Asian Journal of Agricultural Extension, Economics & Sociology
10(2): 1-10, 2016; Article no.AJAEES.23791
ISSN: 2320-7027

SCIENCEDOMAIN *international*
www.sciencedomain.org

Land Management Practices and Technical Efficiency of Food Crop Farmers in North Central Nigeria: A Data Envelopment Analysis (DEA) Approach

W. L. Agboola[1*]

[1]*Department of Agricultural Economics, University of Ibadan, Ibadan, Nigeria.*

Author's contribution

The sole author designed, analyzed and interpreted and prepared the manuscript.

Article Information

DOI: 10.9734/AJAEES/2016/23791
Editor(s):
(1) Ian McFarlane, School of Agriculture Policy and Development, University of Reading, UK.
Reviewers:
(1) Muhammad Hafidz Bin Abdul Raman, Universiti Putra Malaysia, Malaysia.
(2) Mevlut Gul, Suleyman Demirel University, Turkey.
Complete Peer review History: http://sciencedomain.org/review-history/13789

Original Research Article

Received 22nd December 2015
Accepted 22nd January 2016
Published 21st March 2016

ABSTRACT

The study examines the effect of Land Management practices on technical efficiency of food crop farmers in North Central Nigeria. Data for the study were collected with the aid of well-structured questionnaire from 345 food crop farmers, while data analyses were carried out using Data envelopment analysis and tobit regression. About 12.17% of the farmers were relatively technical efficient in their use of resources, with mean technical efficiency being 0.576. Return to scale reveals 6.67% of the farms to be operating under increasing return to scale, none under decreasing return to scale while 93.33% were found to be operating under constant return to scale. Slacks were reported in the use of such inputs as planting materials, quantity of manure, family and hired labour as well as quantity of agrochemicals. Factors that significantly reduced the technical inefficiency of farming households in the study area (P=.05) were education, age, farm size, crop diversification, practicing alley cropping, bush fallowing, cover cropping, crop rotation, mulching and inorganic fertilizer. The need to sensitize farmers on the importance of adopting soil enhancing technologies or enhance retention of soil fertility and introduce policies against land fragmentation since this would help reduce technical inefficiency were recommended.

**Corresponding author: E-mail: agboolawl@gmail.com;*

Keywords: Technical efficiency; land management practices; slacks; data envelopment analysis.

1. INTRODUCTION

Stagnant or declining agricultural productivity has been reported in sub-Saharan Africa (SSA). In the continent, both crop output and yield growth lag behind population growth, with declining per-capita crop yields [1,2,3]. The reduction in crop yield is attributed to land degradation, which is a result of various factors, among others soil erosion, nutrient mining, and the inability of smallholder farmers to adopt technologies that enhance soil conservation and soil fertility [4,5].

In Nigeria, efficiency in food crop production is a topical issue in food security programme of Nigeria government. However, past policies directed towards increased food crop production efficiency have not effectively achieved the desired objectives of food security because of neglect of Livelihood strategy (LS) and attributes of Land Management Practices (LMP) used by farmers in food crop production [6]. This has constrained policy analyst with access to empirical information on the effects of LMP attributes on food crop production efficiency.

Solis et al. [7] assessed the connection between the adoption of soil conservation practices on household technical efficiency by comparing two types of rural farm-households in hillside regions of Honduras and El Salvador. The study made use of data collected from 639 observations while data analyses were carried out using a switching regression approach. Result of probit model which was estimated to evaluate the variables affecting soil conservation investments among the sampled households indicates that education, soil erosion awareness, frequency of rural extension visits and farm ownership play a positive and significant role in determining the level of adoption of conservation practices, while farm size shows a negative and significant effect. The second-step analysis using stochastic production frontier reveals that producers with higher level of investment in soil conservation also exhibit higher average technical efficiency, operate smaller farms and present the higher partial elasticity of production with respect to total cultivated land. Conversely, farms with lower level of investment in soil conservation display the higher elasticities for purchased inputs and hired labor. In addition, accessibility to financial credit was found to be a factor in explaining the sources of inefficiency, The study therefore recommends that rural development projects in the area should focus on improving farmers' human capital by supporting agricultural training, extension and educational programs, strengthening of the rental land market and that resource management programs should consider targeting credit programs to these households as a strategy for development and productivity improvement as well as for helping farmers to undertake the initial investments to adopt soil conservation techniques.

