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Resource Use Efficiency as a Climate Smart Approach: Case of Smallholder Maize Farmers in Nyando, Kenya

Mohamud Salat and Brent Swallow *

Department of Resource Economics and Environmental Sociology, University of Alberta, Edmonton, AB T6G-2H1, Canada; salat@ualberta.ca

* Correspondence: brent.swallow@ualberta.ca; Tel.: +1-780-492-6656

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Abstract: To simultaneously enhance agricultural productivity and lower negative impacts on the environment, food systems need to be much more efficient in using resources such as land, water, and fertilizer. This study examines resource use efficiency of maize production among smallholder farmers in Nyando, Kenya. The main objective is to assess the degree of technical efficiency of smallholder farmers and identify the impact of so-called "climate smart practices" on technical efficiency. The method of Stochastic Frontier Analysis is used to simultaneously estimate a stochastic production frontier and a technical inefficiency effect model. Data for 324 subplots farmed by 170 households were available for this analysis. The study reveals that maize production in Nyando is associated with mean technical efficiency of 45% and that soil conservation practices such as residue management, legume intercropping, and improved varieties significantly increase farmers' technical efficiency. Soil carbon is found to be a critical factor of production. These results imply that there is potential to more than double production using the same resources and that soil conservation practices can be very "climate smart," at once increasing soil carbon, production, climate resilience, and technical efficiency.

Keywords: technical efficiency; climate smart agriculture; residue management; technologies; soil conservation

1. Introduction

Agriculture is portrayed as both victim and culprit in debates about global climate change. In its victim roles, the sector is one of the most vulnerable to the effects of climate change. The characteristics of climate change include increases in mean temperatures, changes in rainfall patterns, increased variability in both the onset and amount of rainfall, and more frequent occurrence of extreme weather events such as droughts and floods. These changes have negative effects on agricultural yields, making it more difficult for smallholder farmers in the tropics to grow certain food crops such as maize, the main staple food for many countries in Africa.

Small-scale farmers and pastoralists in Africa, who are already resource scarce, are facing localized climate change impacts that could push them into new levels of poverty and hunger [1,2]. Empirical studies show that farmers in arid and semi-arid areas of the region are already experiencing shorter growing seasons, lower yields and reduced lands suitable for agriculture, mainly due to the warming climate [3]. Moreover, the human population of Africa is projected to grow to 1.5 billion by 2050 from its current 800 million, and this will mean greater need for food production [4].

In its culprit roles, agriculture contributes to Green House Gas (GHG) emissions. It is estimated that 24% of global anthropogenic GHG emissions are generated by agriculture, forestry, and other land uses [5]. Crop and animal farming contribute to emissions in a variety of ways. For instance, farm management practices such as fertilizer application, crop residue burning, and land preparation lead to GHG emissions in the form of carbon dioxide (CO_2) and nitrous oxide (NO_2) gases. In addition, agricultural practices such as soil cultivation, tillage, manure storage, and crop residue burning degrade soil carbon stocks. Enteric fermentation by ruminant animals releases methane gases, accounting for about 40 percent of the global GHG emissions by the sector [1]. As more lands are cleared for agricultural production, these emissions are projected to grow significantly. For instance, global methane emissions from cattle and livestock manure are projected to jump by 60 percent while nitrous oxide emissions will increase by 35–60 percent by 2030 [1].

Policy makers, researchers, development practitioners, and farming communities are faced with three intertwined challenges related to agriculture and climate change. These are ensuring food security, adapting to climate change, and mitigating GHG emissions. Researchers are challenged to develop and test interventions that can transform food systems to be more efficient, more climate resilient, and more sustainable [1].

One of the most promising approaches so far identified is Climate Smart Agriculture (CSA). CSA was first coined at the 2010 Hague conference on "Agriculture, Food Security, and Climate Change." The concept is defined as agriculture that simultaneously increases productivity, enhances climate resilience, and mitigates GHG emissions [6]. Examples of CSA practices are integrated crop-livestock farming, agroforestry, conservation agricultural practices such as residue management and intercropping, use of stress-tolerant crop varieties, meteorological weather advisories, and index-based insurance [6].

Most studies applying the concept of CSA have thus far focused on specific practices such as those mentioned above and their impacts on production per unit area [7,8]. Recently, we see mention of resource use efficiency as a climate smart approach [1,2]. An increase in resource use efficiency reduces the intensity of GHG emissions per kilogram of output while also improving food security [1]. However, little research has been done to link the agricultural efficiency literature with the concept of climate-smart agriculture. Most previous efficiency studies in the region focussed on quantifying efficiency and examining the effects of socio-economic and farm characteristics such as income, age, and land size [9,10]. Little attention has been paid to how the best management of agricultural practices affects efficiency. Using the case of maize-growing smallholder farmers in Kenya, this study measures farmers' technical efficiency (TE) and examines how their efficiency is affected by the adoption of soil conservation practices such as residue management and intercropping. The study also examines the technical impact of adopting improved seed varieties on farmers' productivity and efficiency.

Improved soil management can be a critical element of climate smart agriculture. Soils in most African countries are depleted of key nutrients, as population pressures make traditional fallow practices less viable and high prices for inorganic fertilizer limit use [11]. These lost nutrients can be replaced through organic resources such as composting manure, crop residues, and legume intercropping. These measures have the potential to increase soil organic matter while acting as substitutes or complements to high cost inorganic fertilizers [6]. Another possible climate smart practice is to use crop varieties that are better suited to local agro-ecological conditions and adapted to erratic rainfall and drought conditions.

