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Comparing the economic efficiencies of rice and maize production in Amuru and Nwoya districts, Northern Uganda

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Abstract

Maize and rice are important sources of both food and income in Uganda. As such, the government of Uganda has promoted these crops through research and extension programs. However, there are glaring yield gaps between farmers' fields and research stations. In order to close the yield gaps, emphasis is being put on enhancing productivity through efficient use of resources for production as area expansion is unattainable. A random sample of 156 rice and maize farmers from which data were collected in Amuru and Nwoya districts was used in the study. Analysis was conducted using STATA software to determine the drivers of economic efficiency. Stochastic frontier and one stage procedure for estimating inefficiency models were employed. Results revealed that the mean economic efficiencies were 66.56% and 67.91%, for maize and rice, respectively. Further, it was established that seed cost, labor cost, and land rental cost ($p<0.01$) positively influenced production cost of rice and maize. Similarly, inefficiency model results disclosed that economic efficiency was significantly influenced by education level ($p<0.01$), age ($p<0.01$), distance to main road ($p<0.01$) and distance to market ($p<0.01$). In light of our results, we attest that farmers have opportunities to increase output by 16% and reduce cost by 21% and 20% for maize and rice respectively. We recommend that policies to enhance basic education for farmers under informal arrangements such as farmer training centers be instituted, incentivize youth to engage in agriculture, ease access to main roads and markets should be implemented so as to promote economic efficiency of producers.

Key words: Inefficiency Model, Stochastic Frontier, Uganda

Introduction

Maize (*Zea mays* L.) and Rice (*Oryza sativa* L.) are among the most essential cereals in the world. Both maize and rice are staple foods for around half the population in the world and have the second and third highest world-wide production levels, respectively (Ahmed *et al*., 2013). In Africa, the major cereals include sorghum, pearl millet, finger millet, teff, maize and rice, with maize and rice as the major staple foods for most of the population. Maize consumption in East and Southern Africa (ESA) accounts for almost half of the calories intake and one-fifth of the calories consumed in West Africa (Shiferaw *et al.*, 2011). In Sub-Saharan Africa (SSA), an estimated 208 million people derive food security and economic wellbeing from maize (Shiferaw *et al.*, 2011). Rice production in Africa is on the rise due to the high demand driven by urbanization, changes in consumption habits and population growth. These two crops have greatly gained importance in respect to reduction of poverty and food security of households in Uganda (Okello *et al*., 2019).

However, in Uganda, the cereal-based cultivation has been largely unvaried and is deemed incapable of sustaining food demand of the ever-increasing population. The cereal-based systems are characterized by low productivity levels, high rainfall dependency, high population pressure and traditional technology. In an attempt to sustain demand for these crops, new varieties and modern technologies have been introduced for small, medium and large-scale farmers to adopt; but considerable farm outputs have remained insufficient. For instance, attainable output levels at research stations for both maize and rice is 3,750 kg ha^{-1} while average outputs at farmers' fields for maize was reported at 230 kg ha^{-1} (Kibirige, 2008). Further, Musebe *et al*. (2013) and Okello *et al*. (2019) reported on-farm rice outputs in northern Uganda at about three times less than those recorded on-station. The disparity in output between research stations and farmers' fields is attributed to the level of inefficiency with respect to allocation and utilization of resources at the farmers' fields (FAO, 2014). Variations in outputs are further associated with high population growth, socioeconomic factors, as well as natural and political causes that create problems of productive resources reallocation among different smallholder farms (Norton *et al*., 2019). Land is a major driver of productivity in agriculture, and the small acreages in SSA need to become more productive as farm sizes further contract (Lowder *et al*., 2016). The increasing land scarcity implies that the anticipated potential of agriculture is dependent on efficient resource use for production.

Production efficiency refers to achievement of a production goal without waste and maximum output per given input bundle (Ajibefun and Daramola, 1999). Economic efficiency on the other hand is concerned with the relative performance of transforming given inputs into output (Onyenweaku *et al*., 1995). Several studies conducted on efficiency have mostly focused on technical efficiency (for instance, Tung, 2013; Madau *et al*., 2017; Ahmed and Melesse, 2018) and profit efficiency (Kaka, 2016). Technical efficiency deals with farmers' ability to maximize output whereas profit efficiency is the combination of both technical and allocative efficiency but hardly displays specific factors accountable to observed technical or allocative efficiency. Technical and allocative efficiencies are indispensable and when they happen together, then the sufficient conditions for attaining economic efficiency are met (Biam *et al*., 2016).

