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Technical Efficiency in Agriculture and Its Implication on Forest Conservation in Tanzania: The Case Study of Kilosa District (Morogoro)

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Abstract

This paper examines technical efficiency in farming activities and its implication on forest conservation in Kilosa District. The empirical analysis is based on data collected from 301 households selected randomly from five villages in Kilosa district, of which three villages were under the REDD+ project. Two empirical models were estimated: stochastic frontier Translog production function, and forest resources extraction model. The stochastic frontier Translog production function was estimated using the FRONTIER 4.1 program, whereas Ordinary Least Square (OLS) method was used to estimate the forest extraction model. The empirical findings indicated that the mean technical efficiency of small-scale farmers in Kilosa district was 64 percent, implying that farmers in Kilosa District still have a room to improve their farming efficiency by 36 percent. In addition, farming technical efficiency among the households indicated to be influenced by the level of farming inputs usage, gender and educational level of the household head, extension services, farm experience and access to formal credits. Furthermore, the study indicated that technical efficiency, sex and distance of a village from the forest are significantly negatively related to extraction of forest resources; whereas household size and primary education of the household head showed to be strongly positively related to forest extraction. The results suggest that efficiency can be improved with appropriate policy intervention, and which will hence reduce deforestation and forest degradations.

Key words: *REDD+, forest, deforestation, agriculture, technical efficiency, stochastic frontier.*

JEL *Classification: Q1, Q12*

1. Introduction

About 55 percent of Tanzania's total land area of 88,359,000 hectares is covered by forests and woodlands (FAO, 2015). Such forest area is categorised based on five ecological regions: Eastern Arc, Mountains in the East, The Albertine Rift in the West, volcanic mountains in the North, Miombo woodlands in semi-arid areas and Acacia commiphora in the most arid regions (Chamshama & Vyamana, 2010). In addition, the country has various forest types include woodlands, montane, mangrove, acacia forests and coastal woodlands.

The forest sector contributes about 3.5 percent to the country's GDP, and annually brings around USD340m from its exports (NBS, 2015). The sector provides employment to an estimated 3m people in the government and other forest related

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activities and industry (FAO, 2010; MNRT, 2008; Blomley & Iddi, 2009). Moreover, the sector is considered as the main source of wood fuels, construction materials and other forests products for the majority of rural households, as it provides over 90 percent of national energy supply through wood fuel and charcoal, and approximately 75 percent of construction materials (Milledge et al., 2007; Miles et al., 2009).

Concerning management and ownership, forest resources in Tanzania is classified as a forest area that has been gazetted as forest reserves and protected areas (which is about 18m hectares, equivalent to 43 percent (URT, 2012)); and forest area under the participatory forest management (PFM) (which constitute up to 3.67m hectares, equivalent to 10.8 percent). PFM is divided into forest management under joint forest management (JFM) arrangement on government-owned forest reserves, and community-based forest management (CBFM) on village land forest reserves (VLFR) (Blomley & Iddi, 2009). Over 150,000 hectares of the gazetted area is under plantation forestry, and about 1.6m hectares are under water catchment management (URT, 2012). Forestry in Tanzania is also guided by a number of policies and legal frameworks that ensure sound, effective and sustainable management of forest resources, as well as support development and poverty reduction objectives.

The enforcement and implementations of various forest laws and policies support participatory forest management (PFM), and provide forest conservation incentives. These are among measures that have been undertaken by the Tanzanian government, international agencies and non-governmental organizations (NGO's) toward protecting forests. In spite of this, however, natural forests have been disappearing at an estimated rate of 372,000 hectares per annum (FAO 2015). FAO (2015) also estimates that between 1990 and 2015 the country cumulatively lost 9,860,000 hectares of forest cover, equivalent to 17.6 percent of its total forest cover.

The main drivers of deforestation and forest degradation in Tanzania are heavy pressure from agricultural expansion, overgrazing, wild fires, charcoal making, over-exploitation, unsustainable utilization of wood resources, and the lack of land use planning (FAO, 2015; Blomley & Iddi, 2009; Blomley et al., 2008). The agricultural sector, though is singled as the main driver of deforestation, plays a major role in Tanzania's economy. It contributes about 29 percent of the GDP, and accounts for 66.3 percent of people with employment in the country (NBS, 2014; NBS, 2015). Moreover, the sector has been contributing between 13 and 20 percent to total merchandise export through traditional agriculture exports for the past 10 years (BOT, 2018), which makes the country's economy to be sensitive to the sector's performance, especially on crop production.

Despite its importance, the sector's practice and performance in Tanzania is not well: it is dominated by smallholder farmers cultivating average farm size of 3.0 hectares, with about 84 percent owning less than 4 acres of land (NBS, 2017). In addition, more than 97 percent of Tanzanian's households use hand hoe, 33 percent use ox-plough, less than 10 percent utilize tractor, and about 97 percent depends on rainfall (NBS, 2017). Due to its traditional practices, agricultural activity has been among the factors affecting forest conditions through forest clearing for cultivation purposes. According to the NBS (2003), the area under cultivation recorded in 2002 was 9.1m hectares, which increased to 10.2m hectares in 2008 (Sulle & Nelson, 2009). The agricultural land increase between the two periods was about 12 percent (2 percent average annual increase, equivalent to 182,000 hectares). Consistently, the average annual agricultural growth since 1970 was recorded as 2.9 percent in the 1970s, 2.1 percent in the 1980s, 3.6 percent in the 1990s and 4.7 in the 2000s (URT, 2006; NBS, 2010). This shows that agriculture has been growing at a rate of less than 5 percent annually in the past four decades.