2. Materials and Methods

The site chosen for this study is the Nyando river basin, a research site of the Climate Change, Agriculture and Food Security Program in Western Kenya. The majority of the inhabitants throughout the Basin are poor smallholder farmers who depend on rain-fed mixed agriculture for their livelihoods. Smaller numbers of farmers practice irrigation farming in the lower areas, large-scale commercial sugarcane farming in the mid-altitude areas, and large scale tea production in the upper altitudes [12]. The Nyando river basin lies approximately between longitudes 34°47″ E and 35°44″ E and latitudes 0°07″ N and 0°20″ N. The area is characterized by a historical pattern of severe land degradation and deforestation as human settlement and farming expanded along the basin, with water and soil conservation structures used on less than 20 percent of farm plots [13,14]. Land degradation is made worse by frequent floods, particularly in the low-lying areas, rendering 75% of the plains unsuitable for farming [13]. The area is also characterized by severe soil erosion. For instance, severe gully erosion in the lower areas of the basin is the most visible sign of land degradation, and land conversion and farming degradation have increased the severity of soil erosion and sedimentation over the past 60–100 years [12].

The Nyando River basin is characterized by humid to sub-humid climates with annual rainfall ranging from less than 1100 mm in areas near Lake Victoria to over 1700 mm in the highland areas [15]. An analysis of rainfall data from 1950 to 2010 shows that annual rainfall has had stable variance but a downward shift in mean rainfall from 1520 mm/year between 1950 and 1979 and 1403 mm/year between 1979 and 2010 [15]. There are two main rainy seasons in this area. The long rains occur between March and June, while the short rains occur between October and December [16]. In an informal interview, farmers in the Nyando area mentioned experiencing periods of missed rains, shorter growing seasons, and at times, periods of heavy precipitation leading to flooding especially in the low-lying areas of Nyando.

The lower part of the study area is best suited to drought-resistant crops like sorghum and millet. However, like other areas of Western Kenya, farmers in the Nyando basin exhibit a strong preference toward maize production. Maize is the most important cereal crop in Kenya, making up one third of caloric intake and 56% of the cultivated land in the country [17]. Sorghum and millet are considered to be inferior substitutes for maize, while rice and wheat are preferred. Since every farmer in our sample produced some maize, we focus our study on maize.

The Western Kenyan Integrated Management Project (WKIEMP) classified the Nyando River basin into three blocks, namely Lower, Middle, and Upper Nyando based on biophysical features identified through satellite imagery and ground survey [14]. The Lower Nyando has lowest elevation, moderate slopes, and unreliable rainfall. The Middle Nyando is characterized by higher elevation, steep slopes, and less intermittent rains. The Upper Nyando is characterized by large farms, higher elevation, and steep slopes. According to yield data for 1991, large differences exist in the per hectare value of agricultural yield among the three blocks [12]. Lower altitude areas were characterized by per hectare value of production of less than Ksh 5000, mid altitude areas produced Kenyan Shillings (Ksh) 5000–15,000 per hectare, while upper altitude areas produced Ksh 45,000–50,000 per hectare (in July 2018, 100 Ksh = 1 US dollar) [12].

2.1. Data

The data used for this study come from three sources. The production data and household socio-economic characteristics come from the Climate Change Agriculture and Food Security (CCAFS) IMPACTlite data collected through a survey in Nyando, Kenya in 2012. The survey technique was characterized by the development of village lists based on Nyando's three production systems: maize-sorghum in Lower Nyando, sugarcane-maize in Middle Nyando, and dairy-perennials-maize in Upper Nyando. Eight villages were selected to represent the production system of Lower Nyando, and six villages were selected to represent each of the Middle Nyando and Higher Nyando production systems. Ten households were randomly selected from each of the 20 villages and 200 households were surveyed in all. The survey asked farmers to identify their various farming activities, crops grown, seed varieties used, and improved technologies adopted in a particular subplot during a particular season of the year. A subplot is a sub-unit within a plot for recording differences in land use pattern in space and/or in time [18]. The purpose of the sub-plot concept is to describe farming activities that could change in space or in time and to record labour and inputs requiring activities, production and use of crop residues. 183 of the 200 surveyed households grew maize. Data on 13 households whose maize yield was less than 10 kg were dropped to minimize the effect of outliers on the stochastic production frontier estimation. Meanwhile, there were no subplots with extremely high output values. Outliers and extreme values affect the maximum likelihood method used to estimate stochastic frontier models [19].

Data on soil erosivity come from the Reconnaissance Soil Survey collected at scale of 1:25,000 by Kenya Soil Survey (KSS) in 2003 for Nyando, Kenya. Data on climate (precipitation and evapotranspiration) are sourced from a digital climate surface produced by the USAID Development Strategies for Fragile Lands project (DESFIL) project, downloaded from the GIS services website of the International Livestock Research Institute (ILRI). Measures of soil organic carbon for Nyando were primary data obtained from ILRI. ArcGIS 10.1 software (ESRI, Redlands, CA, USA) was used to merge the climate, soil and IMPACTlite data using the geographic coordinates of the surveyed households.