Efficiency of agricultural production is paramount because it allows farmers to expand and sustain the production frontier. As a result, efficiency has continued being an essential subject of empirical investigation especially in developing countries. Therefore, strategies aimed at increasing productivity of agriculture in Sub-Saharan African countries should be oriented to attainment of technical and allocative efficiency of smallholder farming operations. Although most smallholder farmers are reported to be inefficient, there exists a knowledge gap on the exact levels of inefficiency in their farming systems (Dalipagic and Elepu, 2014). Understanding economic efficiency levels and drivers thereof is of great importance for policy aspects in production of maize and rice crops.

In empirical studies on efficiency, the Data Envelopment Analysis (DEA) and Stochastic Frontier Approach (SFA), are the popular approaches used. Both procedures have merits, shortcomings and assumptions to be satisfied. The SFA is a parametric method that disintegrates not only random errors into error of farmer's unmanageable factors, but also farm specific inefficiencies (Khan, 2012). SFA allows for statistical testing of the validity of the underlying assumptions (Cullinane *et al*., 2006). However, a Stochastic Frontier Approach model is mostly constricted to a single output production, and some assumptions about the functional forms of the production frontier need to be made. A key assumption about the production frontier specification is that empirical results can be affected by the fixed nature of parameters and random error component (Madau *et al*., 2017). In contrast, the DEA approach is a non-parametric method widely used for estimating efficiency of poor quality data compared to SFA. In the DEA approach, it is unconditional to make assumptions about the distributions of the errors, the functional forms for cost frontier or production frontier (Charnes *et al*., 1978). Inability to disaggregate inefficiency component from the disturbance is the major limitation of the DEA. In this study, the SFA was preferred for assessing efficiency because of its ability to decompose the error components into statistical noise and an inefficiency part (Coelli, 1995). We employed the parametric SFA to estimate economic efficiency level and its determinants in rice and maize production by fitting the Cobb-Douglas stochastic frontier cost function. The cost function approach combines the concepts of technical and allocative efficiency in cost relationship. The study analyzed inefficiency sources and its causes in maize and rice production in the study area. The aim was to bridge the knowledge gap in literature as well as contribute to discussion on efficiency of crop production by answering the research questions: i) what factors are accountable to the variation in the levels of frontier and observed production of maize and rice, and ii) how do such factors affect economic efficiency?

Materials and methods

Study area and sampling procedure

The study was conducted on economic efficiencies of maize and rice producers in northern Uganda, in the districts of Nwoya and Amuru. These two districts are both high potential agricultural areas for major cereals but with contrasting attributes. The level of commercialized agriculture is higher in Nwoya compared to Amuru district. However, Amuru district is on the gateway to South Sudan, a major trade destination especially for agricultural commodities. Nwoya district is located at 2° 37' 59.99" N, 32° 00' 0.00" E. While Amuru district is located at 2° 48' 59.99" N, 31° 56' 59.99" E. Nwoya district is approximately 330 kilometers (210 miles) by road north of the capital city Kampala. It covers a total land area of 4,736.2 square kilometers (1,828.7 square miles), receives an average annual rainfall of 1500mm and has a population of 133,506 people (UBOS, 2014). Amuru district on the other hand covers a total land area of 3,625.9 square kilometers (1,400.0 square miles) and a population of 186,696 people (UBOS, 2014).

In the study areas, farmers are predominantly smallholders engaging in both crop and animal production. However, crop production dominates the economic activities and the major crops grown include: sweet potatoes, maize, cassava, sorghum, millet, rice, sesame, beans, pigeon peas, cow peas, egg plants, tomatoes and groundnut among others. Animals kept in the study areas include: pigs, goats, cattle and birds such as chicken, ducks and pigeons.

The study adopted a cross-sectional survey to obtain primary data from rice and maize farmers of Nwoya and Amuru districts. A multi-stage sampling procedure involving both purposive and random selection was employed to select 156 respondents. Quantitative data were collected using pretested structured questionnaires on inputs used, outputs of maize and rice enterprises obtained, their prices, socioeconomic variables, and factors that determine efficiency of the farm. The study collected data during the second season of production in 2017 (July to November) as well as in 2018 (March to June) for first production season. This was done in order to smoothen out seasonal differences in the study areas.

