmers. To determine efficiency of the sugarcane farmer predetermined production and cost variables, the maximum likelihood estimation methods of both Cobb Douglas Stochastic Production frontier and its dual stochastic cost frontier were estimated in tandem with their respective specificized variables; and corollary, the scores of the technical efficiency (TE), allocative efficiency (AE), and economic efficiency (EE) were computed. Further, Tobit regression was specifically deployed to estimate the effect of farmers' socio-economic and institutional factors on the indices of the technical, allocative and economic efficiencies.

The research study established that the sector is predominantly male 84% (167) with an average age of 41years-thus pretty age levels synonymous with productivity; and the incredible majority of the farmers 94% (187) had attained formal education, with an average of 14 years of farming experience. The average household size among the selected sugarcane farmers was approximately 7; nonetheless, the farmers were able to access extension services more than 10 times every growing season; and 61.5 percent of the farmers (127) were able to access loan services. Furthermore, approximately 65% (129) of the famers possessed property, and over 90% owned a variety of cattle with a higher average TLU of 28.3 units than the national average.

The estimates of Cobb Douglass stochastic production frontier maximum likelihood and its dual stochastic cost function indicated that fertilizer, seed-cane cuttings, herbicides, land size, and labour significantly determined the output of sugarcane yields. The results of stochastic cost frontier demonstrated that the costs of land, seed, fertilizer, labor, and capital sufficiently influenced the total cost of production. Furthermore, the results revealed that average levels of 90% TE, 85% AE and 77% EE suggest that farmers in the region are operating at greater levels of efficiency and that there is room for a further increase in output without raising the current level and costs of inputs. Overall, the TE, AE and EE levels observed in Trans Mara West were very higher than most sugarcane growing regions in Kenya; however, they were comparable to those found in African countries that are efficient in the sugarcane cultivation.

According to the study, land ownership, access to extension services, credit, and the Tropical livestock unit are major determinants of technical efficiency. In contrast, experience, access to credit, and tropical livestock unit are important drivers of allocative efficiency. The most important economic efficiency factors are land ownership, credit accessibility, and tropical livestock unit.

The most important policy implication of this study is that there is sufficient potential for increased productivity among sugarcane farmers in Trans Mara West. The study recommends a policy measure that creates platforms where farmers would share evidence, knowledge and experiences on operating efficiently. To increase implementation and outcomes, a practical exchange program among farming communities might be designed to harness interactive, participatory, and tailored experience sharing methodologies. This enhances the relevancy, uptake, and utility of the experiences shared.

The study further recommends increase of contact and access to extension services, also including updating extension learning materials with knowledge that will assist sugarcane farmers in improving technical inefficiencies. This will necessitate preparing extension workers through incentives, training, and educational development. Additionally, a review of agricultural extension policies, as well as ongoing public and private support for the agricultural extension system, is therefore essential. The area's extension services must be improved in terms of quality and content. Furthermore, policymakers should diligently pay attention to financing policies that promotes inclusive and improved access to credit to farmers, which can assist farmers in covering production and marketing costs.

Interventions to address land ownership should be upscaled in the area to facilitate credit access and long-term investment in the area since land is the most preferred and handy collateral in loan acquisition by farmers. To spread risk and address vulnerabilities associated with reliance on one enterprise, policy initiatives promoting livestock keeping (TLU) as part of diversification should be adopted and encouraged among sugarcane farmers.

REFERENCES

Adam, A. M. (2021). *Table for Determining Minimum Returned Sample Size for a Given Population Size for Continuous and Categorical Data by Adam (2020) Population Size Sample Size*. *May*, 1–3. https://doi.org/10.13140/RG.2.2.13393.66401

Adewale, A.T, Lawal O.A, Aberu, F, & Toriola A.K. (2022). Effect of Credit to Farmers and Agricultural Productivity in Nigeria. *East Asian Journal of Multidisciplinary Research*, *1*(3), 377–388. https://doi.org/10.55927/eajmr.v1i3.99

Bank, W. (2021). *World Development Report 2021: Data for Better Lives*. https://doi.org/10.1596/978-1-4648-1600-0

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*(2), 325–332. https://doi.org/10.1007/BF01205442

Belotti, F., Daidone, S., Ilardi, G., & Atella, V. (2013). Stochastic frontier analysis using Stata. In *Stata Journal* (Vol. 13, Issue 4). https://doi.org/10.2139/ssrn.2145803

Berhan, T. H. (2015). Determinants of technical, allocative and economic efficiencies among onion producing farmers in irrigated agriculture: Empirical evidence from Kobo district, Amhara region, Ethiopia. *African Journal of Agricultural Research*, *10*(20), 2180–2189. https://doi.org/10.5897/ajar2015.9564