Table 1 describes the variables used in the study and provides summary statistics for each of the variables. Overall, those statistics reveal extremely high variability between plots. The yield variable shows harvested amount of maize grains in Kilograms obtained from a specific subplot for a specific crop-growing season. Average subplot yield for maize was about 479 kg, ranging from 12 kg to about 8100 kg per subplot. The labour variable is defined by total days of labour spent on a subplot and includes family and hired labour. Average labour spent on the subplots was about six days, with a minimum of one day and a maximum of 60 days. Land size is measured in hectares. The average subplot size allocated to maize is about one hectare and ranges from 0.02 to 7.5 hectares.

The seed variable represents the amount of money in Kenya shillings (Ksh) spent on seeds used in a subplot. The seed variable is reported in the data as the amount of seeds used for a particular crop, the type of seed (local or improved variety) and market value in Ksh per Kilogram. The market value of seeds has been chosen to account for the possibility that local and improved seed varieties are not equally productive. On average, 4232 Ksh in seeds is spent on the subplots, and the amount ranges from 37.5 to 375,000 Ksh (In July 2012, 1 US$ was the equivalent of 83.8 Kenya Shillings). Farmers noted purchasing the following improved varieties: Hybrid, DH14, DH04, KenyaSeed, 505, Yellow maize and H614. The Kenya Seed Company recommends short duration varieties such as DH04 for lower altitudes and longer varieties such as H614 for higher altitudes (http://www.kenyaseed.com/index.php?option=com_content&view=article&id=243&Itemid). "Yellow maize" and "hybrid" are more general designations that are difficult to interpret.

The carbon variable is defined by the percentage amount of organic carbon in the soil (%C). The average soil carbon content is 1.788% and ranges from 1.3 to 3% with standard deviation of 0.553%. These soil carbon measures are very low, even compared to other parts of Western Kenya. For example, on 445 plots in seven villages in Vihiga and Nandi districts, soil carbon ranged from 0.90% and 6.50%, with an average of 3.70% [20]. Soil erosivity refers to the susceptibility of soil to be eroded by rain, wind or surface runoff [21]. The susceptibility of the soil to erosion is a function of the slope, soil cover, soil carbon, silt/clay ratio, soil depth, level of exchangeable sodium, and flocculation index [16]. Based on these factors, the erosion hazard of the Nyando basin was classified as being slight, moderate, high, or severe. An erosion index has been constructed for these erosion hazard levels and ranges from one to four with one being slight and four depicting severe.

The P/EP variable is defined as precipitation (P)/evapotranspiration (EP) obtained by dividing annual precipitation by annual evapotranspiration. Evapotranspiration is the sum of evaporation and plant transpiration. When P/PE is more than one, precipitation is higher than evapotranspiration and there is more than sufficient moisture available for crops to grow. When the ratio is less than one, evapotranspiration is greater than precipitation and the risk of drought could be higher and more water is lost from plant crops through transpiration and evaporation. For the sample data, average P/EP is 0.950 and ranges from 0.759 to 1.077.

The variables for improved crop variety, residue management, and legume intercropping are binary, equal to one if a specific practice was adopted on the subplot, zero otherwise. In this study, the crop variety variable is defined by whether a household used an improved or a local maize variety on a subplot. Residue management is defined by whether or not crop residues were left on fields after harvest. Intercropping is the growing of two or more crop types in one sub-plot. In this study, the variable is defined by whether or not a farmer grew maize with beans in the same subplot. The average adoption rate of improved seed varieties was found to be 81.8%, which is relatively higher compared to residue management (69.1%) and legume intercropping (2.1%).

Table 1. Descriptive statistics.

Variable	Description	Mean	SD	Min	Max
Yield	Maize Yield in Kg/sub-plot	478.5895	830.6019	12	8070
Labour	Days per month	5.867284	6.437913	1	60
Land	Size in hectares	0.9649383	0.9686518	0.02	7.5
Seeds	Value in Kenyan Shilling	4232.529	28,979.04	37.5	375,000
Carbon	% Organic Carbon in soil	1.788	0.553	1.3	3.000
P/PE	Precipitation/Evapotranspiration	0.950	0.084	0.759	1.077
Variety	1 if improved seed variety	0.818	0.387	0	1
Residue Mngment	1 if residue is left on subplot	0.691	0.463	0	1
Intercrop	1 if maize is intercropped with Beans	0.207	0.406	0	1
Gender	1 if subplot is farmed by male	0.688	0.464	0	1
Distance	Distance of plot from homestead in meters	160.785	530.288	0	5000
Ploughs	1 if HH * owns a plough	0.485	0.501	0	1
Radio	Number of Radios in the HH	0.941	0.629	0	3
Age	Age of HH head in Years	52.559	15.389	20	84
Adults	Number of adults $\geq$ 18 years	2.799	1.388	1	7
Income	Total Income in Ksh per HH	3761.281	4796.653	0	35,000

* HH denotes household.

The gender variable is defined by whether a subplot is farmed by a male or a female and represented by a binary variable—one if a subplot is farmed by a male, zero otherwise. About 68% of the subplots are farmed by males. The distance variable refers to the distance of the subplot from the homestead in meters. Average subplot distance is about 160 m, with a range of 0 to 5000 m. The plough variable is defined by whether a household owns a plough or not. 49% of the households own a plough. The radio variable is defined by the number of radios the household owns. Average radio ownership per household is about 1 and ranges from 0 to 3 for the households. The adult variable represents the number of adults who are 18 years and above living in the household. On average, about three adults live in a household, and the range is from one to seven. The income variable represents average monthly off-farm income in Kenyan Shillings. Households mentioned income from off-farm activities such as employment, business, and remittances. Average household income for the sample ranges from 0 to 35,000 Kenyan Shillings.