Data analysis and management

Data obtained were coded and entered into SPSS version 20 statistical package. Subsequently, the data were scrutinized for possible outliers before statistical analysis. To identify inconsistencies and non-normality in data entry, Exploratory Data Analysis (EDA) was conducted. Data distribution issues were identified using scatter plots and histogram plots. Where problems occurred, appropriate remedies like logarithmic transformations were implemented. Data transformations were performed on cost of seed, cost of renting land, cost of labour, cost of ox-traction hire, cost of tractor hire, cost of transport for produce from garden to farmer's home, quantities of maize and rice produced and off-farm income. Then analyses were run using STATA version 13 statistical package.

Stochastic frontier approach

The rationale for the stochastic frontier model is that the composition of error term comprises of two parts. One part accounts for effects of measurement errors as a result of random shocks beyond the farmer's control. While the second part accounts for the effects of inefficiency comparative to the frontier level of output/profit. The stochastic frontier approach was favored compared to nonparametric DEA because the former uses Maximum Likelihood Estimation (MLE) method and yields robust results unlike Data Envelopment Approach that uses mathematical programming (Erkoc, 2012).

We estimated the technical efficiency (TE) and economic efficiency (EE) scores for the i^{th} farming household and proceeded to use both EE and TE indices to compute allocative efficiency through dividing economic efficiency by technical efficiency. A stochastic production function (SPF) was used to estimate TE, whereas for economic efficiency, stochastic cost function (SCF) was applied. The stochastic production function is therefore specified as follows:

$$Y_i = f(X_i; \beta) exp \varepsilon_i \quad \text{.......... 1}$$

Where:

The error term $\varepsilon_i = v_i - u_i$

Y_i represents the i^{th} farm's output of the enterprise under study,

X_i represents input variables used by i^{th} farm in cultivating rice and maize, and

ε_i represents both the random error term named as v_i, permits random variations in output due to factors outside the control of the farmer like weather and diseases as well as measurement error in the output variable, and is assumed to be identically, independently and normally distributed with mean zero and constant variance (σ_v^2) that is, $v_i \sim N(0, \sigma_v^2)$ and the inefficiency parameter u_i a one-sided non-negative ($u > 0$) error term responsible for deviating potential production from the frontier, is assumed to be independently distributed as truncations at μ of the normal distribution and variance (σ_u^2), that is, $u_i \sim N(\mu_i, \sigma_u^2)$ but if $u_i = 0$, the assumed distribution is half-normal.

Equation (1) above can be fitted using trans-log production function, transcendental function, or Cobb-Douglas (CD) function (Battese and Coelli, 1995).Using Shepherd's Lemma, equation 2 was obtained as below:

$$\delta P_i = \frac{\delta Y}{X_i(w, y, a)} \quad \ldots\ldots \quad 2$$

In estimating economic efficiency level of the farm, the stochastic frontier cost function model was specified as below:

$$C_i = h(Y_i, P_i; \alpha_i) + \varepsilon_i \quad \ldots\ldots \quad 3$$

Where:

C_i is the total cost of production, Y_i is output produced, P_i is input prices, α_i represents cost function's parameters to be estimated and ε_i is the error term. Error components exhibit positive signs because inefficiencies always add to cost.

Using Shepherd's Lemma, Equation 4 was therefore presented as below:

$$\delta P_i = \frac{\delta C}{X_i(w, y,)} \quad \ldots\ldots \quad 4$$

This represents a system of minimum cost input demand equations (Bravo- Ureta and Pinheiro, 1997). Substituting input prices and their quantity as output in equation 4 yields the economically efficient input vector X_c. Relative to observed given output levels, the corresponding technically and economically efficient production cost was equal to $X_u p$ and $X_{ie} p$, respectively. However, the actual operating input combination of the farm is $X_i p$. The cost measure was then used to compute the economic efficiency scores as follows:

$$TE = \frac{(X_{ii}P)}{(X_iP)} \quad \text{.......} \quad 5$$

$$EE = \frac{(X_{ie}P)}{(X_iP)} \quad \text{.......} \quad 6$$

Combining equations (5) and (6) by dividing EE by TE was done to obtain allocative efficiency (AE) index following Farrel (1957).

$$AE = \frac{EE}{TE} = \frac{(X_{ie}P)}{(X_{ii}P)} \quad \text{.......} \quad 7$$