Similarly, there was a similar trend in major cash crops production (cotton, coffee, tea, sisal, cashewnuts, sugar and tobacco), and the size of the area cultivated between 2002 and 2008 (MAFC, 2008). This clearly indicates that agricultural growth in Tanzania, as in many Sub-Saharan African (SSA) countries, may largely be determined by area expansion, and to a lesser extent by increased productivity (Nkonya et al., 2008; Lokina et al., 2011). Given that rural communities heavily depend on two mostly natural endowed resources (namely agricultural land and forests), giving forest ownership rights to village communities and the enforcement of the rules will only lead to displacement effects: communities will continue to extend their extractions efforts into unprotected forests (Robinson & Lokina, 2011). This is to say, farmers will be expanding their farm size by encroaching forestland.

Generally, agricultural production affects conditions of forest resources, especially in villages adjacent to forests. The literature is not clear about the existing relationship between improvement in agricultural production and the condition of forest resources (Angelson & Kamowitz, 2001). Some scholars argue that improvement in farming productivity increase agricultural incentives that induces further conversion of forest land to agriculture (Van Soest et al., 2002). On the other hand, the Brundtland Commission (1987) and Shively (2001) point out that increase in returns to agriculture enhances rural income; thus, hiring more labour in agricultural activities, and consequently pulling rural households out of forest extraction. However, most of the empirical literatures support the argument that improvement in agricultural production reduces the degradation and extraction of forest resources (Lepatu et al., 2009; Fisher & Shively, 2006; Prabodh, 2005). Thus, the objective of this paper is to examine the existing relationship between agricultural production and forest resources conditions in the Tanzanian context. The study investigates farming efficiency, and the social-economic factors that affect such efficiency; which will in turn provides the basis for improving agricultural productivity, and consequently reduce deforestation and forest degradation.

2. Methodology

2.1 Data and Data Type

This paper utilizes data collected from Kilosa District in Morogoro, Tanzania. The district constitutes of villages located along the forest peripheries, and a majority of villagers practicing farming and forest extraction activities. Five villages in

Kilosa District were selected for the study: Nyali, Changarawe, Chabima, Dodoma-Isanga and Mamoyo. Of these, three villages were under the REDD+[1] project (Nyali, Chabima & Dodoma Isanga). A total of 301 households were randomly selected from the sampled villages, and questions were directly asked to household heads through a structured questionnaire. Basic district information—such as demographic, location of forests and villages—was collected from the district and natural resources offices.

Stochastic Production Frontier

Stochastic production frontier models were simultaneously introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977). This approach is used to obtain measures of technical efficiency by estimating a stochastic frontier, where technical inefficiency is measured as the deviation of an individual farm's production from the best-practice production frontier. In this approach, production is assumed to be stochastic because farming is sensitive to random factors such as weather, resource availability, and environmental influences.

The potential for the misspecification of functional form resulting in biased estimates of technical inefficiency is considered to be a weakness of the stochastic frontier approach, relative to non-parametric approaches such as data envelopment analysis (DEA). Another disadvantage of stochastic frontier is that the selection of a distributional form for the inefficiency effects may be arbitrary (Coelli, 1995). However, the disadvantage of DEA, relative to stochastic frontier modelling, is that it is not stochastic and hence it is not possible to isolate technical efficiency from random noise (Lovell, 1993). Given the inherent stochasticity involved in small-scale agriculture, the stochastic frontier approach appears to offer the best method for assessing the efficiency of farmers in rural economy (Kirkley et al., 1995; Campbell & Hand, 1998).

Other models have been suggested and applied in the analysis of cross-sectional and panel data. Reviews of some of these models and their applications are given by Battese (1992), Bravo-Ureta and Pinherio (1993) and Coelli (1995). Some models have been proposed in which the technical efficiency effects in the stochastic frontier model are also modelled in terms of other observable explanatory variables (Kumbhakar et al., 1991, Huang & Liu, 1994, Battese & Coelli, 1995).

The stochastic production function is defined by

$$y_i = f(x_i, \beta) exp(V_i - U_i) \; i = 1,2, \dots \dots . . N \; (1)$$

Where V_i is a random error having zero mean, which is associated with random factors, e.g., measurement errors, weather condition, etc. not under the control of the farmer.

[1]REDD+ is an acronym for Reducing Emissions from Deforestation and Forest Degradation. It is a move by the United Nations as a mechanism for conservation and sustainable management of forests.

The model is such that the possible production y_i, is bounded above by the stochastic quantity, $f(x_i, \beta)\exp(Vi)$; hence the term stochastic frontier. The random errors, V_i, i = 1, 2,……N were assumed to be independently and identically distributed as N(0,σ_v^2) random variable independent of the $U_i's$, which were assumed to be non-negative truncations of the N(0,σ_u^2) distribution (i.e., half normal distribution), or have exponential distribution. The variance parameters σ_v^2 and σ_u^2 are of critical importance in this model as far as technical efficiency is concern. They are expressed as follows:

$$\sigma^2 = \sigma_v^2 + \sigma_u^2 \qquad (2)$$

$$\gamma = {\sigma_u^2}/{\sigma^2} \qquad (3)$$

Where σ2= overall farmers' output deviations, γ is the ratio of farmers' output deviations due to technical inefficiency to overall deviations. It ranges between [0, 1], when $\gamma = 0$ indicates that all output deviations are due to factors outside the farmers control ($\sigma_u^2 = 0$ thus $\sigma^2 = \sigma_v^2$), when $\gamma = 1$ indicates that all deviations are due to technical inefficiency ($\sigma_v^2 = 0$, thus $\sigma^2 = \sigma_v^2$).