2.2. Method

Productivity is defined as the ratio of output(s) produced to input(s) used [22]. Economic theory postulates that changes in productivity arise from a combination of three sources: technical change, technical efficiency change, and change in scale of operations [22]. An improvement in technical efficiency involves a movement towards the "best practice" production, whereas technical change is realized when a firm produces more output(s) with the same level of input(s) through a shift in the production frontier due to technological improvement. Meanwhile, a change in scale comes from an increase in firm's scale of operations; and involves a movement along a particular production function. While also capturing technical change, this study mainly focusses on technical efficiency. Using the approach of stochastic frontier analysis (SFA), the measurement of technical efficiency starts with specifying and estimating a stochastic production frontier function from which measures of technical inefficiency are estimated. A competing approach to SFA is Data Envelopment Analysis (DEA), which uses a non-stochastic mathematical programming approach to estimate the production frontier. Both DEA and SFA have widely been used in the efficiency literature and theory does not favour one method over the other. Unlike DEA, SFA requires the specification of a functional form, and distributional assumptions for the inefficiency error term, both of which could have consequences for the efficiency results. DEA, on the other hand, does not impose a particular functional form nor does it require assumptions on the error structure. In doing so, DEA lets the data "speak for themselves" [23] (p. 356). Despite this, SFA is advantageous in that it accounts for the influence of random factors that are outside of the decision maker's control. Also, the use of SFA enables one to perform formal statistical test of hypotheses. While aware of the tradeoffs in choosing a particular approach, we use the framework of SFA for this analysis.

For this study, the technical inefficiency effects model of Battese and Coelli [24], which assumes a truncated normal distribution for the inefficiency error term, has been specified to estimate the farmers' stochastic production frontier. The model consists of a stochastic production function and a technical inefficiency effects model, both of which are simultaneously estimated using maximum likelihood estimation.

The stochastic production function takes the following form:

$$Y_i = f(Labor_i, Land_i, Seeds_i, Carbon_i, Erosivity_i,\ P/PE_i, Variety_i; \beta)exp(v_i - u_i) \quad (1)$$

where for each of the *i*th household;

f = the stochastic production frontier function to be estimated;
Y_i = Subplot maize production in Kilograms;
$Labour_i$ = Adult labour days including family and hired labour;
$Land_i$ = size of subplot in hectares;
$Seeds_i$ = market value in Kenyan Shillings of maize seeds;
$Carbon_i$ = Percentage amount of carbon in the soil;
$Erosivity_i$ = Indexed extent of soil erosion (1 = Slight; 2 = Moderate; 3 = High; 4 = Severe);
P/PE_i = Ratio of Precipitation to Potential Evapotranspiration;
$Variety_i$ = 1 if household adopted an improved maize variety;
$v_i - u_i$ = Combined random error term;
v_i = Random error term;
u_i = Technical inefficiency

The dependent variable is maize produced in Kilograms per subplot. The variables labour, land, and seeds are inputs directly used in the production of maize. Soil organic carbon is considered as an environmental input in production. Use of soil carbon in production functions is justified in the literature [25–27]. Erosivity, P/PE, and Variety are used as control factors in maize production. In addition, the adoption of climate smart improved maize varieties is hypothesized to increase maize productivity through a shift in the production frontier (technological effect).

The v_is are assumed to be independently and identically distributed random variables that account for deviations from the frontier output due to random shocks and measurement error. The u_is are assumed to be identically distributed non-negative variables independent of the v_is that account for deviations from the frontier output due to technical inefficiency. Prediction of technical efficiency involves decomposing the combined random error, $(v_i - u_i)$, into its components to obtain firm specific technical inefficiency effects that are then used to compute firm specific technical efficiency effects. This is achieved through the prediction of the conditional distribution of, u_i, given that the combined random error, $(v_i - u_i)$, is observable and could be estimated.

The technical inefficiency effects model captures the determinants of variation in technical inefficiency. The model is specified as follows:

$$\begin{aligned} u_i = \delta_0 + \delta_1(Resid_i) + \delta_2(Intercrop_i) + \delta_3(Distance_i) + \delta_4(Radio_i) + \delta_5 plough_i \\ + \delta_6(Age_i) + \delta_7(Adults_i) + \delta_8(Gender_i) + \delta_9(Inc_i) + \omega_i. \end{aligned} \quad (2)$$

where for each of the *i*th household,

$u_{i\,=}$ Subplot level technical inefficiency;
$Resid_i$ =Residue management (=1 if residue is left on the field);
$Intercrop_i$ =Intercropping (=1 if a subplot is intercropped with Beans);
$Distance_i$ =Distance in Metres of the subplot from the household;

$Radio_i$ =Number of radios in the household;
$Plough_i$ = 1 if the household owns a plough;
Age_i =Age of the household head in years;
$Adults_i$ = Number of persons above 15 years of age in the household;
$Gender_i$ = 1 if subplot is farmed by male;
Inc_i =Average off-farm income of the household;
ω_i = A randomly distributed statistical error term.