Allocative efficiency index value ranges from 0 to 1. The upper values represent efficient production, whereas the lower values show a higher level of inefficiency. Using the method postulated by Bravo-Ureta and Pinheiro (1997) which was based on the work of Jondrow *et al.*, (1982), efficiency is then measured using the adjusted output as indicated in equation (8)

$$Y^* = f(X_i\beta) - \mu \quad \text{.......} \quad 8$$

Where μ can be estimated using equation (9) as below:

$$E(u_i/\varepsilon_i) = \frac{\frac{\sigma\lambda}{1+\lambda^2}}{\left[\frac{f^*\left(\frac{\varepsilon_i\lambda}{\sigma}\right)}{1-f^*(\varepsilon_i\lambda)-\varepsilon_i\lambda}\right]} \quad \text{.......} \quad 9$$

Where $f^*\left(\frac{\varepsilon_i\lambda}{\sigma}\right)$ is normal density and $f^*(\varepsilon_i\lambda)$ represents cumulative distribution functions.

$\lambda = \frac{\sigma_u}{\sigma_v}$; $\varepsilon_i = v_i - u_i$ and

f^* = observed output adjusted for statistical noise. Substituting the estimate of λ, σ and ε_i in equation 7, it will yield v_i and u_i estimates. The term v represents a symmetric error, responsible for random disparities in output because of factors beyond the farmer's control. The term u refers to non-negative random variable symbolizing inefficiency in production relative to the frontier output.

In order to achieve profit maximization, firms should produce at the point where the marginal value product (MVP) and price are equal. Empirically, our study used Cobb-Douglas functional form to measure economic efficiency for rice and maize production, using the MLE method. Following the framework proposed by Battese and Coelli (1995), our analytical model is specified as follows:

$$lnC_i = \beta_0 + \beta_1 lnP_{1i} + \beta_2 lnP_{2i} + \beta_3 lnP_{3i} + \beta_4 lnP_{4i} + \beta_5 lnP_{5i} + \beta_6 lnP_{6i} + \beta_7 lnY_i + (v_i - \mu_i) \quad \text{......} \quad 10$$

Where: C_i represents cost of production for the i^{th} farmer (in UGX); P_1 represents cost of seed (in UGX); P_2 represents price of land rental (in UGX); P_3 represents average wage rate per man-days (in UGX); P_4 represents cost of ox-traction hire(in UGX); P_5 represents cost of tractor hire(in UGX); P_6 cost of transport from garden to home (in UGX); Y_i represents output of the i^{th} farmer (in kg). β_0 represents a constant; β_1 *to* β_7 represents parameters to be estimated; v_i and u_i=are the errors as earlier defined

Inefficiency leads to a rise in costs of production, which ultimately causes a decline in profit, thus, to study the influence of possible factors on economic efficiency, the dependent variable used was the inefficiency term. Socio-economic variables and other factors were modeled and hypothesized to affect economic efficiency. Finally, economic efficiency and their determinants were simultaneously estimated as below:

$$exp(U_i) = \delta_0 + \delta_1 X_1 + \delta_2 X_2 + \delta_3 X_3 + \delta_4 X_4 + \delta_5 X_5 + \delta_6 X_6 + \delta_7 X_7 + \delta_8 X_8 + \delta_9 X_9 + \delta_{10} X_{10} + \delta_{11} X_{11} + \delta_{12} X_{12} + (v_i - \mu_i) \quad \text{......} \quad 11$$

Where:

exp (U_i) = economic efficiency; δ_0=constant$\delta_1, \delta_2, \ldots \delta_{12}$= coefficients; X_1= age X_2= Sex X_3= household size X_4= education X_5= production experience X_6= distance to main road X_7= land cultivated X_8= distance to market X_9= credit access X_{10}= extension visits and X_{11}= off-farm income for both maize and rice models.

Stochastic frontier Cobb-Douglas cost model variables

The effects of crop output and different input prices on the cost of production were modelled such that the dependent variable was the cost of producing maize or rice per season (Table 1). Explanatory variables that were expected to affect the cost of producing maize or rice are explained and presented in Table 1.

Table 1. Variables in stochastic frontier Cobb-Douglas cost model

Variables	Dependent variable: Total production cost		
.	Description	Measurement	Expected sign
P1	Cost of seed	UGX	+
P2	Cost of land rental	UGX	+
P3	Cost of labour	UGX	+
P4	Cost of ox-traction hire	UGX	+
P5	Cost of tractor hire	UGX	+
P6	Cost of transport	UGX	+
Yi	Output of crop	kg	+

Variables in the inefficiency model

Various institutional and socio-economic variables that influence economic efficiencies were hypothesized (Table 2). The dependent variable was economic efficiency scores whereas the independent variables included institutional and socio-economic factors for rice and maize production.

