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Data evelopment analysis of the technical efficiency of maize-based agroforestry system in Oyo state, Nigeria

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Abstract

This study applied Data Envelopment Analysis (DEA) model to estimate technical efficiency of maize-based agroforestry farmers using the assumption of variable returns to scale (VRS) and input-orientation. A total of one hundred and fifty copies of questionnaire were randomly administered on the respondents through a multi-stage random sampling technique. Both descriptive and inferential statistics were used to analyze the data. The descriptive statistics used were frequency tables, percentages and mean, while the inferential statistic used was DEA and ordinary Least Square (OLS) Regression. The DEA was used to determine the technical efficiency of the farmers while the OLS was used to ascertain the factors that influenced technical efficiency of the farmers. The result showed the mean technical efficiency to be 69%. This is an indication that maize-based agroforestry farmers were operating at 69% level of technical efficiency. This implies that total inputs could be reduced by 31% while still maintaining existing level of output. The results of the return to scale also revealed that increasing return to scale (IRS) is the dominant form of return to scale, having the highest percentage of 57.33 compared to constant return to scale (CRS) and decreasing return to scale (DRS) which had percentages of 17.33 and 25.33 respectively. In addition, the estimates of the OLS regression show that educational qualification of the farmers, farming experience; age of the farmer and access to extension services had positive and significant relationship with the technical efficiency of the farmers while farm size had negative and significant relationship with their technical efficiency.

Key words: Technical efficiency, return to scale, agroforestry, maize, Oyo State

Introduction

Maize (*Zea mays* L.) is the world's highest supplier of calorie with caloric supply of about 19.5%. It provides more calorie than rice (16.5%) and wheat (15.0%). Maize is one of the most important staple foods in the world today; maize, rice and wheat combine to supply more than 50% of global caloric intake (World Atlas, 2017). Maize is the most important food in Nigeria and it has grown to be local 'cash crop' most especially in the southwestern part of Nigeria where at least 30% of the crop land has been devoted to small-scale maize production under various cropping systems (Ayeni, 1991).

Introduced in Nigeria in the 16th century, maize is the fourth most consumed cereal, ranking below sorghum, millet and rice (FAOSTAT, 2015). It is the third most important cereal after sorghum and millet (Juma, 2010). It has been recognized to be one of the longest ever cultivated food crops. Maize is also grown in several regions of the world and is referred to as the world best adapted crop (IITA, 2008). In Nigeria, the demand for maize is increasing at a faster rate daily (Sadiq et al., 2013). This may be due to the fact that the grain is being used for feeding poultry and also serve as the main food for many households (Ogunniyi, 2011). According to Ogunsumi et al. (2005), growing maize by small-scale farmers can overcome hunger in the households and the aggregate effect could double food production in Africa. Food and Agricultural Organization also asserted that about 4.7 million tonnes of maize were produced on the average between 1990 and 2015 in Nigeria and the contribution of maize to total grains produced in Nigeria increased from 8.7% in 1980 to about 22% in 2003. About 561, 397, 29 hectares of Nigerian land were planted with maize, which constitutes about 61% of total cultivable land in Nigeria. Furthermore, the FAO in 2017 reported that Nigeria produced 10.7 and 10.5 Million metric tons of maize respectively in 2015 and 2016/2017, while the consumption of maize in Nigeria in 2017, according to the Mundi Index (2018), stood at 10.9 million metric tons. Uses of maize alone or in combination with other food material as staple food or snacks in Nigeria included but are not limited to kunu, akamu, ogi (in hot and cold forms), tuwo, donkunnu, maasa, couscous, akple, gwate, nakia, egbo, abari, donkwa, ajepasi, aadun, kokoro, elekute (Olaniyan, 2015).