The literature shows a number of factors affecting technical efficiency, including the use of specific production practices, attributes of the plot or farm, and more general demographic characteristics that could affect crop management. Crop residue management is a good example of a climate smart soil conservation practice that can affect farmer's maize productivity. Leaving the crop residues of last year's harvest on the farm aids in sequestering soil organic carbon, prevents soil erosion by acting as a ground cover, improves soil tilth, and adds organic matter after its decomposition [26]. Legume intercropping is another example of a climate smart practice that can potentially improve maize productivity. Legumes have nitrogen-fixing capacity and increase the nitrogen uptake of intercropped plants. Intercropping may also reduce productivity since the different plant crops compete for resources such as water, nutrients and sunlight. However, studies conducted in Africa [28,29] investigated this using LER (Land Equivalent Ratio)—obtained by dividing the amount of intercropped yields by the amount of monocropped yields. The studies found LER to be greater than 1.0, implying that intercropped fields are more productive than monocropped fields. The distance from the subplot to the homestead affects the manner in which the household allocates resources which could have different implications for productive efficiency. The farmer may, for example, prefer to cultivate subplots nearer to their home first and the rest later due to transport and other transaction costs. The nearby subplots may thus get adequate resources thus generating higher yields. However, all else equal, the farmer may have more incentive to devote more supervision and care time to subplots further from the homestead due to fear of theft and being grazed by animals. For example, a study by [30] found a strong gradient of soil fertility with distance to the house, indicating that farmers deliberately concentrate scarce resources on the plots closest to their house. Both ploughs and radios may be considered agricultural assets, but also could be interpreted as indicators of household wealth. The age of the household head in years is used here as a proxy for experience and also physical ability to do farming. Households with more adult members have a potential supply of family labour and are expected to be more technically efficient than other households. Subplots owned and controlled by males are expected to be more efficient compared to female-owned subplots at least in the context of the developing world. Off-farm income can increase efficiency if part of the earning is used in the investment of farm inputs and sustainable technologies, however, it is also possible that off-farm income takes time and attention away from production management thus resulting in low productive efficiency.

3. Results

3.1. Production Function Estimates

Two functional forms of the production function were estimated and compared—Translog and Cobb-Douglas—although the Translog results are not reported here. While the Translog has the advantage of greater flexibility, it is susceptible to multi-collinearity and degrees of freedom problems due to the numerous interaction terms. The Cobb-Douglas imposes more restrictions but can be more readily estimated with limited data sets as available in this study. The Cobb-Douglas results are also easily interpreted. While the Translog function provided better goodness-of-fit, as indicated by the log-likelihood ratio, it generated many statistically insignificant parameter estimates, both for first-order and second-order coefficients. Here, we report the focus on the results for the Cobb-Douglas function, which generated statistically significant results consistent with expected signs.

Table 2 presents the results of the Cobb-Douglas stochastic production frontier estimation. The coefficient estimates have the expected signs. All inputs have positive effects on yield and all their coefficient estimates are statistically significant at 1% level of confidence. Concerning the environmental factors, the effects of soil carbon and P/PE were found to be positive and significant. The coefficient estimate of the carbon variable is positive and significant at 5% level of confidence. The Erosivity variable is negative but statistically insignificant. The variety variable is significant at the 5% level and implies that adoption of improved maize varieties has a significant effect on maize output. The coefficient on Variety indicates that adoption of one of the improved maize varieties increases maize productivity by 37%.

Table 2. Coefficient estimates for parameters of the Cobb-Douglas production frontier.

Variable	Coefficient	T-Ratio
Constant	3.814 ***	8.900
Labour	0.311 ***	4.640
Land	0.304 ***	4.890
Seeds	0.323 ***	7.220
Carbon	0.423 **	2.160
Erosivity	−0.107	−1.490
P/PE	3.123 ***	4.270
Variety	0.371 **	2.840
σ_u	0.973 ***	7.300
σ_v	0.463 ***	6.800
λ	2.101 ***	13.340
Log-Likelihood	−387.785	
Number of Obs	324	

Note: *** and ** represent significance at 1% and 5%, respectively.

The parameter λ refers to the ratio of the standard deviation of technical inefficiency to the standard deviation of the random error. The value of this parameter is positive and significant (p-value < 0.01) and implies that variance due to inefficiency is greater than variance due to random shocks.

Table 3 presents the output elasticities of the four inputs (labor, land, seeds, carbon) along with returns to scale. Output elasticity refers to the percentage increase in maize yield as a result of increasing one of the inputs by 1%, holding all other inputs constant. Returns to scale is the long run proportional rate of increase of output relative to the associated increase in all the inputs by the same proportion. When the proportional increase in output is equal to the proportional increase in all inputs, the production process is said to exhibit constant returns to scale (CRS). When the proportional increase in output is less than the proportional increase in all inputs, the production process is said to exhibit decreasing returns to scale (DRS), and if output increases by more than that proportional increase in inputs, the production process is said to exhibit increasing returns to scale (IRS). The formula of the elasticity of output is given as

$$\frac{\partial ln(\hat{Y})}{\partial ln(X_j)} = B_j \tag{3}$$

where $\hat{Y}$ is the mean of yield for the sample and X_j is the jth input. The output elasticities for the Cobb-Douglas production function are simply the coefficients of the log-linear stochastic production model.