Oyekale [8] analyzed the intensive land use and efficiency of food production in south western Nigeria. Data were collected from random selection of 303 farmers in Osun, Oyo and Ekiti states. Indices of agricultural intensification showed Osun State farmers to be the highest with respect to land use intensity, fertilizer intensity and crop diversification. Result of Stochastic production frontier shows that farmers in the study area were grossly inefficient with average technical efficiency of 24.78%. The parameters of chemical fertilizer and land area were statistically significant (P=.01) with land area having the highest elasticity of 0.625. The study therefore recommends farmers' increased access to effective soil conservation technologies in order to increase food production efficiency in the face of land degradation.

Mugonola et al. [9] carried out a study on Soil and water conservation (SWC) technologies and technical efficiency (TE) in banana production in upper Rwizi micro-catchment, Uganda. Data for the study were collected from 246 randomly selected smallholder banana farmers. A Cobb-Douglas stochastic production frontier and a probit selection model fitted to generate inverse Mills ratios for adopters and non-adopters were used in the analysis. On average, the adopters of SWC technologies were found to own more land and livestock and to obtain more output per unit of land than their non-adopter counterparts. In addition, adopters exhibit higher average TE than non-adopters. Banana production technology in the study area exhibits decreasing returns to scale, and determinants of TE (P=.05) include education, adoption of SWC and distance to markets. Smallholder farmers who adopted SWC technologies in the study area attain higher productivity. The study therefore recommends promotion of SWC, improved level of education and improved market access.

Studies have been carried out on soil conservation and technical efficiency, most of whom did not identify the land management practices by the farmers let alone their effects on efficiency [7,9] while most of those who did in Nigeria have used production frontier and were carried out in southern part of the country [6,8] this study made use of Data Envelopment Analysis and was carried out in the North Central part of the country.

2. MATERIALS AND METHODS

2.1 Area of Study

The study was carried out in the North Central Nigeria which serves as a gateway between the Northern and Southern part of the Country. The selection of the study area was based on the criteria that the area is prone to nutrient mining as a result of intensive cultivation practices. The zone comprises Kwara, Kogi, Niger, Benue, Nassarawa, Plateau States and the Federal Capital Territory (FCT) representing about 13% of the land mass in the country [10], with an estimated population of 20,266,257 [11]. The zone is located between Latitude 11° 07 and 13° 22 North and Longitude 06° 52 and 09° 22 East of Greenwich meridian. Two seasons can be distinguished – the rainy season from May to September/October and a long dry season from October to May. Temperature during the rainy period is between 27.0-34.0℃ (maximum) and 18.0-21.0℃ (minimum). Soil in the zone have sandy loam to clay loam textured topsoil with a pH of 5 to 7 and an organic carbon content ranging between 0.5 and 1.5%. The soil properties are leached ferruginous tropical soil, the surface soil is reddish fine loam clay to sandy loam. Among the states in the zone, two states were randomly selected namely Benue and Kogi states.

2.2 Sampling Technique and Data Collection Method

The study population was crop farmers living in the study area; the data used were collected from the 2012 production season. A multistage sampling technique was used in the study. The first stage was the selection of Benue and Kogi states from the states in the North Central geopolitical zone; the second stage was the random selection of four (4) local government areas from each of the states, the third stage was the random selection of twelve (12) communities/ villages from each of the states, with the number of communities/villages selected from each local government based on probability proportion to the number of communities/villages in each local government. The last stage was the proportionate selection of the farmers from the selected villages/communities. A total of 400 questionnaire were administered with only 345 returned with useful information that could be used for the analysis.