Chatterjee, S., & Price, B. (1992). CHAI-TERJEE, S., B. PRICE: Regression Analysis by Example. 2nd Edition, John Wiley & Sons, New York, 1991, xvii, 278 pp., US$ 32.60, ISBN 0-471-88479-0. *Biometrical Journal*, *34*(6), 734. https://doi.org/https://doi.org/10.1002/bimj.4710340613

Chiona, S., Kalinda, T., & Tembo, G. (2014). Stochastic Frontier Analysis of the Technical Efficiency of Smallholder Maize Farmers in Central Province, Zambia. *Journal of Agricultural Science*, *6*(10). https://doi.org/10.5539/jas.v6n10p108

Coelli, T. J., Prasada Rao, D. S., O'Donnell, C. J., & Battese, G. E. (2005). An introduction to efficiency and productivity analysis. In *An Introduction to Efficiency and Productivity Analysis*. https://doi.org/10.1007/b136381

Corlett, W. J., & Aigner, D. J. (1972). Basic Econometrics. In *The Economic Journal* (Vol. 82, Issue 326). https://doi.org/10.2307/2230043

Debertin, D. L. (2002). *Agricultural Production Economics - 2nd Edition*.

Debertin, D. L. (2012). *Agricultural Production Economics: Second Edition*. Pearson Education Corporate Editorial Offices One Lake Street Upper Saddle River, N.J. USA 07458.

Effiong, E. O., Idiong, C. I., & Emem, D. (2018). Analysis of farm size and resource use efficiency in selected arable crop production in Uruan Local Government Area of Akwa Ibom State, Nigeria. *Agro-Science*, *16*(2), 1. https://doi.org/10.4314/as.v16i2.1

Fonjong, L. N., & Athanasia, M. F. (2007). The fortunes and misfortunes of women rice producers in Ndop, Cameroon and the implications for gender roles. *Journal of International Women's Studies*, *8*(4), 133–147.

Food, W. (2020). World Food and Agriculture - Statistical Yearbook 2020. In *World Food and Agriculture - Statistical Yearbook 2020*. https://doi.org/10.4060/cb1329en

Francis, L. A., Samuel, C. M., & Samuel, N. N. (2020). Technical efficiency and its determinants in sugarcane production among smallholder sugarcane farmers in Malava sub-county, Kenya. *African Journal of Agricultural Research*, *15*(3), 351–360. https://doi.org/10.5897/ajar2020.14703

Freedman, D. A. (2006). On the so-called "Huber Sandwich Estimator" and "robust standard errors." *American Statistician*, *60*(4), 299–302. https://doi.org/10.1198/000313006X152207

Ike, P. C., & Inoni, O. E. (2006). Small-Holder Farmers in Southeastern Nigeria. *October*, *7*(2), 337–342.

Ismail Khan Khyber Pakhtonkhawa Pakistan Muhammad Amjad Saleem, D., & Ali Jan Director Finance, F. (2014). The Impact of Agricultural Credit on Agricultural Productivity in. *European Journal of Business and Management*, *42*(4). www.iiste.org

Jacob, A., Edward, E. O., & Yaw, B. O. A. (2016). Efficiency of chili pepper production in the volta region of Ghana. *Journal of Agricultural Extension and Rural Development*, *8*(6), 99–110. https://doi.org/10.5897/jaerd2016.0765

Kenya National Bureau of Statistics. (2018). *Economic Survey 2018*. http://www.knbs.or.ke

Kombo, J. B., & Ndiema, A. C. (2022). A review of the state of sugar cane crisis in Kenya. *International Journal of Agricultural Policy and Research*, *11*(1), 27–34. https://doi.org/10.15739/ijapr.23.003

Kumbhakar, S., Horncastle, A., & Wang, H.-J. (2015). *A Practitioner's Guide to Stochastic Frontier Analysis Using STATA*. https://doi.org/10.1017/CBO9781139342070

Londiwe Thabethe, E. M., & Marlene Labuschagne. (2014). Estimation of Technical, Economic and Allocative Efficiencies in Sugarcane Production in South Africa: A Case of Mpumalanga Growers. *Journal of Economics and Sustainable Development*, *5*(16), 86–95.

Nchare, A. (2007). *Analysis of factors affecting the technical efficiency of arabica coffee producers in Cameroon* (Issue January).

Nyanjong, OJ and Lagat, J. (2012). *Analysis of efficiency in sugarcane production: the case of men and women headed households in SONY sugar out-grower zone, Rongo and Trans-Mara districts, Kenya*. *10679*, 1–21.

Obwona, M. (2006). Determinants of Technical Efficiency Differentials Amongest Small- and Medium-Scale Farmers in Uganda: A case of Tobacco growers. *Africaln Economic Research Consortium*, *January*, 1–27.

Ochi, J. E., Sani, R. M., & Idefoh, F. K. (2015). PP 14-21 International Journal of Research in Agriculture and Forestry V2 • I2. *International Journal of Research in Agriculture and Forestry*, *2*(2), 14.