The technical efficiency of an individual farmer can be defined as the ratio of observed or realized (actual output) to the stochastic frontier output (potential output). The stochastic frontier output is the maximum output possible given the technology available and inputs used, and it is given by:

$$Q_i^* = \exp(x_i\beta + V_i) \qquad (4)$$

Where $U_i = 0$ because production is technically efficient on the stochastic frontier.

Then TE is expressed as:

$$TE_i = \frac{actual\ output}{potential\ output} = \frac{Q_i}{Q_i^*} = \frac{exp(x_i\beta + V_i - U_i)}{exp(x_i\beta + V_i)} = exp(-U_i) \qquad (5)$$

Where TE is technical efficiency. The inefficiency term U_i is always between 0 and 1. When $U_i = 0$, then production is on the frontier $Q_i^* = exp(x_i\beta + V_i)$, and $TE = 1$, therefore a farmer is technically efficient. When $U_i > 0$ the farmer is technically inefficient ($TE < 1$) since production will be below the frontier.

Empirical Specification for Stochastic Frontier Model

The stochastic frontier model can take either Cobb-Douglas production function or the Translog production function. The Cobb-Douglas production function imposes restrictions on a farm's technology by assuming constant production elasticities and setting the elasticity of input substitution to unity. In addition, it assumes fixed returns to scale, and a linear relationship between outputs and inputs used in production. On the other hand, the Translog production function assumes production elasticities are not constant and the existence of nonlinear relationship between outputs and inputs.

The model can be expressed in the general form as:

$$\ln(Q_i) = \beta_o + \beta_1\ln(X_{i1}) + \beta_2\ln(X_{i2}) + \beta_3\ln(X_{i3}) + \beta_4\ln(X_{i1})^2 + \beta_5\ln(X_{i2})^2 + \beta_6\ln(X_{i3})^2 + \beta_7\ln(X_{i1})\ln(X_{i2}) + \beta_8\ln(X_{i1})\ln(X_{i3}) + \beta_9\ln(X_{i2})\ln(X_{i3}) + (V_i - U_i) \qquad (6)$$

Where:

Q_i is the total value of the output in the ith farm produced in the year.
X_{i1} is the farm size in acres cultivated by the ith household in the year (i = 1,2, ... 301).
X_{i2} is the total number of labour used by the ith household in the year.
X_{i3} is the value of capital in Tshs used by the ith household in a year.
β*'s* are unknown parameters of the model. If $\beta_4 = \beta_5 = \cdots = \beta_9 = 0$, this will imply Cobb-Douglas production function.
V_i is the random variable assumed to be independently and identical distributed $N(0, \sigma_v^2)$ and independent of U_i.
U_i is the random variable that accounts for technical inefficiency and assumed to be independently as truncation of normal distribution with mean μ_i and variance $\sigma_u^2 \sim N(\mu_i \sigma_u^2)$.

The technical inefficiency model can be specified as either neutral technical inefficiency effects model, or non-neutral technical inefficiency effects model, which was originally proposed by Huang and Liu (1994). The neutral technical inefficiency model assumes that a change in frontier for different farms is independent of changes in factor input use and neutral. On the other hand, non-neutral technical inefficiency model implies that a shift in the frontier for different farms depends on the level of input use. In addition, elasticities of the mean output for different farms are the function of input variables, as well as of farm specific variables involved as technical inefficiency explanatory variables.

The inefficiency model is specified as:

$$\mu_i = \alpha_o + \alpha_1 ln(X_1) + \alpha_2 ln(X_2) + \alpha_3 ln(X_3) + \alpha_4 sex + \alpha_5 primary + \alpha_6 secondary + \alpha_7 ext + \alpha_8 crdt + \alpha_9 primary * ext + \alpha_{10} faexp * crdt + \varepsilon_i \qquad (7)$$

Where μ_i represents technical inefficiency; X_1, X_2 and X_3 are the factor inputs (farm size, labour and capital) used by a household; and α's are parameters of the model. *If* $\alpha_1 = \alpha_2 = \alpha_3 = 0$, this will imply a neutral technical inefficiency effects model. ε_i is a symmetric error term, independently and identically distributed $\sim N(0, \sigma^2)$.