Results and discussion

Characteristics of producers of maize and rice

The descriptive statistics show that the average production experience was higher for producers of rice than for maize (9.5 vs. 8.8 years) in the study areas. The average age for the respondents was 39.9 years (Table 3), falling within an age bracket of 15–64 years that accounts for 49.2% of the total population in Uganda (UBOS, 2016). These results are in line with earlier studies. For example, Okello *et el*., (2019) pointed out an average age of 37 years and average farming experience of 18 years for rice producers in Amuru and Gulu districts of northern Uganda; and (Hyuha *et al*. (2007) reported average age of 41 years and average experience of 16 years for rice farmers in Tororo district, Uganda. The average number of years spent in school was 6.36 (Table 3). The average household size for the sample was 7 people per household. This exceeded both the district and national averages of 5 persons per household for Amuru and Nwoya districts (UBOS, 2014).

The average distance to input and output markets for farmers was 7.67km, with maize farmers having to travel 5.96 km compared to 9.34 km for rice ($P<0.001$, Table 3). Distance to markets is key determinant of market participation for smaller holder farmers. Moreover, the road conditions in the districts especially during the rainy season, renders movement of goods burdensome to farmers and traders. This

Table 2. Inefficiency model variables

Dependent variable: Economic Efficiency Scores			
Variables	Description	Expected Sign	Source
Age	Age of the farmer in years	-/+	Bealu *et al*. (2013)
Gender	1 if male,0 otherwise	-/+	Bealu *et al*. (2013)
Education level	Number of years spent at school by the farmer	+	Debebe *et al*. (2015)
Farming experience	Number of years spent in farming	+	Haile (2015)
Household size	Number of household members	-/+	Sihlongonyane *et al.* (2014)
Distance to market	Distance from home to market in kilometers	-	Bealu *et al*. (2013)
Distance to main road	Distance from home to main road in kilometer	-	Bealu *et al*. (2013)
Farm size	Total acreage of maize and rice (ha)	-/+	Biam *et al*. (2016)
Access to extension services	Received training on maize and rice production	+	Bealu *et al*. (2013)
Access to credit	Utilization of credit for maize farming	+	Debebe *et al*. (2015)
Off-farm income	Income generated from non-farm activities	-/+	Bealu *et al*. (2013)

Table 3. Socio-economic characteristics of maize and rice producers (continuous variables)

Continuous variable	Maize N=77 Mean	Rice N=79 Mean	Mean Dif.	t-value
Age (years)	39.99(1.12)	39.87(1.41)	00.11	00.06
Household size (no.)	07.49(0.31)	07.47(0.32)	00.03	00.06
Education level (years)	06.04(0.35)	06.67(0.38)	-00.63	-01.22
Farming experience (years)	19.01(1.20)	18.24(1.35)	00.77	00.43
Maize production experience (years)	08.87(0.88)	-	08.87***	10.18
Rice production experience (years)	-	09.49(0.66)	09.49***	-14.18
Oxen owned (no.)	00.09(0.07)	00.37(0.15)	-00.28*	-01.66
Distance to main road (km)	03.44(0.30)	03.79(0.45)	-00.34	-00.62
Land holding (acres)	16.31(4.28)	42.34(20.68)	-26.03	-01.22
Maize acreage (ha)	02.5(0.21)	-	02.50***	12.31
Rice acreage (ha)	-	04.165(0.741)	04.17***	05.55
Distance to market (km)	5.96(0.63)	09.34(0.91)	03.37***	03.03
Maize quantity harvested (kg)	1,594(148.85)	-	1,594***	10.85
Rice quantity harvested (kg)	-	3,435(633.27)	3,435***	-05.36

*, **, and *** indicate levels of significant at 10%, 5% and 1% respectively. Figures in parentheses stand for standard errors

increases the transaction costs and further erodes the farmers' margins. Maize farmers travelled less distance to places of sale compared to rice producers. This was probably because of selling in village markets and at farm gate in the case of maize.