To estimate the effects of different land management practices on technical efficiency, this was achieved using Data Envelopment Analysis (DEA) which involves the use linear programming methods to construct a non-parametric piecewise surface (or frontier) over the data, so as to be able to calculate efficiencies

Table 1. Sampling procedure for the selection of farmers

States	LGAs	Communities	Number of questionnaire administered	Number of questionnaire retrieved
Benue	Buruku	Abwa, Biliji, Mbatsaase and Mbaya	66	53
	Oju	Obotu Ororu-Ainu, Okpoma Ainu, Oyinyi Iyeche and Uchuo	66	52
	Otukpo	Otukpo icho and Okete	34	29
	Ushongo	Sati Ikov and Bilaja Ikom	34	27
Kogi	Adavi	Edavi Eba, Inoziogolo and Osara	50	48
	Bassa	Gbokolo, Oguma and Sheria	50	44
	Igalamela	Akpanya, Amaka and Ogboligbo	50	45
	Yagba East	Ilafin Ishanlu, Itedo Ishanlu and Mopo	50	47

Source: Field survey 2013

relative to this surface. The three principal options are: First, Standard Constant Return to Scale (CRS) and Variable Return to Scale (VRS) DEA model that involves the calculation of the technical and scale efficiencies (where applicable). Second, the extension of the above models to account for cost and allocative efficiencies. Third, application of Malmquist DEA methods to panel data to calculate indices of total factor productivity (TFP) change; technical efficiency change; and scale efficiency change. All the methods are available in either an input or an output orientation (with the exception of the cost efficiencies option).

According to [12], the constant returns to scale (CRS) DEA model is only appropriate when the farm is operating at an optimal scale. Some factors such as imperfect competition, constraints on finance, etc. may cause the firm to be not operating at an optimal level in practice. To allow for this possibility, [13] introduced the variable returns to scale (VRS) DEA model. Therefore, technical efficiency in this study was estimated using the input-oriented variable returns to scale (VRS) DEA model. Following [12,14,15], the VRS model is discussed below.

Let us assume there are data available on K inputs and M outputs in each of the N decision units (i.e., farms). Input and output vectors are represented by the vectors xi and yi, respectively for the i-th farm. The data for all farms may be denoted by the K x N input matrix (X) and M x N output matrix (Y). The envelopment form of the input-oriented VRS DEA model is specified as:

$$\begin{aligned} &\text{Min}_{\theta,\lambda} \quad \theta \\ &\text{St} \quad -y + Y\lambda \geq 0 \\ &\theta X_i - X\lambda \geq 0 \\ &N1'\lambda = 1 \\ &\lambda \geq 0 \end{aligned} \tag{1}$$

Where θ is the input technical efficiency (TE) score having a value $0 \leq \theta \leq 1$. If the θ value is equal to one, indicating the region is on the frontier, the vector λ is an *N* x1 vector of weights which defines the linear combination of the peers of the i-th farm. Thus, the linear programming problem needs to be solved *N* times and a value of θ is provided for each farm in the sample.

Because the VRS DEA is more flexible and envelops the data in a tighter way than the CRS DEA, the VRS TE score is equal to or greater than the CRS or 'overall' TE score. The relationship can be used to measure scale efficiency (SE) of the i-th farm as:

$$SE_i = \frac{TE_{iCRS}}{TE_{iVRS}} \tag{2}$$

Where SE = 1 implies scale efficiency or CRS and SE <1 indicates scale inefficiency. However, scale inefficiency can be due to the existence of either increasing or decreasing returns to scale. This may be determined by calculating an additional DEA problem with non-increasing returns to scale (NIRS) imposed. This can be conducted by changing the DEA model in equation (1) by replacing the $N1'\lambda=1$ restriction with $N1'\lambda\leq1$. The NIRS DEA model is specified as:

$$\begin{aligned} &\text{Min}_{\theta,\lambda} \quad \theta \\ &\text{St} \quad -y + Y\lambda \geq 0 \\ &\theta X_i - X\lambda \geq 0 \\ &N1'\lambda \leq 1 \\ &\lambda \geq 0 \end{aligned} \tag{3}$$

If the NIRS TE score is unequal to the VRS TE score, it indicates that increasing returns to scale exist for that region. If they are equal, then decreasing returns to scale apply.