Elasticity and Returns to Scale
As far as Translog stochastic frontier production function (equation 6) is concerned, the estimated coefficients will not have straightforward

interpretation. This is because, for a Translog production function, the output elasticities with respect to the inputs are functions of the first order and second order coefficients, together with the level of inputs used. Moreover, since the paper includes input variables (farm size, labour and capital) in both, the stochastic frontier function (6) and inefficiency function (7), the output elasticity with respect to the inputs is the function of the values of the inputs in both the frontier and inefficiency models. Following Battesse and Broca (1997), the elasticity of mean output is decomposed into the frontier elasticity and the elasticity of technical efficiency as follows:

$$\frac{\partial lnE(Y_i)}{\partial lnX_{ji}} = \left\{\beta_j + \beta_{jj} lnX_{ji} + \sum_{j \neq k} \beta_{jk} lnX_{ki}\right\} + C_i \left\{\frac{\partial \mu_i}{\partial X_{ji}}\right\} \quad (8)$$

$$\text{Where, } C_i = 1 - {}^1\!/_\sigma \left\{\frac{\emptyset\left({}^{\mu_i}\!/_{\sigma} - \sigma\right)}{\Phi\left({}^{\mu_i}\!/_{\sigma} - \sigma\right)} - \frac{\emptyset\left({}^{\mu_i}\!/_{\sigma}\right)}{\Phi\left({}^{\mu_i}\!/_{\sigma}\right)}\right\} \quad (9)$$

μ_i is defined by model (7), and ($\emptyset$) and (Φ) are density and distribution functions of the standard normal variables, respectively. The first component of the model (8) is referred to as the elasticities of frontier output, and second part is called elasticity of technical efficiency. The elasticity of technical efficiency is zero for the neutral stochastic frontier model, but non-zero for the non-neutral model. The sum total of the output elasticity is the estimated scale elasticity (ε). When $(\varepsilon) > 1$, it is referred to as increasing return to scale (IRS), $(\varepsilon) < 1$, implies decreasing return to scale (DRS), whereas, if $(\varepsilon) = 1$, it is referred to as constant return to scale (CRS). Stochastic frontier and technical inefficiency models (equations 6 and 7) are simultaneously estimated by the FRONTIER 4.1 program.

Empirical Specification for Forest Resources Extraction Model

Forest resources extraction model is used to examine the influence of farming efficiency on forest resources extraction. It is specified as follows:

$$Q_f = \alpha_o + \alpha_1 TE + \alpha_2 sex + \alpha_3 age + \alpha_4 agesq + \alpha_5 primary + \alpha_6 secondary + \alpha_7 hhw + \alpha_8 offinc + \alpha_9 hsize + \alpha_{10} dist + \varepsilon_i \quad (10)$$

Where

Q_f = Total market value of forest products collected by the household in a year.
TE = estimated farming technical efficiency of the household,

Others are variables reflecting household characteristics: sex of the household head, age of the household head, primary and secondary education, household wealth, off-farm income and household size. $dist$ represents the distance of a village from the forest; and ε is the error term of the model. Table 1 provides the detailed descriptions of the variables used in the analysis.

Table 1: Description of the Variables Used in the Analysis.

Variable	Description
qi	Total value of output produced by a household in a year
fsize	Farm size
l	labour (family and hired labour)
k	The value of equipment and machinery used in the farm
age	Age of the household head
sex	Sex of the household head (1 for male, 0 for female)
faexp	Farm experience of the household head
Primary	Primary as the highest level of education (1 for primary, 0 otherwise)
Secondary	Secondary as the highest level of education (1 for secondary, 0 otherwise)
ext	Extension service (1 if farmer received the service, 0 otherwise)
irr	Irrigation (1 if irrigation was applied, 0 otherwise)
crdt	Formal credit (1 if formal credit can be accessed, 0 otherwise)
Qf	Total value of products collected from the forest
Ac	Area cleared by the household in the past 1 year.
offinc	Off-farm income
hhw	Total value of household wealth
hsize	Household size
dist	Distance of the village from the forest

Table 2 presents the descriptive statistics of the variables used in the analysis. As it can be seen from the Table, about 77 percent of the household sampled are male-headed, whereas 23 percent are female headed, with an average household size of 4.3 persons, which is relatively less than the national average of 6 members (NBS 2012). More than 96 percent of the household interviewed depended on agriculture

Table 2: Descriptive Statistics of the variables used in the analysis

Variable	Units	Obs.	Mean	Std. Dev	Min	Max
Output	Tshs.	300	556184.3	796031.8	16250	9489000
Farm size	Acres	300	3.23	2.39	0.3	16
Labour	Numb	300	3.53	1.81	1	12
Capital	Tshs.	300	50886.67	92232.8	5000	700000
Age	Years	301	46.91	15.19	18	95
Sex	1 or 0	301	0.77	0.42	0	1
Primary	1 or 0	301	0.60	0.49	0	1
Secondary	1 or 0	301	0.07	0.25	0	1
Farm exp	Years	298	13.39	12.93	1	70
Exte service	1 or 0	299	0.54	0.5	0	1
Irrigation	1 or 0	299	0.06	0.24	0	1
Credit	1 or 0	300	0.17	0.38	0	1
Forest extrac	Tshs.	300	169340.7	326275.5	0	5290000
Land clearing	Acres	20	1.98	0.9	0.5	3.5
Off-farm income	Tshs.	217	256559.9	759270.9	0	9360000
Forest expe	Years	299	31.65	17.93	1	87
HH wealth	Tshs.	286	312218.5	446051.9	6000	2786000
HH size	Numb	301	4.31	1.83	1	13
Distance	Km	301	5.42	3.07	0.5	12

as the main economic activity, while less than 4 percent depended on mining, labour employment, own businesses and other activities. The average farm size cultivated by a household is 3.2 acres; with a majority cultivating between 2.0 to 3.9 acres. Only 7 percent of the households had cleared new land for crop cultivation during the year under study. Further, agricultural activities undertaken are mainly subsistence and depended heavily on climatic condition. Only 6 percent of the households indicated to apply irrigation in at least one of their plots during cropping seasons. Application of farm inputs is low; while a majority used hand hoe, with 20 percent using tractor, less than 1 percent using ox-plough. Similarly, access to formal credits by farmers was very low: about 82 percent of the households interviewed indicated that they had no access to formal credits from financial institutions. With regard to the level of education, more than 33 percent of the household heads had education below Std. VII, with about 60 percent having completed primary school (Std. VII), and less than 7 percent having completed secondary education. There was no household head having tertiary level of education in the sample interviewed.