Okunlola, J., Oludare, A., & Akinwalere, B. (2011). Adoption of new technologies by fish farmers in Akure, Ondo state, Nigeria. *Journal of Agricultural Technology*, *7*(6), 1539–1548.

Onyango, K., Njagi, T., Kirimi, L., & Balieiro, S. (2018). Policy Options for Revitalizing the Ailing Sugar Industry in Kenya. *Retrieved*, *11*(4), 2019.

Perez, L. A. B.-, Reyes, L. F. L.-, & Tyner, W. E. (2017). Characteristics that Influence Technical Efficiency of Corn Production in Mexico. *Journal of Economics and Development Studies*, *5*(3). https://doi.org/10.15640/jeds.v5n3a3

Rahman, S. ., & Umar, H. . (2010). Measurement of technical efficiency and its determinants in crop production in Lafia local government area of Nasarawa state, Nigeria. *Agro-Science*, *8*(2), 90–96. https://doi.org/10.4314/as.v8i2.51103

Richard, W., Justus, M. O., Bernard, A. N., & Leonard, S. W. (2015). Sugarcane in vitro culture technology: Opportunities for Kenyas sugar industry. *African Journal of Biotechnology*, *14*(47), 3170–3178. https://doi.org/10.5897/ajb2015.14440

Sekaran, U. (2003). Research Methods for Business; Skills Building Approach, 4th edition,. In *Journal of MultiDisciplinary Evaluation*.

Severini, S., & Sorrentino, A. (2017). Efficiency and coordination in the EU agri-food systems. *Agricultural and Food Economics*, *5*(1). https://doi.org/10.1186/s40100-017-0086-9

Sigelman, L., & Zeng, L. (1999). Analyzing Censored and Sample-Selected Data with Tobit and Heckit Models. *Political Analysis*, *8*(2), 167–182. https://doi.org/10.1093/oxfordjournals.pan.a029811

Simonyan, J. (2012). Productivity and Technical Efficiency among Beneficiary Farmers of Second National Fadama Project in Kaduna State, Nigeria. *American Journal of Experimental Agriculture*, *2*, 102–110.

https://doi.org/10.9734/AJEA/2012/854

Solomon Bizuayehu, 2012. (2015). *Economic Efficiency of Wheat Seed Production: The Case of Smallholders in Womberma Woreda of West Gojjam Zone. M.Sc. Thesis presented to the School of Graduate Studies of Haramaya University*. *May*, 2010–2013. https://doi.org/10.13140/RG.2.1.1678.8089

Song, B., Zhao, J., & Zhang, P. (2022). A Study on Factors Influencing the Efficiency of Rural Agriculture Financial Support in China. *Sustainability (Switzerland)*, *14*(22). https://doi.org/10.3390/su142214954

Statistics, K. N. B. of. (n.d.). *Economic Survey 2019* (Issue c).

Sugar Directorate, A. (2018). *Sugar Market Newsletter June 2018*.

Sugiarti, Meylinah, & Osinski, J. (2021). *Report Name : Sugar Annual Report*. *April*, 1–12.

Tafesse, A., Mena, B., Belay, A., Aynekulu, E., Recha, J. W., Osano, P. M., Darr, D., Demissie, T. D., Endalamaw, T. B., & Solomon, D. (2021). Cassava Production Efficiency in Southern Ethiopia: The Parametric Model Analysis. *Frontiers in Sustainable Food Systems*, *5*(January 2022). https://doi.org/10.3389/fsufs.2021.758951

Tamirat, N., & Tadele, S. (2023). Determinants of technical efficiency of coffee production in Jimma Zone, Southwest Ethiopia. *Heliyon*, *9*(4), e15030. https://doi.org/10.1016/j.heliyon.2023.e15030

Tesema, T. (2022). Determinants of Production Efficiency of Maize-Dominated Farmers in Western Parts of Ethiopia in Gudeya Bila District: Evidence under Shifting Cultivation Area. *Scientific World Journal*, *2022*. https://doi.org/10.1155/2022/3355224

The Wood Foundation. (2020). *TWF-SC037957.pdf*.

Wassie, S. B. (2014). *Efficiency of Agricultural Production*. *January*.

Wassie, S. B. (2019). *Technical Efficiency of Major crops In Ethiopia : Stochastic Frontier Model Efficiency of Agricultural Production Technical Efficiency of Major crops In Ethiopia : Stochastic Frontier Model*. *January 2014*. https://doi.org/10.13140/RG.2.2.25688.34569

Wongnaa, C. (2016). *Economic Efficiency and Productivity of Maize Farmers in Ghana* (Issue October) [Kwame Nkrumah University Of Science and Technology]. https://doi.org/10.13140/RG.2.2.19830.80962

Zulu, N. S., Sibanda, M., & Tlali, B. S. (2019). Factors affecting sugarcane production by small-scale growers in ndwedwe local unicipality, South Africa. *Agriculture (Switzerland)*, *9*(8), 1–14. https://doi.org/10.3390/agriculture9080170