DEA is a relative measure of efficiency where the general problem is given as:

$$\text{Max } Z = \frac{\sum_{j=1}^{n} U_{kj} Y_{rj}}{\sum_{j=1}^{m} V_{ij} X_{ij}} \tag{4}$$

Subject to**:**

$$\frac{\sum_{j=1}^{n} U_{kj} Y_{kj}}{\sum_{j=1}^{m} V_{ij} X_{ij}} \leq 1 \tag{5}$$

and

$$U_{kj}, V_{ij} \geq 0 \tag{6}$$

Where

Z is the technical efficiency
Y_{kj} is output k produced by decision-maker j
X_{ij} is input I used by decision-maker j,

U_{kj} and V_{ij} are output and input weights respectively

The dependent variable according to [6] is

Y = total crop output in grain equivalent

While the independent variables in line with [16-18] are:

Production factors

X_1=Farm size (ha)
X_2=Family labor (man days)
X_3=Hired labor (man days)
X_4= Quantity of inorganic fertilizer (kg)
X_5=Cost of planting materials (Naira)
X_6= Quantity of manure (Kg)
X_7= Quantity of agrochemicals (Lt)

In order to examine the effects of farm-specific and land management factors on farm inefficiency, a regression model was estimated where the level of inefficiency obtained by deducting the level of efficiency from one is expressed as a function of these factors. However, as indicated in [19], the efficiency scores from DEA are limited to values between 0 and 1. That is, farmers who achieved Pareto efficiency always have an efficiency score of 0. Thus, the dependent variable in the regression equation cannot be expected to have a normal distribution. This suggests that the ordinary least squares regression is not appropriate as it will give biased parameter estimate. Because of this, Tobit estimation, as mentioned in [20], was used in this study. The model can be estimated as:

$$y_i^* = \beta x_i + u_i, u_i \sim N(0, \sigma^2) \quad (7)$$

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \quad (8)$$

The efficiency factor can be estimated as follow:

$$E=\beta o + \beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \beta_4 Z_4 + \beta_5 Z_5 + \ldots\ldots\ldots\ldots\ldots + \beta_{15} Z_{15} + e \quad (9)$$

E= inefficiency index

β =Unknown parameter vector associated with farm specific attribute

Z= Vector of independent variable related to farm specific and land management attributes

e= is an independently distributed error term assumed to be normally distributed with zero mean and constant variance, σ2.

Inefficiency factors in line with [16-18] are:

Z_1=Level of education (years)
Z_2=Household size (number)
Z_3=Farming experience (years)
Z_4=Age (years)
Z_5=Farm size (ha)
Z_6=Crop diversification (number)
Z_7=Extension contact (number)
Z_8=Gender
$X_{9\,=}$ Alley cropping (dummy)
$X_{10\,=}$ Bush fallow (dummy)
$X_{11\,=}$ Cover crop (dummy)
$X_{12\,=}$ Crop rotation (dummy)
$X_{13\,=}$ Inorganic fertilizer (dummy)
$X_{14\,=}$ Mulching (dummy)
$X_{15\,=}$ Organic manure (dummy)

3. RESULTS AND DISCUSSION

3.1 Technical Efficiency Estimate in the Study Area

The Data envelopment analysis which is a non-parametric linear programming approach to frontier estimation was used using software DEAP 2.1.

3.1.1 Technical efficiency distribution of respondents

The distribution of the efficiency score among the farms is uniform, i.e. it's about the mean and is as shown in Table 2.

Employing DEA under constant returns to scale (CRS) and variable returns to scale (VRS) models, technical efficiency and scale efficiency for each farm was estimated. The summary statistics for technical efficiency under constant returns to scale (CRS), technical efficiency under variable returns to scale (VRS) and scale efficiency were presented in Table 2. The mean technical efficiency (CRS), technical efficiency (VRS) and scale efficiency for the farms were 0.549 (54.9%), 0.576 (57.6%) and 0.971 (97.1%) respectively. This result which is close to that of [6] suggests that the farms could potentially reduce input by 45.1 percent and 42.4 percent without altering the output quantities produced. Furthermore, the corresponding mean scale efficiency of 97.1 percent for the farms suggests that by operating on an optimal scale a further decrease in input can be achieved beyond their projected value by as much as 2.9 percent.