Household use of forest products revealed that the majority of households collected products from the forest due to their proximity to the natural resources collected. The most common forest products collected were firewood, followed by building materials (poles, logs, thatching grass, palm leaves and ropes), food products (mushroom, wild meat, honey), charcoal and medicine plants.

3. Econometrics Results

3.1 Stochastic Frontier Production Model

The paper performed model specification tests to examine the significance of the model specified and the relevance of variables in inefficiency function. The tests were examined by using the generalized likelihood ratio statistics (LR), which is given by $LR = -2[ln\{L(H_o)\} - ln\{L(H_1)\}]$, where $L(H_o)$ and $L(H_1)$ are values of likelihood function under the null (H_o), and alternative (H_1) hypotheses, respectively. LR has approximately a Chi-square/mixed distribution. The calculated likelihood ratio statistics (LR) is then compared with the critical Chi-square value from the Chi-square table, corresponding to the degree of freedom, which is equal to the number of parameters assumed to be zero in null hypothesis. Tests were performed separately under neutral and non-neutral model specification, as shown in Table 3. The first hypothesis, which tests the absence of inefficiency effects, is strongly rejected in both neutral and non-neutral models. It confirms the presence of one-sided error component in the model, thus rendering the use of ordinary least square (OLS) inadequate in representing the data.

The second hypothesis tests whether Cobb-Douglas production function is the appropriate model for the analysis, and is rejected irrespective of whether neutral or non-neutral model specification is used. The test implies that Translog production function is adequate in representing the data. Further, the hypothesis that all parameters in inefficiency function are zero is accepted in neutral model specification, suggesting that all parameters used in inefficiency model are not significantly different from zero.

Table 3: Stochastic Frontier Production Model Specification Tests

Null Hypothesis	log-likelihood	LR Statistics	Critical $\chi 2$	Decision
Neutral model specification				
Test 1 Ho: $\gamma = 0$	-443.31	175.42	5.14	Reject Ho
Test 2 Ho: $\beta_4 = \beta_5 = \cdots = \beta_9 = 0$ (Cobb-Douglas)	-370.86	30.52	12.59	Reject Ho
Test 3: Ho: $\delta_4 = \delta_5 = \cdots = \delta_{10}$ (No tech inefficiency function)	-360.51	9.81	14.07	Accept Ho
Non-neutral model specification				
Test 1: Ho: $\gamma = 0$	-443.31	192.49	5.14	Reject Ho
Test 2: Ho:$\beta_4 = \beta_5 = \cdots = \beta_9 = 0$ (Cobb-Douglas)	-359.46	24.79	12.59	Reject Ho
Test 3: Ho: $\delta_4 = \delta_5 = \cdots = \delta_{10}$ (No tech inefficiency function)	-360.30	26.47	14.07	Reject Ho
Test 4: Ho: $\delta_1 = \delta_2 = \delta_3 = 0$ (Neutral Vs Non neutral model)	-355.60	17.07	7.81	Reject Ho

Source: Mixed $\chi 2$ values are taken from Kodde and Palm (1986)

However, the hypothesis is rejected in non-neutral model specification. Thus, the decision of whether to or not to include inefficiency variables depends on the last test, which investigates if a neutral or non-neutral model specification is adequate in representing the data. The last hypothesis is strongly rejected, which suggests that the more general non-neutral Translog production frontier model adequately represents the data.

Table 4 presents the results of Translog production frontier model. The diagnostic statistics of the model indicates that the gamma (γ) coefficient is 0.95 and statistically significant at 1 percent level. It is close to 1, thus assuring the stochastic nature of the production function. This implies that about 95 percent of variation in the output level among the farmers in Kilosa district is attributed to technical inefficiency effects. The coefficient of sigma square (δ^2) is 6.30 and significant at 1 percent level, which indicates the correctness of specified assumption of distribution of composite error term.

The results show that only capital inputs have the expected positive sign, which is consistent with the theory of production; whereas, farm size and labour have unexpected negative signs. However, estimated input coefficients in the Translog frontier production function presented in Table 4 do not have straightforward interpretations. Thus, it is necessary to estimate the output elasticity for each of the inputs used so as to have meaningful interpretation (Awudu & Eberlin, 2001; Hepelwa, 2011).