All of the output elasticities are positive, increasing each input increases output. Maize yield is most responsive to changes in carbon, followed by seeds, labor, and land, in that order. One percent increases in the inputs lead to the following increases in maize output: carbon—0.423%, seeds—0.323%, labor—0.311%, and land—0.304%. Returns to scale is the sum of the values of the elasticities. The returns to scale value is greater than one, implying increasing returns to scale: a 1% increase in all inputs increases output by 1.361%. The high responsiveness of maize yield to soil carbon shows that soil carbon is a critical determinant of maize productivity, which has significant implications for climate smart agriculture in this part of Kenya. Low soil carbon is a major problem in most areas along the Nyando River basin.

Table 3. Output elasticities and returns to scale.

Input	Elasticity
Carbon	0.423
Seeds	0.323
Labour	0.311
Land	0.304
Returns to Scale	1.361

3.2. Technical Efficiency

The presence of technical inefficiency was tested using a Likelihood Ratio (*LR*) test. The null hypothesis of this test is formulated as H_0: $\lambda = 0$, where lambda is the ratio of the standard deviation of the inefficiency error term to that of the random error term (i.e., $\lambda = \frac{\sigma_u}{\sigma_v}$). The null hypothesis is that there is no significant technical inefficiency in the subplot level maize production. Failing to reject the null hypothesis implies that all deviations from potential output are due to random shocks. The log-likelihood function values of the Ordinary Least Squares and the stochastic frontier model were used for the test. The test is formulated as follows:

$$LR = -2(LLF_R - LLF_U) \tag{4}$$

where LLF_R and LLF_U represent the log-likelihood function values for the restricted (OLS) and unrestricted (Stochastic Frontier) model respectively. The results of the test are presented in Table 4. The null hypothesis of no inefficiency is rejected at 5% level of significance. This implies that subplot level maize production in Nyando is associated with significant technical inefficiency. Figure 1 presents the percentage distribution of the technical efficiency scores.

Table 4. Likelihood ratio tests for the hypotheses of inefficiency effects model.

Hypothesis	Test	Result
(a) H_0: $\lambda = 0$ Estimated Frontier not different from OLS	LLF_U	−387.785
	LLF_R	−424.187
	LR	72.04
	Critical Value (5% level)	20.41
	Decision	Reject H_0
(b) H_0: $\delta_1 = \delta_2 = \ldots = \delta_{10}$ Variables in the inefficiency effects model are simultaneously equal to zero (No TE effects)	LLF_U	−387.785
	LLF_R	−416.131
	LR	56.69
	Critical Value (5% level)	17.67
	Decision	Reject H_0
(c) H_0: $\delta_1 = \delta_2 = 0$ TE effects of Soil Conservation variables are simulatenously equal to zero	LLF_U	−387.87
	LLF_R	−397.23
	LR	12.58
	Critical Value (5% level)	5.14
	Decision	Reject H_0

Template modified from [31]. The *LR* test statistic does not have a standard chi-square distribution. The test has a mixture of chi-square distributions [32]. We therefore use the critical values of [33] that take this assumption into account. TE: technical efficiency.

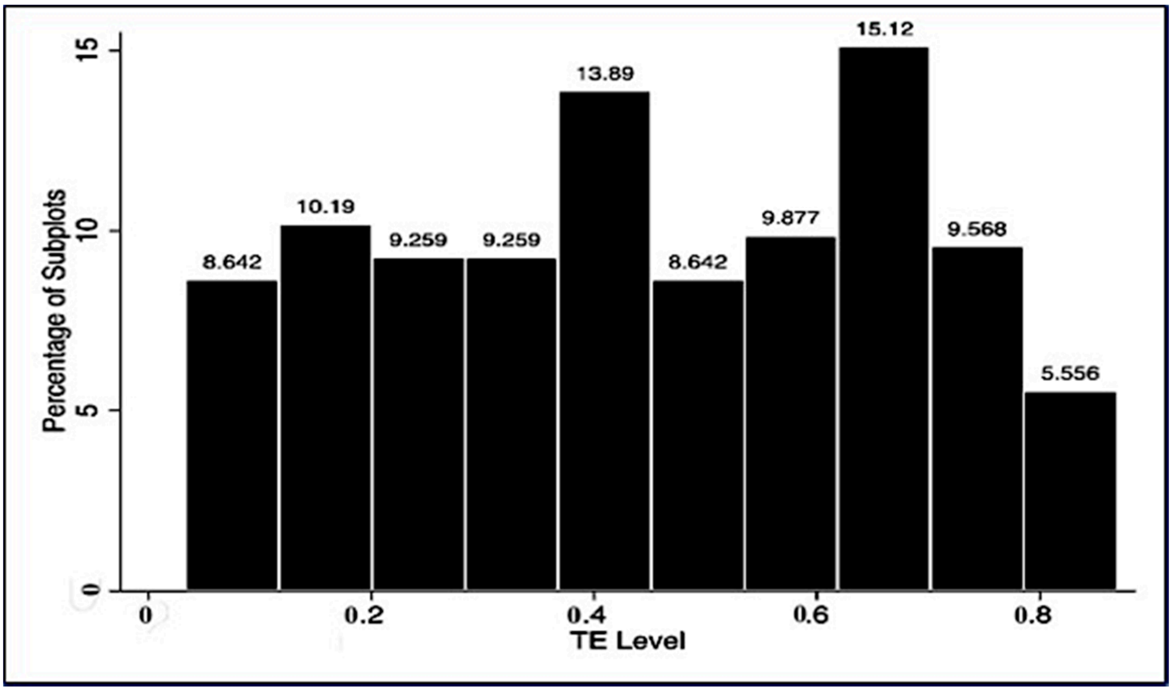

Figure 1. Percentage distribution of technical efficiency (TE) scores.