In addition, it was observed that 24 farms (6.96%) under CRS assumption were efficient.

However, when the assumption of CRS was relaxed because of market imperfection and credit constraint condition and the VRS model was estimated, the impact on technical efficiency was much evident as the number of efficient farms rose to 42 (12.17%). This improvement in the VRS model was mainly due to the inclusion of scale efficiency, which the CRS model did not take into account [21]. As regards the scale efficiency, majority of the farms (93.04%) were on the efficiency frontier.

3.2 Returns to Scale

This section reports the nature of scale with which the sampled farms operates. This is important because in addition to knowing the number of efficient farms, degree of inefficiency and optimal scale of operation, it is also vital to know how many farms were operating under increasing returns to scale (IRS), decreasing returns to scale (DRS) or constant returns to scale (CRS). Using DEA each farm was evaluated, given its size level to determine its scale measures. This type of analysis according to [21] would be useful to each farm as they could determine the implications for expansion. The number of farms operating under constant, increasing, and decreasing returns to scale was presented in Table 3.

Out of the 345 farms; 23 (6.67%) farms were found to be operating under IRS or sub-optimal scale. This implies that production scale of these farms could be increased by decreasing costs, given that they were performing below optimum. On the other hand, no farm was operating under DRS or supra-optimal scale that is the farms were operating above the optimum scale, suggesting that these farms could increase their technical efficiency by reducing their production levels. While 322 (93.33%) were found to be operating with CRS or optimal scale (Table 3). Given that majority of the farms were operating under CRS suggests that farms in general were scale efficient. Although in the short run, farms may operate with increasing returns to scale (IRS) or decreasing returns to scale (DRS). In the long run however, farms must shift towards constant returns to scale (CRS) to be efficient in order to achieve the desired increase in production. For the inefficient farms, the causes of inefficiency may be either due to inappropriate scale or misallocation of resources. Inappropriate scale suggests that the farm is not taking advantage of economies of scale, while misallocation of resources refers to inefficient input combinations. In this study, scale efficiencies are relatively high. Therefore, inefficiencies are mainly due to improper input use.

3.3 Output and Input Slacks

The output slack was found to be zero for all the farms. This result indicates that, given the present scale of operation and the available resources, the farmers could not do anything to increase their output levels beyond the present values irrespective of the adjustment in their input levels because of resource fixity. The mean input slacks and excess input use percentages were presented in Table 4. Since a slack indicates excess of an input, a farm can reduce its expenditure on an input by the amount of slack without reducing its output. The greatest slacks were in cost of planting materials, quantity of manure, family labour, quantity of agrochemical and hired labour use. Previous studies that have found excess use of such input such as planting materials, family labour, hired labour, fertilizer include [20,22].

Table 2. Frequency distribution of technical efficiency of farming households in the study area

Efficiency score	CRSTE	VRSTE	SE
0.000 – 0.099	23(6.67)	21(6.09)	2(0.58)
0.100 – 0.1990	36(10.43)	33(9.57)	2(0.58)
0.200 – 0.299	36(10.43)	34(9.85)	3(0.87)
0.300 – 0.399	22(6.38)	21(6.09)	2(0.58)
0.400 – 0.499	33(9.57)	31(8.99)	2(0.58)
0.500 – 0.599	38(11.01)	38(11.01)	-
0.600 – 0.699	36(10.43)	35(10.14)	1(0.29)
0.700 – 0.799	31(8.99)	27(7.83)	4(1.16)
0.800 – 0.899	28(8.12)	27(7.83)	2(0.58)
0.900 – 0.999	38(11.01)	36(10.43)	6(1.74)
1.000	24(6.96)	42(12.17)	321(93.04)
Total	345(100)	345(100)	345(100)
Mean	0.549(54.90)	0.576(57.60)	0.971(97.10)

Figures in parentheses are percentages; Source: DEA estimate from field survey, 2013