In Oyo State, particularly areas outside Ibadan Metropolis, maize is cultivated under a system where it is planted with others crops like cassava, yam, and cocoyam in between trees. This system of farming is therefore called agroforestry system. Agroforestry is a land use management system in which woody perennials are grown with food crops and/or livestock leading to many beneficial, ecological and economic interactions between trees and non-trees components. It is one of methods designed to create a climate-smart agriculture, increase food security, alleviate rural poverty and achieve a truly sustainable development (Garrity & Stapleton, 2011). Agroforestry supports food and nutrition through the direct provision of food, by raising farmers' income, providing fuel for cooking and through various ecosystem services (Dawson et al, 2013).

Despite the tremendous importance and the various uses of maize in Nigeria and Oyo State in particular, there are still very few studies conducted on efficiency of maize production in Nigeria and none was found to have used Data Envelopment Analysis (DEA) approach to evaluate the efficiency of maize production under an agroforestry system. However DEA application has recently been popularized in the estimation of efficiency in agriculture. Few of such studies in developing countries include those by Coelli et al. (2002) who adopted DEA method to analyse the technical efficiency, allocative efficiency, economic efficiency and scale efficiency of rice cultivation in Bangladesh; Murthy et al. (2009) used DEA to study the technical efficiency and scale efficiency of tomato farmers in Karnataka, India; Javed et al. (2010) used DEA to measure the technical efficiency of rice-wheat system in Punjab region of Pakistan; Ogunniyi & Oladejo (2011) employed DEA methodology in the estimation of technical efficiency of tomato production in Nigeria; Koc et al. (2011) determined the technical efficiency of second maize crop growing farms in East Mediterranean in Turkey; Dube & Guveya (2012) studied the technical efficiency of Smallholder Out-grower Tea Farming in Chipinge District of Zimbabwe using DEA technique; Baležentis (2012) applied DEA to estimate technical efficiency and expansion of Lithuanian family farms; using DEA; Nan Wutyi et al. (2013) analysed farm level technical efficiency and socioeconomic determinants of rain-fed rice production in Myanmar; Iliyasu & Mohamed (2016) used two-stage DEA in evaluation of contextual factors influencing the technical efficiency of fresh water pond culture systems in Peninsular Malaysia.

This study therefore made use of DEA technique to estimate technical efficiency under the assumptions of constant returns to scale (CRS) and variable returns to scale (VRS). Fare et al. (1985) highlighted that the CRS assumption requires that every increase in input will result in a proportional output increase and this measure of efficiency is also known as a measure of overall technical efficiency as it will include both controllable and non-controllable sources of inefficiency. In contrast, VRS incorporates scale inefficiencies and assumes output will not proportionally increase with an increase in inputs and as a result, the estimated production frontier envelopes the data points tighter than under the assumption of CRS. This measure is also known as a measure of pure technical efficiency and does not attribute inefficiencies to differences in scale (Fare et al., 1985). As the VRS assumption advocates that not all farms are operating at optimum scale and the assumption of CRS states that farmers are scale efficient. This implies that if there is a difference in efficiency under both assumptions (CRS and VRS), then scale inefficiencies exist.

Coelli et al. (1998, 2005) describes Scale efficiency as an indication of the quantity by which productivity may possibly increase by moving to a point of technically optimal scale. This is because an enterprise may be technically efficient but not scale efficient. If, for instance, a farm is experiencing increasing returns to scale (IRS), this indicates that the farm is sub-optimum in terms of its scale and if a change in inputs is less than the change in output then productivity should increase by increasing the size of operation. Decreasing returns to scale (DRS) elucidates that the farm is supra-optimum, stressing that the productivity of these producers may potentially increase by reducing the scale of operation. In a situation where productivity of the farm cannot be increased by varying its scale and every increasing in resources lead to a proportional increase in output then the farmer is operating at CRS (optimum scale). Therefore, changing the scale cannot improve productivity (Kelly et al., 2012).

Theoretical Framework on efficiency

The theoretical framework on efficiency by Farell (1957), Battesse (1992) and Coelli (1996) is graphically illustrated in the Figure 1 below. An input orientated production process with two inputs (X_1 and X_2) and one fixed output was considered by Farrell (1957). Fully efficient farms are represented by the isoquant curve SS* that shows technical efficiency.