There existed a significant difference in land cultivated for maize and rice. Maize farmers had smaller land acreages allocated for production during the year compared to their rice growing counterparts (Table 3). The quantities of maize harvested followed the same trend as acreage and were less than that of rice. The lower productivity of maize could also have been because of the outbreak of fall army worms in 2017. The study further showed that there were significant differences in the gender of respondents between the two agricultural enterprises ($p<0.05$), with 63% of rice producers being male compared to 44% male producers of maize (Table 4). Other studies have also reported more male respondents for the rice enterprise (Hyuha *et al.*, 2007; Tijjani and Bakari, 2014). Of the two crops, rice fetches more money in the market compared to maize and thus attracts more male participants.

Distribution of economic efficiency estimates of smallholder maize and rice farmers

Results of efficiency estimates of maize and rice show that technical efficiencies TE ranged from 09.34 to 99.99% with a mean technical efficiency of 84.35% for both

Table 4. Socio-economic characteristics of maize and rice producers (categorical variables)

Categorical variable	Maize N=77 Mean	Rice N=79 Mean	Chi-Square	p-value
Gender	0.44(0.06)	0.63(0.06)	05.75**	0.02
Marital status	0.92(0.03)	0.95(0.03)	00.48	0.49
Off-farm activity	0.84(0.04)	0.80(0.05)	00.58	0.45
Farming practice	0.14(0.04)	0.34(0.05)	08.38***	0.01
Extension visit	0.27(0.05)	0.38(0.06)	02.03	0.15
Radio ownership	0.69(0.05)	0.85(0.04)	05.61**	0.02
Group membership	0.73(0.05)	0.72(0.05)	00.01	0.94
Ownership of oxen	0.03(0.02)	0.08(0.03)	02.00	0.16
Access to credit	0.47(0.06)	0.30(0.05)	04.42**	0.04

*, **, and *** symbolize levels of significance at 10%, 5% and 1% respectively. Figures in parentheses represent standard errors

maize and rice producers (Table 5). This implies that on average, farmers can increase their production levels by 15.65% if they were to attain technical efficiency. The results are in line with earlier findings of TE in Uganda that showed that farmers do not attain maximum efficiency. For instance Kalule (2013) reported a mean technical efficiency of 87% among smallholder banana farmers in Sheema district, Uganda and the mean technical efficiency of 69% for potato farmers in south western Uganda (Bonabana-Wabbi *et al*., 2013).

Allocative efficiencies AE ranged from 43.54 to 93.22% and 50.82 to 92.80% with mean allocative efficiency of 78.75% and 80.37% for maize and rice, respectively (Table 5). This implies that farmers in the study area can on average reduce their production cost by 21.25% and 19.63% for maize and rice, respectively if they

Table 5. Distribution of efficiency scores of maize and rice farmers

Efficiency parameter	Maize				Rice			
	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev
TE	09.34	99.99	84.35	00.17	09.34	99.99	84.35	00.17
AE	43.54	93.22	78.75	00.10	50.82	92.80	80.37	00.08
EE	08.07	93.22	66.56	00.16	08.09	92.80	67.91	00.16

were to improve allocative efficiency. Bealu *et al*., (2013) also reported mean allocative efficiency for maize production in Sidama zone, southern Ethiopia at 70% whereas Bakari (2014) reported a mean allocative efficiency for rain-fed rice production in Taraba state at 69%. Economic efficiencies EE ranged from 08.07 to 93.22% and mean economic efficiency was 66.56% for maize producers. For rice producers it ranged from 08.09 to 92.80% with mean economic efficiency of 67.91% (Table 5). This implies that on average 33.44% and 32.09% of production costs for maize and rice farmers, respectively, were in excess relative to comparable farms producing on the frontier and facing the same technology. This finding is in line with that of Sihlongonyane *et al*., (2014) who found the mean economic efficiency of maize production in Swaziland at 64%. Other studies have reported reported comparable results (Ahmed and Melesse, 2018; Haile, 2015; Biam *et al*., 2016).