Table 4: Results from Translog Stochastic Frontier Production Function

Variable	Parameters	Coefficient	t-ratio
Constant	β_o	0.51	0.57
Ln(farm size)	β_1	-0.65	-0.87
Ln(Labour)	β_2	-0.83	-0.93
Ln(capital)	β_3	2.34***	10.50
Ln(farm size) ln(farm size)*	β_4	-0.01	-0.07
*Ln(labour) * ln(labour)*	β_5	0.37	1.64
*Ln(capital)*ln(capital)*	β_6	-0.11***	-7.80
*Ln(farm size)*ln(labour)*	β_7	-0.52***	-2.69
*Ln(farm size)*ln(capital)*	β_8	0.18**	2.31
*Ln(capital)*ln(labour)*	β_9	0.06	0.55
Variance parameters			
Sigma-square	δ^2	6.30***	5.28
gamma	γ	0.95***	71.14
Constant	δ_o	-3.72*	-1.94
Ln(farm size)	δ_1	1.98***	5.94
Ln(Labour)	δ_2	6.19***	10.48
Ln(capital)	δ_3	-1.77***	-13.57
Sex	δ_4	2.57***	3.55
Primary	δ_5	5.57***	8.47
Secondary	δ_6	-1.51	-1.46
Extension services	δ_7	-0.76	-0.55
Credits	δ_8	-3.70***	-4.48
*Primary*extension services*	δ_9	-3.85***	-3.94
*Farm experience*credits*	δ_{10}	-0.07***	-2.69
Likelihood function		-347.06	
Mean efficiency		0.64	

Note: *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent level.

The parameters in the inefficiency model are interpreted as change in inefficiency with respect to change in the variable. The model specified inefficiency as the dependent variable; hence the negative sign indicates decrease in inefficiency (increase in efficiency). The results presented in Table 4 show that most of the parameters in the inefficiency model are statistically significant; explaining farming inefficiency. The results show that the size of a farmland significantly affects the efficiency of a farmer; while increase in the size of a farm reduces farming efficiency. The possible reason is that the majority of farmers in Kilosa district use traditional and inferior farming inputs like hand hoes, which renders them inefficient whenever they cultivate large farmlands.

Likewise, the results indicate that an increase in labour significantly reduces farming efficiency. However, an increase in capital indicated to increase the efficiency of farmers (reduce inefficiency). This is due to the fact that farming implements and equipment like tractors enable a farmer to cultivate relatively large plots of land, and as a result harvest more.

The gender of a farmer indicated to influence farming efficiency. This sex parameter has unexpected positive sign and significant at 1 percent level, implying that being a male farmer increases inefficiency (reduces efficiency) in cultivation. The possible reason for this may be due to the sample size interviewed, which comprised of more male-headed households than female-headed ones, thus male heads of households who were less efficient may outweigh those who were more efficient. Education also seems to affect the level of farming efficiency. The results indicate that primary education significantly reduces farming efficiency, while secondary education improves efficiency, although it is not statistically significant. The results also show that access to formal credits significantly increases the level of farming efficiency.

Further, the paper examined interaction between variables influencing efficiency by combining primary education and extension services, as well as farm experience and access to formal credit. The results show that the coefficient of interaction between primary education and extension services is negative and statistically significant at 1 percent; implying that to the farmers who have primary level of education, farming efficiency may be improved by providing them with extension services. Likewise, the coefficient of farm experience and access to formal credit, which is negative and significant at 1 percent, suggests that farming efficiency may be improved if experienced farmers have access to formal credits.

The elasticity of mean frontier output with respect to the j^{th} input variable has two components: (i) the elasticity of the frontier output with respect to the j^{th} input, given by the estimated β_j parameters; and (ii) the elasticity of TE with respect to the j^{th} input. Elasticities of mean output with respect to the input variables (farm size, labour and capital) are estimated by using equation (8). In this equation, the respective mean values presented in Table 2, and the coefficients parameters from Table 4 are used to estimate elasticities. Table 5 summarises the results of the input elasticity and returns to scale.

Table 5: Elasticity Parameter Estimates with Respect to all Inputs

Variable	Frontier Output Elasticity	Technical Efficiency Elasticity
Farm size	0.008 (0.870)	1,677 (0.344)
Labour	-3.555 (1.107)	5.230 (0.590)
Capital	1.261 (0.285)	-1.499 (0.131)
Returns to scale	0.914 (1.436	5.407 (0.691)

Note: Figures in the parenthesis are standard errors

The results indicate that, elasticity the coefficients of farm size and capital have positive signs for the frontier output, whereas labour coefficient has a negative sign. In technical efficiency elasticity, farm size and labour have positive signs, while capital has a negative sign. Further, only capital coefficient is significant for the frontier output elasticity, while in technical efficiency elasticity, all input coefficients are statistically significant at 1 percent level.

Specifically, the results indicate that the capital input has the highest frontier output elasticity of 1.261, and is statistically significant at 1 percent. This implies that 1 percent increase in capital usage increases output level by 1.26 percent, other factors remaining constant. This suggests high responses of harvests with respect to the capital usage, and suggests that the uses of farm implements and machinery in cultivation enable a farmer to cultivate large plots of land, and as such more output is harvested. Labour inputs is found to have a negative elasticity, suggesting input congestions, which would in turn also mean that a farmer might be operating at the third stage of production frontier.

Farm size and labour coefficients are positive and statistically significant for the technical efficiency elasticity, with labour coefficient being the highest elasticity. This implies that farm technical inefficiency increases with increases in farm size and labour usage. The possible reason is that a majority of farmers in Kilosa district use hand hoes, which may not be able to utilise large farmlands efficiently. It can also mean that farm size may be subject to labour congestion, thus leading to inefficiency increases with an increase in labour usage.

The coefficient of capital input for TE elasticity is negative and statistically significant at one percent, indicating that farming technical efficiency increases (inefficiency decreases) with the increase in capital usage. The estimated returns to scale are 0.914 and 5.407 for frontier output elasticity and TE elasticity, respectively; although it is statistically significant only for TE elasticity. It is greater than 1 ($\varepsilon > 1$), implying increasing returns to scale (IRS). This may be attributed to the little capital usage by farmers; suggesting that farming inefficiency may be reduced by increasing capital input usage.