Technical Efficiency = OZ/OK (1)

Allocative Efficiency = OA/OZ* (2)

Economic Efficiency = OZ/OK X OA/OZ= OA/OK (3)

Z represents technically efficient farm (any point on SS*) and Z* is an allocatively efficient farm (Slope = ratio of price of X_1 and X_2). LL* signifies the isocost line (where SS* is tangential to isocost line). For instance, farm K has a level of inefficiency equal to the distance QK which is the quantity by which all inputs could be proportionally reduced without decreasing output quantity, because it is not operating on the isoquant curve SS*. Therefore, ZK/OK is a ratio that represents the reduction required in all inputs to attain technical efficiency. Thus, allocative efficiency and economic efficiency of farm P can be measured by the ratios included in Figure 1. An efficient farm is indicated by score of 1 and a measure of inefficiency is 1 the relative efficiency value or the distance from the inefficient point to the frontier.

This study therefore focuses on the cultivation of maize under agroforestry system in Oyo State. The main objective of the study is to assess the economics of maize production in the study area. Specific objectives include examining the socioeconomic characteristics of maize farmers in the area as well as investigating the efficiency of farmers involved in maize production through the use of Data Envelopment Analysis (DEA) approach.

Methodology

Study Area

The study was carried out in Oyo State, Nigeria. The state is one of the six (6) states in southwest geopolitical zone of Nigeria. It has an equatorial climate with dry and wet seasons and relatively high humidity. The study population comprised arable farmers who engaged in crops such as maize, sorghum, cassava, cocoyam and yam production.

Sources of Data, Method of Data Collection and Sampling Technique

Both primary and secondary data were used for this study. Primary data was collected with the aid of structured questionnaire from farmers in the study area. Secondary data and other relevant information were gathered from journals, internet and text books.

A multistage sampling procedure was adopted in this study. The first stage involved random selection of two Agricultural Development Project (ADP) zones from the four ADP zones in the state. The four ADP zones in the state are Shaki, Ogbomoso, Oyo and Ibadan/Ibarapa, with 8, 5, 6 and 14 Local Government Areas respectively. The randomly selected zones were Shaki and Ibadan/Ibarapa zones. The second stage involved the random selection of two LGAs from Shaki zone and three LGAs from Ibadan/Ibarapa zone, being the zone with the largest LGAs. Third stage involved the random selection of three communities each from the LGAs selected, making a total of fifteen (15) communities selected. The last stage involved the random selection of ten (10) respondents from each of the selected communities. In all, one hundred and fifty (150) respondents were selected for the study.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) method was used in this study to obtain efficiency scores of maize production in Oyo State of Nigeria. DEA was decisively used for the analysis of technical efficiency. This is because it has the capability to integrate technical parameters that might not be captured by parametric method of measuring efficiency and its ability of tackling multiple inputs and outputs (Coelli et al., 2005). The efficiency of a firm is calculated based on the Decision Making Units (DMUs) observed best practice (Coelli et al., 2005). Those DMUs lying on the frontier, with a score of 1 are considered as efficient relative to the rest of the samples, whereas those lying below the frontier, with a score of less than 1 are classified as inefficient. All efficiency scores in DEA fall within 0 and 1. Inefficiency level of a DMU is determined by how far this DMU is from the frontier. The further away from the frontier the DMU is, the less efficient it is. DEA essentially measures the excessive use of resources for a given level of output (input orientated) or possible increase in output for an assumed level of resources (output orientated). According to Coelli et al. (2005) both output and input orientated models recognize the same group of efficient and inefficient DMU. Also, as the DEA approach does not acknowledge statistical complications such as simultaneous equation bias, the selection of particular orientation is not as critical as opposed to econometric techniques. Argued by Coelli et al. (2005) that selection of any particular orientation should be based on the quantities over which the farmer has utmost control. Input-oriented method was adopted to calculate technical efficiency in this study. This technique was used because in agricultural production farmers have more control on their inputs than output (Coelli et al., 2005).