Determinants of economic efficiency of maize and rice farmers

Table 6 shows the inefficiency model estimates of selected institutional and socioeconomic factors. Among the variables selected, eight turned out to contribute significantly to economic efficiency for maize namely: educational level, maize production experience, distance to main road and distance to market negatively influenced economic efficiency, while age, sex, off farm income and extension visits had positive influence on economic efficiency. For rice, the results showed that coefficients of age, educational level, distance to main road, and distance to market were significant but negative whereas sex, credit access, extension visits and off farm income had positive significant coefficients. The variables with positive significant coefficients imply that they increase inefficiency while those with negative significant coefficients lower economic inefficiency. The estimated gamma parameters were 0.91 and 0.75 in the study area for the maize and rice models, respectively. The gamma value connotes that at least 91% and 75% of deviations observed from frontier economic efficiency for rice and maize, respectively are as a result of existing variations in levels of efficiency among the farmer categories. The sigma squared estimates of 0.045 for maize and 0.018 for rice were both significant at 1% pointing goodness of fit for each model (Rahman, 2003). The estimates of parameters for the determinants of economic inefficiency are presented in the lower part of Table 6.

Sex of household head had negative and significant effect on economic inefficiency at 1% for the maize model. The result indicated that a male headed household was more economically efficient than female. The probable explanation is that male household head carried out most of the farming activities on time and efficiently on the farm. This finding corroborates a study conducted by Melese *et al.* (2019), who concluded that male households concentrated on land preparation and had more frequent follow up and supervision of their farm and they are likely to accomplish the

Table 6. Maximum likelihood estimates of the stochastic frontier

Explanatory variable	Maize		Rice	
	Coefficient	p-value	Coefficient	p-value
Constant	7.863 (0.512)	0.000	7.633 (0.588)	0.000
Log of seed cost	0.026 (0.011)	0.016	0.022 (0.009)	0.012
Log of land rental cost	0.030 (0.006)	0.000	0.026 (0.006)	0.000
Log of labour cost	0.253 (0.029)	0.000	0.265 (0.032)	0.000
Log of ox-traction cost	0.068 (0.007)	0.000	0.074 (0.007)	0.000
Log of tractor cost	0.060 (0.009)	0.000	0.069 (0.006)	0.000
Log of transport cost	0.039(0.044)	0.376	0.079 (0.040)	0.045
Log of output	0.110 (0.058)	0.059	0.053(0.050)	0.289
Inefficiency model				
Constant	0.718 (0.045)	0.000	0.685 (0.015)	0.000
Age	0.022 (0.006)	0.025	-0.011 (0.002)	0.002
Sex (1=male, 0=otherwise)	-0.034 (0.007)	0.000	0.046 (0.014)	0.000
Household size	-0.012(0.005)	0.601	0.020(0.002)	0.134
Education	-0.004 (0.002)	0.021	-0.018 (0.001)	0.000
Production experience	-0.002 (0.013)	0.000	-0.005(0.003)	0.279
Distance to main road	-0.004 (0.002)	0.006	-0.007 (0.005)	0.000
Land cultivated	-0.015(0.012)	0.997	0.014(0.002)	0.540
Distance to market	-0.003 (0.001)	0.015	-0.005 (0.003)	0.000
Access to credit (Dummy variable)	0.032(0.021)	0.382	0.009 (0.001)	0.000
Extension visits (Dummy variable)	0.023 (0.012)	0.000	0.017 (0.010)	0.000
Log of off-farm income	0.006 (0.003)	0.000	0.025 (0.002)	0.001
Sigma square	0.045(0.005)		0.018(0.003)	
Lambda	3.000(0.015)		1.800(0.008)	
Gamma	0.91		0.75	

VIF test had a mean 1.43 and 1.46 for maize and rice respectively, none of the variables in these models had VIF values exceeding 2.5, which is highly acceptable.

farming activities on time and efficiently than female smallholder farmers. Contrary to the maize model, the rice model indicated that sex of household head had positive and significant impact on economic inefficiency at 1% level of significance which implied that female headed household may have been responsible for many household domestic activities, and used of less inputs than male headed household. This is supported by earlier findings of Degefa *et al.* (2017) who reported that female headed households have relatively better capacity for optimal allocation of inputs.

The study showed that formal education level attained by a farmer improves the economic efficiency of such a farmer. This is because an educated farmer has capacity to understand and rapidly adopt improved agricultural technologies that enables an upwards shift in production frontier. Educated farmers can easily access agricultural information and have higher propensity to take up and utilize improved inputs more optimally and efficiently. Khan (2012) reported that the higher the level of formal schooling by farmers, the higher their technical, allocative and economic efficiencies.