The mean technical efficiency of the subplots was found to be 0.45 with a minimum of 0.03 and a maximum of 0.87. An empirical restriction of stochastic frontier analysis models is that no producer is found to have a technical efficiency equal to 1, that is, no farmer is fully efficient in their use of inputs [34]. Nonetheless, the technical efficiency results show that the farmers in Nyando are not efficiently using available production resources. The farmers are on average operating 55% below the output frontier. The results presented on Figure 1 show a relatively uniform distribution of technical efficiency across the sub-plots included in this analysis. The low TE associated with maize production has implications for food security given the effects of climate change, land scarcity due to population pressure, and increasing prices of agricultural inputs. There exists a large scope for improving farmers' productivity through technical and TE improvements in order to tackle the challenges of food security.

The existence of inefficiency effects was tested using the Likelihood Ratio test. The results are reported in Table 4. The null hypothesis of the test is defined as Ho : $\delta_1 = \delta_2 \ldots . = \delta_{10}$, which implies that the mean of the inefficiency error term is constant and not a function of the exogenous variables. The results reject the null hypothesis of no technical inefficiency effects. This implies that at least one of the specified determinants has an effect on technical efficiency.

The results of the inefficiency effects model are presented in Table 5. A negative coefficient implies a positive impact on technical efficiency and vice versa. The maximum likelihood coefficients of the technical effects model are not marginal effects due to the non-linearity in the relationship between $E(u_i)$ and the Z_is [35]. Given the model, $U_i = {Z_i}'\delta$, the marginal effect of the kth element of Z_i on $E(u_i)$ is given by the formula:

$$\frac{\partial E(u_i)}{\partial Z[k]} = \delta[k]\left[1 - \Lambda_i\left[\frac{\phi(\Lambda_i)}{\Phi(\Lambda_i)}\right] - \left[\frac{\phi(\Lambda_i)}{\Phi(\Lambda_i)}\right]^2\right], \quad (5)$$

where $\Lambda_i = \frac{\mu_i}{\sigma_{u\ ,i}}$, and $\delta[k]$ is the corresponding coefficient. The average marginal effect for each variable is computed and reported alongside its coefficient estimate in Table 5.

Table 5. Results of the determinants of technical efficiency.

Variable	Coefficient	Marginal Effect	T-Ratio
Constant	1.724 ***	-	3.660
Residue Mngment	−0.492 **	−0.25	−2.280
Intercrop	−0.701 *	−0.35	−2.02
Distance	−0.001 *	-0.43×10^{-3}	−1.700
Radio	−0.421 **	−0.21	−2.400
Plough	−0.598 **	−0.30	−2.420
age	0.009	4.5×10^{-2}	1.390
adults	−0.131	−0.07	−1.580
Income	0.325×10^{-4}	0.162×10^{-4}	−1.320
Gender	0.073	0.04	0.330

Note: ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

The coefficient on residue management is negative and statistically significant at 5%. The negative sign means subplots in which the farmers leave the residue are more technically efficient compared to subplots where residue is removed for use as fuel or animal feed, all else being equal. The marginal effect of adopting residue management is −0.25. Residue management increases the subplot level mean TE of the farmers by 25% on average, leading to an increase in mean subplot level TE from 45 to 56.25%.

The coefficient on intercropping is negative and statistically significant at 5%. The negative sign implies a positive effect on TE. The marginal effect is −0.35. That is, intercropped subplots are on average about 35% more technically efficient compared to monocropped subplots and adoption of intercropping increases subplot level TE from 45 to 60.75% on average.

In addition, we tested the hypothesis of whether the given climate smart soil conservation practices, residue management and intercropping simultaneously affect technical efficiency levels. Results of the test are presented in Table 4. We reject the null hypothesis that the technical efficiency effects of these two practices were simultaneously equal to zero. The results imply that residue management and legume intercropping jointly affect technical efficiency levels.

The coefficient on subplot distance from the homestead is negative and statistically significant at 10%. The negative sign on the coefficient implies that distance from the homestead positively affects TE. The marginal effect on the coefficient of this variable is very small and hence its impact on TE is negligible.

The coefficient on radio is negative and statistically significant at 5%. The effect of radio ownership on TE is positive. The marginal effect is −0.21. This implies that radio ownership increases subplot level TE by about 21%. The coefficient on plough ownership is negative and statistically significant at 5%. Plough ownership increases the subplot level TE of the farmers on average by about 30%. Coefficients on age, number of adults, income, and gender are statistically insignificant and thus inconclusive.

3.3. Linking Soil Conservation Practices to Soil Capital

As mentioned earlier, the soils of Nyando are characterized by severe depletion and soil erosion which has consequences for food insecurity. Improving soil capital through climate smart soil conservation measures is necessary to improve food security and farmers' welfare. Residue management enhances soil organic matter and biodiversity thus improving soil structures, nutrient cycling, and also increases agricultural productivity while also decreasing soil erosion, water runoff and fertilizer loss [36]. The adoption of residue management combined with other climate smart technologies can help in sequestering soil organic carbon. In addition, intercropping with legumes increases soil fertility by enhancing both carbon and nitrogen accumulation over time [37]. Here we investigate whether there is any difference in soil carbon content (%C) between farmers adopting residue management and intercropping and those who do not. This is achieved through an equality of means test.