Table 3. Distribution of farms according to returns to scale

Farms	Types of return			
	IRS	CRS	DRS	Total
	23	322	0	345

Source: Generated from DEA result

3.4 Determinants of Technical Inefficiency in the Study Area

In the context of policy implications, it is more important to determine what influences efficiency/inefficiency (or to which variables it is related) than simply to measure it. Hence, the DEA scores were regressed on farm specific characteristics and land management variables using the Tobit model in STATA Version 11 software. Limited dependent variables (scores of DEA are bounded by 0 and 1) were used instead of the usual regression system. Since the parameter estimation of the Tobit model is usually done by maximum likelihood, it provides consistent and asymptotically efficient estimators for parameters and variance [22].

The result in Table 5 shows the estimate from the two-limit Tobit regression of selected socio-economic and land management factors against predicted technical efficiency scores. The model was correctly estimated since the model chi-square was 426.89 and it was strongly significant at P=.10 level. In addition, the pseudo R^2 was 87.5%, against the recommended level of 20% [23]. Thus it is evident that the explanatory variables chosen for the model were able to explain 87.5% of the variations in technical inefficiency levels. Among the selected variables, eleven were found to have a significant contribution to technical inefficiency namely: numbers of years of formal education, age, farm size, crop diversification, extension contact, practicing alley cropping, bush fallowing, cover cropping, crop rotation, mulching and the use of inorganic fertilizer.

The coefficient of level of education was negatively related to inefficiency and significant at P=.10 level of significance. A year increase in the number of years of education brings about a .31% reduction in technical inefficiency. The implication of this is that inefficiency of resource use in the study area decreases with the level of education. The likely implication of this is that the more educated a household head is, the more attention he/she pays to effective management of their farms. Presumably, due to their enhanced ability to acquire technical knowledge, which makes them closer to the frontier output. Besides, farmers who had some level of education respond readily to the use of improved technology, such as application of fertilizers, use of pesticides and improved planting materials, thus producing closer to the frontier. The negative coefficient agrees with the findings of [24-26]. The coefficient of crop diversification was negative and significant at P=.10 level implying its negative contribution to technical inefficiency of farmers. The implication is that increase in the number of crops grown in a farm unit and could lead to decrease in the technical in-efficiency of food crop farmers in the area and hence an increase in the technical efficiency of the farmers. The negative coefficient is in line with [8].

Age of the household head showed a negative effect on technical inefficiency and it was significant at P=.01 level. The results revealed that an increase in the farmer's age by one year reduced the level of technical inefficiency by 1%. This means that older farmers were more technically efficient in production than their younger counterparts, this is consistent with findings by [24,26,27]. This will mean to say that older farmers are more familiar with the technologies in agricultural production than the younger ones. Farm size was found to have a negative effect on technical inefficiency and it was significant at P=.01 level. According to the results, an increase in the size of the farm by a

Table 4. Input slacks

Inputs	Mean slack	Mean input use	Excess input use (%)
Farm size	0.000	2.166	-
Family labour	7.646	70.689	10.816
Hired labour	1.258	99.122	1.269
Fertilizer	0.000	192.964	-
Planting materials	60.795	28675	21.201
Manure	10.936	87.667	12.474
Agrochemicals	1.558	10.712	14.544

Source: Computed from field survey 2013 hectare reduces farm technical inefficiency by 2.53%. This implied that farmers with large farm sizes enjoy economies of scale which translate to increased production efficiency. The negative coefficient disagrees with the findings of [23] and [24]. The coefficient of access to extension was found to be positive and significant at P=.05, implying that a unit increase in access to extension contact decreases efficiency by 6.15%. This negates apriori expectation but could be attributed to low level contact with extension personnels. The positive coefficient contradicts the findings of [25].