According to Coelli et al (1998) and Koc et al (2011), technical efficiency for N decision making units can be evaluated using an input-oriented measure as solution to linear programming:

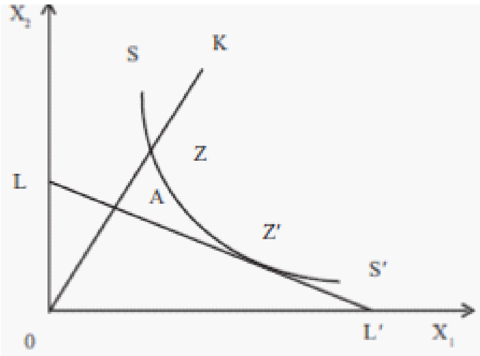

Fig. 1. Input-Oriented Measure for Technical, Allocative and Economic Efficiencies
Source: Farell (1957); Coelli et al. (1998)

Minimize θ, λ^{θ}
Subject to: $-y_i + Y\lambda \geq 0$ (4)
$x_i - X\lambda \geq 0$; $NI' \lambda = 1$; $\lambda \geq 0$

Where x and y denote inputs and output matrices of the DMU to be calculated. θ is the TE score for the ith farm and having a value $0 \leq \theta \leq 1$. According to the Farrell (1957) definition, the value of θ equals 1, implies that the farm is on the frontier (farm is technically efficient); NI' is convexity constraint; the vector λ is an N x1 vector of weights which defines the linear combination of the peers of the ith farm.

It has been observed from previous studies that after the application of DEA technique to estimate technical efficiency in the stage one, most researchers used Tobit regression model to investigate the determinants of technical efficiency in the second-stage. However, since technical efficiency scores are fractional in nature and not generated by a censoring procedure, this approach have been extremely criticized for producing inconsistent estimation, hence contextually inappropriate (Banker & Natarajan, 2008). It was argued by Banker & Natarajan (2008); McDonald (2009) that the most appropriate method to use in this situation is the application of Ordinary Least Square (OLS) regression technique, which is believed to produce better results in the second stage DEA than using the Tobit regression model. John & Kuosmanen (2012) added that the OLS regression of the DEA-technical efficiency scores on the contextual variables provides a statistically consistent estimator of the coefficients under more general assumptions. Therefore, in order to understand the determinants of technical efficiency, this study agrees with Banker & Natarajan (2008); McDonald (2009); John & Kuosmanen (2012) and Mukhtar et al. (2018). The model is expressed as:

$$Y_{vrs} = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + b_{10}X_{10} + e$$

X_1 = age of the farmer (years)
X_2 = educational level of farmers
X_3 = Farm size = Farm size (hectare)
X_4 = Cooperative membership (member = 1, otherwise = 0)
X_5 = Farming experience (years)
X_6 = contact with extension agent (yes = 1; no=0)
X_7 = Agrochemicals (1 = used agrochemicals,0 = otherwise)
X_8 = Household size (numbers of persons)
X_9 = Access to credit (Access = 1, otherwise = 0)
X_{10} = Quantity of seeds used (Kg/ha)
b_1-b_{10} = parameters to be estimated
b_0 = constant
e = error term

Results and Discussion

Table 1 shows the socioeconomic attributes of the respondents. From the table, it was observed that the average age of the respondents was 49.8 years. This implies that the respondents were still in their active age, and could therefore easily employ adaptation options to adapt to climate change. This is because old age makes it difficult for people to adapt to climate change, because agricultural activities require intensive labour as well as strong and healthy individuals to perform. The results further reveal that the mean household size was 7. The average monthly income of the respondent was N98, 703. Based on this average monthly income of households in the study area, the respondents are believed to have the capacity to adapt to climate change, since the respondents earned average monthly income that is three times more than the current minimum wage of N30, 000. In addition, since income is believed to reflect the achievements of households and their ability to bear risks, households with higher income are believed to be in better position to adapt to climate change. The table further shows that larger proportion (62%) of the respondents engaged in farming as their main occupation. They also engage in other activities as secondary occupation. It was also discovered from the study that 50% of the respondents did not have more than secondary education. Education, however, is essential for the farmers to understand and interpret information as they relate to climate change. This will also enhance their capacity to utilize such information. The average farming experience of the respondents was about 21 years. This is an indication that farmers with high farming experience were more likely to understand the effects of climate change and embark on measures to adapt to climate change than farmers with less farming experience.