The results of the test and descriptive statistics are presented in Table 6. The results indicate a statistically significant difference (p-value < 0.01) in mean soil carbon content (%C) between subplots in which farmers practice or do not practice residue management, intercropping or neither practice. The average soil carbon content (%C) for subplots under residue management 0.208% higher than subplots not under residue management. Also, the average soil carbon content (%C) for subplots under intercropping is 0.418% more than subplots not under intercropping. These findings may imply that residue management and intercropping enhance the accumulation of soil organic matter leading to increased yields and higher efficiency. Unfortunately, we do not have data on farmers' past use of these conservation practices or soil organic carbon. Hence, we cannot conclude that individual practices have resulted in differences in the content of soil organic carbon among adopters and non-adopters.

Table 6. Results of t-tests and descriptive statistics of soil carbon by soil conservation practice.

Practice	Group						Test	
	Adopters			Non-Adopters			T	Diff
	Mean	SD	n	Mean	SD	n		
Residue Management	1.852	0.597	224	1.644	0.407	100	3.173 ***	−0.208
Intercropping	2.119	0.682	67	1.702	0.480	257	5.775 ***	−0.418

Note: *** represents significance at 1%.

4. Discussion

This study has revealed that maize production in the Nyando area of Kenya is associated with mean technical efficiency of 45%. Previous efficiency studies for smallholder maize farmers in Kenya show similar results regarding mean technical efficiency levels [38–40]. Similarly, other technical efficiency studies conducted in Kenya for other crops such as wheat and sorghum report low mean technical efficiency [41,42].

These results imply that there is a large scope for improving farmers' resource use efficiency in this area of Kenya, which would have positive consequences for farmer income and food security. We found increasing returns to scale for the average plot, which is expected given the small sizes of farm plots in the area. Increasing plot size to capture these scale economies, however, may have unintended negative consequences for equity of land ownership. Another way to increase technical efficiency is through technology. We found that the adoption of improved varieties of maize seed had a positive and significant impact on maize productivity. Informal interviews with farmers in the area suggested that most farmers understand the benefits of improved varieties, with cost and access being the main barriers. This is consistent with the conclusion of [43] (p. 284).

One surprising result from this study was the very low use of inorganic fertilizer, even by farmers who are using improved seed varieties. A central reason for this low adoption is that the low levels of soil organic matter limit the effectiveness of inorganic fertilizer. Another study from Western Kenya found that the marginal value of production of applied nitrogen was less than the price for all levels of soil carbon less than 3%, and the highest marginal returns were for soils with soil organic carbon of 6% or more [20]. In our study area, the maximum soil organic carbon is 3%. This result implies that inorganic fertilizer will not be a primary means for enhancing soil fertility.

This study went beyond most other studies of technical efficiency in the incorporation of biophysical variables. We found soil carbon to be a critical determinant of maize productivity, with an output elasticity of 0.41%, higher than any of the other inputs. This study also found that soil conservation practices known to improve soil carbon, such as residue management, have significant positive effects on technical efficiency. Residue management was found to increase farmer technical efficiency by 25%. The importance of residue management for soil carbon is well documented in other studies and this finding should not come as a surprise. Despite this, the rate of adoption of residue management has been slow in developing countries due to the other competing uses of crop residues such as fuel and animal feed. Previous studies indicate that crop residue retention is the cheapest source of soil nutrient for the productivity of the next crop. However, farmers usually "prioritized its use for cattle feeding" [44] (p. 24). One possible solution would be to secure carbon financing to encourage farmers to use crop residues as soil amendments and thus capture the win-win benefits that this promises [26]. However, any carbon credit policy will need to assess the economics of these competing uses of crop residues by farmers as the societal value of sequestering carbon in the soil must be taken into account to be fair and transparent [26]. In addition, legume intercropping was found to have a significant effect on TE. Practice of intercropping improved TE by 35% on average. Legume intercropping is also known to help in building soil carbon.

5. Conclusions

This study has examined the resource use efficiency of maize production among smallholder farmers in Nyando, Kenya. The main objective was to assess the degree of technical efficiency of smallholder farmers and identify the impact of so-called "climate smart practices" on technical efficiency. The study revealed that maize production in Nyando is associated with low mean technical efficiency, which implies that farmers are not maximizing yield from the resources they are applying to maize production. There is scope for significant increases in production through more effective use of available inputs.

Another finding of this study is the significance of soil nutrient management for farmers' productivity. Soil organic carbon was found to be a critical determinant of maize production. Meanwhile, soil conservation practices such as residue management and legume intercropping that are known to enhance soil carbon also significantly increased farmers' technical efficiency. These results imply that there is potential to more than double production using the same resources and that soil conservation practices can be very "climate smart", at once increasing farm production, climate resilience and soil carbon levels. Overall, we conclude that the triple wins of climate smart agriculture can be a reality in this part of western Kenya. We encourage development projects and extension agents to emphasize these climate-smart practices and other measures to enhance soil carbon. This type of research should also be extended to other parts of Africa.

These results provide a strong case study for the "4 per mille Soils for Food Security and Climate" initiative that was announced at the UNFCCC (United Nations Framework Convention on Climate Change) Conference of Parties meeting in 2015 [45]. "4 per mille" recognizes the dual importance of soil carbon as a productive asset and as a means for sequestration of carbon from the global atmosphere. Reaching the target of increasing soil carbon stocks by 0.4% per year would greatly alleviate food insecurity problems in this case study area.

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