3.2 The Distribution of Technical Efficiency

The study analysed the contribution of the REDD+ project in improving farming efficiency among household farmers in Kilosa district. This is done by grouping together villages under the project, and comparing their efficiency distribution with villages where the REDD+ project is not operating. Figure 1 summarizes the results.

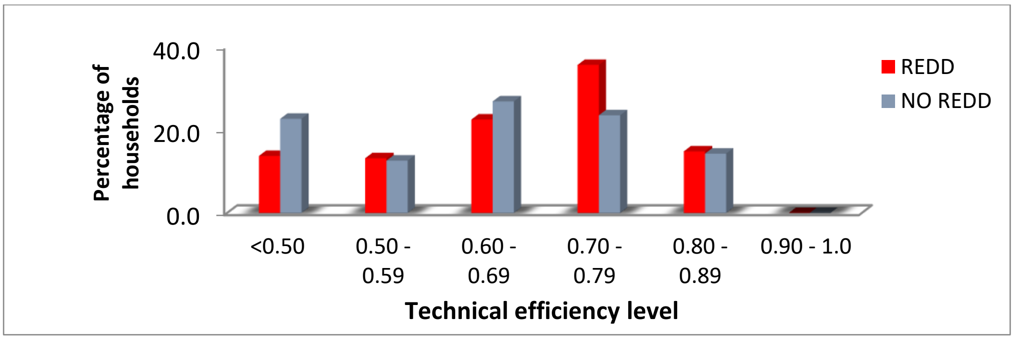

Figure 1: ***Comparison of Distribution of Technical Efficiency between Farmers within versus without REDD+ Project***

Source: Derived from output of FRONTIER 4.1 program

The results in Fig. 1, show that at the lower level of technical efficiency, the percentage of household farmers from villages outside the REDD+ project exceed the percentage of farmers from the villages under the REDD+ project. Specifically, for technical efficiency below 0.50, only 14 percent of the households came from the REDD+ villages, compared to 23 percent from the NO REDD+ villages. The efficiency range of 0.50–0.59 has a percentage of households that is slightly similar for both categories of villages (13 percent), while there was a larger number of farmers from the NO REDD+ villages than in REDD+ villages in the range 0.60–0.69. However, the number of farmers from REDD+ villages seem to be higher than NO REDD+ villages in the range above 0.70 technical efficiency. This may imply that training in modern farming techniques, extension services and other agricultural related services provided under the REDD+ project could have resulted in improving technical efficiency in crop cultivation by a majority of the farmers.

3.3 Forest Resources Extraction Model

Table 6 summarizes the results obtained from OLS estimations. The second column presents the results when off-farm income is included in the model, whereas, the third column shows the results after off-farm income variable is excluded from the model.

Table 6: Results for the Forest Extraction Model

Variable	OLS_Robust (1) Coefficient	OLS_Robust (2) Coefficient
Technical efficiency	-0.763**	-0.513**
	(0.366)	(0.232)
Sex	-0.208**	-0.106
	(0.102)	(0.068)
Age	0.025	0.019**
	(0.021)	(0.010)
Age^2	-0.0002	-0.0001
	(0.000)	(0.000)
Primary	0.231**	0.172**
	(0.101)	(0.074)
Secondary	-0.016	0.043
	(0.204)	(0.153)
Ln(household wealth)	-0.005	-0.006
	(0.042)	(0.028)
Ln(off-farm income)	-0.001	
	(0.031)	
Household size	0.158***	0.163***
	(0.027)	(0.019)
Distance	-0.063***	-0.049***
	(0.020)	(0.011)
Constant	11.273***	11.144***
	(0.554)	(0.390)
Number of observations	156	285
Prob.> F	0.0000	0.0000
R-squared	0.3804	0.3546

Notes: Figures in the parenthesis are standard errors ***, **, * are p<0.005, p<0.05 and p<0.1 respectively. Model (1) includes off-farm income, whereas model (2) exclude off-farm income.

Source: Authors' computation (2013).

The interpretation and discussion of the results in this paper is based on the second column (off-farm income included), as inclusion of the variable significantly increases explanatory power of the model.

Prob. > *F* = 0.0000, implying that the overall fit of the regression is very good, and it is significant at 1 percent level. R-square is 0.3804, indicating that about 38 percent of variation in forest extraction variable is explained by explanatory variables included in the model. The results also show that variables such as Efficiency, sex, primary education, household size and distance, are statistically significant at 5 and 1 percent level in reducing forest extraction. Specifically, the results show that the coefficient of technical efficiency is -0.763 which implies that if farming technical efficiency improved by 1%, then extraction of forest resources will be reduced by 0.8 percent, holding other factors constant. The negative relationship between farming efficiency and forest extractions indicate that, generally, efficient farmers extract fewer products from the forest. The reason for this result is that households adjacent to the forest depend mainly on farming and forest products for subsistence and income generation. Here, inefficiency in farming activities reduces farm output and incomes, thus increasing dependence on forest extraction.