Distance to main road negatively and significantly influenced economic efficiency of smallholder maize and rice producers (Table 6). This Farmers who stay near main road were likely to have higher economic efficiencies. Such farmers could have ease of access to improved technologies, access extension services, movement of inputs and farm output to markets. A 1% reduction in distance to main road by one kilometer increased economic efficiency levels by 0.4% and 0.7% for maize and rice producers, respectively. Distance to the market was also found to have the same effect to economic efficiency as distance to main road. A reduction in distance to market by one kilometer, leads to an increase in farmer's economic efficiency by 0.3% and 1.5% for maize and rice farmers, respectively. This is ascribed to the fact that a farmer located far away from the market incurs relatively higher costs to transport farm inputs from and outputs to the market. Comparable results were posted by Bealu *et al*., (2013). They reasoned that close proximity to factor markets not only increases farmers' access to credit facilities but also enhances non-farm income generating activities that enable timely inputs acquisition and application by farmers.

The results for the rice model reveal that age increases economic efficiency (Table 6). This shows that older farmers tend to be more efficient than younger ones. This is likely because older farmers may take benefit of their experiences to use inputs more efficiently to rice production. This result is in agreement with the study by Chiona *et al*. (2014) but in contrast to the maize model. A number of factors may not work in favor of older farmers. For instance, older farmers are less educated, more risk averse and more declined to new technologies and innovations. The results on maize agree with earlier findings reported by Battese and Coelli, (1992) and Khan (2012). They inferred that younger farmers with more years of formal schooling were more technically and economically efficient in their production decisions. Similarly, Bealu *et al*. (2013), reported negative relation between age of the farmer and economic efficiency and attributed this to the fact that younger farmers had more extension contacts with agents, attended more plot demonstrations and agricultural training meetings.

Contrary to our *a priori* expectations, access to extension services and off-farm income showed significant but positive effect on economic inefficiency for both crop enterprises (Table 6). This is probably due to the fact that farmers are not acquiring new skills and information from extension agents. The findings is line with Bati *et al.* (2017) who reported that efficiencies in resource allocation declines as the frequency of extension contact raises.

The positive and significant effect of non-farm income on economic inefficiency indicates that farmers engaged in non-farm income earning activities tended to exhibit higher level of economic inefficiency. This is plausible if the nature of off farm activity entirely deprives the farmer of his or her time to attend to farm. Similar findings were reported by Kibaara (2005) in a study of maize producers in Kenya. It was observed that farm efficiency reduced with increasing farmer's off-farm incomes.

Experience in farming displayed a negative and significant influence on economic inefficiency for the maize model, implying that the more the years a farmer spent in producing maize, the higher the levels of economic efficiency. Similar findings were also reported earlier by Biam *et al.* (2016) and Laha and Kuri (2011).

Lastly our result on access to credit indicated that it did not increase economic efficiency. This could be due to the fact that credit facilities acquired by farmers are not used for rice/maize production. This contradicted the findings Bealu *et al.* (2013) and Hyuha et al. (2007) among maize and rice producers in Ethiopia and Uganda, respectively. These studies concluded that access to credit was paramount in production because farmers' ability to purchase unaffordable farm inputs can be improved and ultimately improves the farmer's level of efficiency.

Policy recommendations

The general implications of this study are that access and access to main roads and markets in growing areas are vital in spurring maize and rice productivity in Amuru and Nwoya districts. Therefore, policies aimed at improving the infrastructure of rural/feeder roads and hence easing access to markets are key. Furthermore, providing incentives and information to young farmers to engage in maize and rice production would increase productivity. Getting young people into agriculture can contribute to addressing the escalating youth unemployment rates in the country on one hand and spur agricultural productivity on the other.

Education of farmers is another area that this study has unearthed to be in need of policy support. Continuous, adequate and effective farmer education through establishing and strengthening informal education should be reinforced. Farmers need to be trained in value addition, good agricultural practices and post-harvest handling, provided with necessary materials that can be used to understand agricultural instructions easily and have better access to product information and use the available inputs more efficiently. The study further recommends policy and strategies targeted at initiating and supporting gender-sensitive agricultural intervention to counter female headed farm inefficiency.

Conclusion

The economic efficiencies for maize and rice were significantly influenced by distance to main road and markets, and education level. Specifically, for maize, economic efficiency was affected by sex and farming experience; whereas and for rice, by age. On the whole, farmers were not achieving the desired levels of efficiency and strategic allocation of resources could lead to increase in efficiency of both maize and rice production. Efficient resources allocation could enable farmers to increase output by 16% for both maize and rice; whilst cost of production would reduce by 21% and 20% for maize and rice, respectively.

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