Table 5. Results of Tobit model for the determinants of technical inefficiency

Variables	Coefficient	T-value
Education (X_1)	-.0031	-1.75*
Household size (X_2)	-.0003	-0.11
Farming experience (X_3)	-.0007	-0.64
Age of household head (X_4)	-.0042	-3.36***
Farm size (X_5)	-.0253	-4.30***
Crop diversification (X_6)	-.1642	-6.37***
Extension contact (X_7)	.0615	2.39**
Gender (X_8)	-.0108	-0.50
Alley cropping (X_9)	-.7130	-16.62***
Bush fallow (X_{10})	-.5456	-13.51***
Cover crop (X_{11})	-.4956	-12.52***
Crop rotation (X_{12})	-.4122	-10.27***
Inorganic fertilizer (X_{13})	-.2811	-7.05***
Mulching (X_{14})	-.0993	-2.77***
Constant	1.3302	26.43
Sigma	.1669	
Log Likelihood		126.13945
Number of observations		345
LR chi2(14)		426.89
Pseudo R^2		0.8749
Prob > chi2		0.0000

, **, * Is significant at 10, 5 and 1%, respectively*
Source: Computed from survey data 2013

The estimated coefficient of Land management practices viz; alley cropping, bush fallowing, cover cropping, crop rotation, mulching and the use of inorganic fertilizer were all negative but significant at P=.01. The result implies that technical efficiency increases with the use the aforementioned land management practices relative to organic manure by the farming households. The result further shows that the current level of land management practices used by the farming households is sustainable with respect to the output of crop produced. The negative coefficient tallies with the findings of [20,4]. However, the estimated co-efficient of household size, farming experience and gender although negatively signed were not significant. The negative relationship between these variables and technical inefficiency of the farming household head shows the importance of these inputs in increasing the level of output in the study area.

4. CONCLUSION, POLICY IMPLICATION OF FINDINGS AND RECOMMENDATIONS

The study revealed that food crop farmers are yet to achieve their best, as shown by their relatively low technical efficiency (TE) value, meaning that there is room for improving their technical efficiency substantially, thus, calling for critical examination of TE, as a means of examining the role higher efficiency level can have on agricultural output, especially in the study area.

- Reported slacks in input usage implies inefficiency which indicates wrong combination of these inputs, it is therefore suggested that training programs should be available to all farmers in order to improve their knowledge and hence ensure appropriate combination of inputs.
- The study also revealed that education contributes to efficiency in resource use in the study area. Therefore, improvement in the farmers' level of education through adult literacy programme will definitely raise farmers efficiency and hence their income.
- Policy against land fragmentation needs to be formulated as large farm size was found to reduce inefficiency in the area.
- Negative coefficient in respect of land management practices call for the need to further sensitize farmers on the importance of adopting sustainable land management practices as this would help reduce technical inefficiency.

COMPETING INTERESTS

Author has declared that no competing interests exist.

REFERENCES

1. Cornia GA, Farm size, land yields and the agricultural production function: An analysis for fifteen developing countries. World Development. 1985;13(4):513-34.
2. Sanchez PA, Leakay RRB. Land use transformation in Africa: Three