The sex variable has an unexpected negative sign, and is statistically significant at 5 percent. The coefficient of -0.208 implies that being a male-headed household reduces the extraction of forest resources by 0.2 percent, holding other factors constant. The possible reason for this is that men and women collect different products for different uses from the forest: usually women collect firewood, medicine and food products; while the collection of building material products is exclusively done by men. Thus, the influence of gender on the extraction of forest resources mainly depends on the type of forest product extracted by a household. This study found that firewood was the major product collected by households, and this is why female-headed households are shown to collect more forest products than male-headed households.

The primary education coefficient has a positive sign, and is statistically significant. The coefficient of 0.231 implies that, if a person has only primary level of education, extracting forest resources increases by 0.2 percent, other factors being constant. The possible reason is that primary education may only enable a person to recognize that the uses of forest products is more beneficial, without realizing the environmental impacts that may be associate with over-exploitation of such resources.

The household size variable has an expected positive sign, and is statistically significant at 1 percent level. The coefficient of household size is 0.158, implying that, 1 additional member of a household increases forest resources extraction by 0.2 percent, holding other factors constant. The reason for this positive relationship between household size and forest extraction is that, given the subsistence nature of these households, their major source of energy is firewood, and thus the amount consumed depends on the size of a family. In addition, it is easier for a bigger household to allocate part of the household members in agriculture and the rest in forest dependant activities rather than small households, which leads to bigger households being more likely to consume extra forest products than smaller households.

The results also indicate that the distance of a village from the forest has a negative influence on forest resources extraction. The distance coefficient of -0.063 implies that the extraction of forest resources is reduced by 0.06 percent if a village is located 1km away from the forest, other factors remaining constant. The reason is that, generally households in villages close to a forest consume more forest products than those in distant villages because of the easy access from home. Distant villages have high opportunity cost in terms of distance and time spent, which make them consume relatively less forest products.

4. Discussion and Conclusion

Based on the findings above, it is clear that there is a need for increased enforcement of existing rules and regulations. However, it is important also that measures be taken to improve agricultural productivity and identify alternative income-generating activities as a measure to address the issue of deforestation and forest degradation. The study has indicated that there is a room for the improvement of technical efficiency by 36 percent. Also, among individual farmers, the efficiency gap that should be addressed by policy measures ranges from 0.12 to 0.99. The government has to ensure that it undertakes policy programs that will enable farmers to improve their farming efficiency and operate closer to frontier output level without expanding agriculture land towards reserved forest land.

As indicated earlier, technical efficiency may be improved by providing extension and financial services to farmers. A majority of farmers in Tanzania have primary level of education, which may not be enough for improving agricultural productivity. The study showed that primary education reduces farming efficiency. However, providing extension services to a farmer who has at least primary education will improve his/her farming technical efficiency, something that the government can do through its agricultural officers. In addition, technical efficiency may be improved if rural farmers have access to formal credits. This could be done by extending financial services to district and eventually to village levels.

We have seen that the REDD+ project has assisted farmers to raise their farming efficiency levels. Most forest conservation programs support rural communities in all activities that are drivers of forest exploitation and degradation, with agriculture being one of the drivers. Most of these projects/programs are operated by NGOs that are funded by foreign donors for a short period. Moreover, the participation of rural communities in such project is very low. The only way that one can make such agricultural projects sustainable and reach as many farmers as possible is for the government to have its own projects. In this way, technical efficiency of farmers can be improved sustained without extremely depending on donor funded projects. Farmers can benefit and learn from such project, and ultimately increase efficiency. As Shively (2001), Prabodh (2005) Fisher and Shively (2006), and Lepatu at al. (2009) have pointed out, increasing efficiency in farming will enhance rural incomes and reduce pressure on forest resources extraction.

The study findings have shown that female-headed households extract more forest products than male-headed ones. This is because fuelwood is still a main source of energy for a majority of households, and this is mostly collected by females. As pointed out by Prabodh (2005), even though most forest products are considered to be inferior goods by most economies, a notable exception is fuelwood, which is essential for rural developing economies. Thus, improvement in rural income may not reduce dependence on fuelwood, at least in the short-run, unless alternative energy sources are available at affordable prices. This should be a priority for any government that desires to preserve its forest reserves.

Also, the study findings have indicated that there is positive relationship between household size and forest resources extractions. Given the subsistence nature of the rural households, fuelwood is a major source of energy. Consequently, the usage of fuelwood depends heavily on the size of a family in a household. Thus, larger-sized households extract more forest resources than small-sized ones. This is in line with the findings by Kabaija (2003), whose study findings showed that small-sized households (of 1 to 3 persons) in Botswana predominantly used gas for cooking, while larger-sized households used fuelwood, which is the relatively cheaper source of energy. This difference may be attributed to the fact that more energy is used for cooking than lighting, hence larger-sized households cook more food, which requires more energy, and thus are forced to use cheaper sources of energy. In our case, this implies that, for an average household size of 4.3 persons, alternative sources of energy, at least in a short-run, may not reduce extraction of forest resources. This is due to the fact that lager-sized households, which are predominantly in rural areas that mostly neighbours forest reserves, will opt for fuelwood as a 'cheap' energy source than other alternative sources of energy. Thus, there should be favourable policy incentives that should provide cheap source of energy to rural communities.

Lastly, the study indicated that there is negative and significant relationship between the distance of the village from a forest reserve and extraction of forest resources. This is an indication of villages where the government should strongly address the implementation of its forest conservation policies. Villages close to forest reserves consume more forest resources than distant ones, thus the exploitation of forest resources will be reduced significantly if forest conservation policies seriously address villages close to forest reserves.

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