determinants for balancing food security with natural resource utilization. European Journal of Agronomy. 1997;7(1):15-23.
3. Diao X, Hazel P, Thurlow J. The role of agriculture in African development. World Development. 2010;38(10):1375-83.
4. Bojo J. The cost of land degradation in Sub-Saharan Africa. Ecological Economics. 1996;16:161-73.
5. Mbaga-Semgawale Z, Folmer H. Household adoption behaviour of improved soil conservation: The case of North Pare and West Usambara Mountains of Tanzania. Land Use Policy. 2000;17(4): 321-36.
6. Awoyinka YA, Akinwumi JA, Okoruwa VO, Oni AO. Effects of livelihood strategies and sustainable land management practices on food crop production efficiency in South Western Nigeria. Agricultural Journal 2009;4(3):135-143.
7. Solis D, Bravo-Ureta B, Quiroga RE. The effect of soil conservation on technical efficiency: Evidence from Central America. Selected paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California, July 23-26; 2006.
8. Oyekale AS. Intensive land use and efficiency of food production in South West Nigeria. Agricultural Journal. 2007;2(2): 174-179.
9. Mugonola B, Vranken L, Maertens M, Deckers J, Taylor DB, Bonabana-Wabbi J, Mathijs E. Soil and water conservation technologies and technical efficiency in banana production in upper Rwizi micro-catchment, Uganda. African Journal of Agricultural and Resource Economics. 2013;8(1):13-29.
10. Manyong VM, Makinde KO, Sanginga N, Vanlauwe B, Diels J. Fertilizer use and definition of farmer domain for impact oriented research in the Northern Guinea Savanna of Nigeria. Nutr. Cycl. Agro Eecosyst. 2001;59:129-141.
11. NPC. National Population Commission (Nigeria): Report on the Survey of Demographic and Health survey; 2006.
12. Coelli TJ, Rao DSP, Battese GE. An introduction to efficiency and productivity analysis. 2nd edition. Kluwer, Boston; 1998.
13. Banker RD, Charnes A, Cooper WW. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science. 1984; 30(9):1078-1092.
14. Fare R, Grosskopf S, Lovell CAK. The Measurement of efficiency of production. Kluwer Academic Publishers, Boston; 1985.
15. Sharma KR, Leung P-S, Zaleski HM. 'Technical, allocative and economic efficiencies in swine production in Hawaii: A comparison of parametric and nonparametric approaches'. Agricultural Economics. 1999;20(1):23-35.
16. Ashaolu OF, Momoh S, Ayinde IA, Ugalahi UB. Analysis of resource-use efficiency in beniseed production in Obi and Doma local Government areas of Nassarawa State, Nigeria. Journal of Humanities, Social Sciences and Creative Arts. 2010;5(1): 79-90.
17. Okon UE, Enete AA, Bassey NE. Technical efficiency and its determinants in garden egg (*Solanum Spp*) production in Uyo Metropolis, Akwa Ibom State, Nigeria. Field Actions Science Report. 2010;1-6.
18. Simonyan JB, Olukosi JO, Omolehin RA, Atala TKA. Productivity and technical efficiency among beneficiary farmers of second national fadama project in Kaduna State, Nigeria. American Journal of Experimental Agriculture. 2012;2(1):102-110.
19. Dhungana BR, Nuthall PL, Nartea GV. Measuring the economic inefficiency of nepalese rice farms using data envelopment analysis. The Australian Journal of Agricultural and Resource Economics. 2000;48(2):347-369.
20. Ogunniyi LT, Oladejo JA. Technical efficiency of tomato production in Oyo State Nigeria. Agricultural Science Research Journal. 2011;1(4):84-91. Available:http://www.resjournals.com/arj ISSN-L: 2026-6073 ©2011 International Research Journals.
21. Abu O. Fertilizer usage and technical efficiency of Rice farms under tropical conditions: A Data Envelopment Analysis (DEA). Journal of Agric Science. 2011; 2(2):83-87.
22. Koc B, Gul M, Parlakay O. Determination of technical efficiency in second crop maize growing farms in Turkey: A Case study for the east mediterranean in Turkey. Asian Journal of Animal and Veterinary Advances. 2011;6:488-498.
23. Sibiko KW, Owuor G, Birachi E, Gido EO, Ayuya OI, Mwangi JK. Analysis of determinants of productivity and technical efficiency among smallholder common

bean farmers in Eastern Uganda. Current Research Journal of Economic Theory. 2013;5(3):44-55.
24. Ogunyinka AI, Bifarin JO. Farm size and the determinants of productive efficiency among rice farmers in Ekiti State. Journal of Applied Agricultural Research. 2012; 4(1):17-24.
25. Tijani AI, Okoruwa VO, Shittu AM. Determinants of cost inefficiency among small holding Plantain producers: A decomposed error term approach. Journal of Applied Agricultural Research. 2012; 4(2):15-24.
26. Wakili AM. Technical efficiency of maize farmers in Gombi local government of Adamawa State, Nigeria. Agricultural Journal. 2012;7(1):1-4.
27. Akinbode SO, Dipeolu AO, Ibrahim DA. Effect of disease burden on technical efficiency among lowland rice farming households in North Central Nigeria. World Journal of Agricultural sciences. 2011;7(3): 359-367.

Peer-review history:
The peer review history for this paper can be accessed here:
http://sciencedomain.org/review-history/13789