Technical Efficiency Estimates

Table 2 shows the results of the input-oriented DEA analysis. The results show the global technical efficiency (GTE), which is the constant return to scale technical efficiency (TECRS).This ranges from 37% to 100%, having a mean of 56%. The local pure technical efficiency, which is the variable return to scale technical efficiency (TEVRS), has a mean of 69% and ranges from 39% to 100. The scale efficiency ranges from 40% to 100% with a mean of 74%.

The result implies that on average, maize-based agroforestry farmers were 31% inefficient. This means that for the farmers to be efficient, they need to reduce the existing usage of inputs in maize production by an average of 31%, and still achieve the same level of output given the existing level of technology. It was also observed from the result that only 10.67% of the respondents were efficient with respect to CRS and 14.67% were also efficient with respect to VRS. This result therefore gives credence to the theory that the VRS frontier is more elastic and envelops the data in a tighter way than the CRS frontier. In addition, the results show that the technical efficiency scores obtained under CRS are either equal to, or less than those calculated under the VRS DEA model. Therefore, from this relationship, we obtain the measure of scale efficiency, as the ratio of the CRS efficiency score to VRS efficiency score. The result therefore showed that a scale inefficiency of 26% may occur due to the fact that farmers were operating at a scale that is 26% below the optimal scale. The assumption of CRS only holds when all farms are operating at an optimal scale. But according to Coelli et al (2005), unfair competition, government regulations, financial constraints etc., may cause a firm not to operate at optimal scale. Therefore the use of CRS specification when not all firms are operating at the optimal scale results in measures of technical efficiency that are confounded by scale efficiency. However, the use of the VRS specification permits the calculation of technical efficiency that is free of these scale efficiency effects.

In addition, for the farms that are inefficient, this could be attributed to either misallocation of resources or inappropriate scale. Inappropriate distribution of resources refers to inefficient input combinations; while the inappropriate scale is an indication that the farm fails to take advantage of economies of scale, according to Alemdar and Oren (2006). However, since we have obtained relatively high scale efficiencies, with a mean score of 74%, it could therefore be deduced that inefficiencies result largely from improper use of resources.

Returns to Scale (RTS)

Table 3 reveals the proportion of maize-based agroforestry farmers that were operating at optimal (CRS), sub-optimal (IRS), and super-optimal (DRS) levels. From the one hundred and fifty sampled farmers, 17.33% were found to be operating at constant return to scale, with 57.33% and 25.33% operating at increasing return to scale and decreasing return to scale respectively.

Table 1. Socio-economic Characteristics of Respondents

Variable	Frequency	Percentage	Mean
Gender			
Male	129	86	
Female	21	14	
Total	**150**	**100**	
Age (Years)			**49.8**
<30	8	5.33	
30-40	19	12.67	
41-50	55	36.67	
51-60	48	32	
>60	20	13.33	
Total	**150**	**100**	
Marital Status			
Single	2	1.3	
Married	145	96.7	
Widowed	3	2.0	
Total	**150**	**100**	
Household Size			**7**
1-5	51	34	
6-10	69	46	
11-15	19	12.67	
Above 15	11	7.13	
Total	**150**	**100**	
Educational Status			
No formal	5	3.33	
Primary	15	10.0	
Secondary	60	40.0	
Tertiary	47	13.33	
Vocational	23	15.55	
Total	**150**	**100**	
Primary Occupation			
Farming	93	62.0	
Artisanship	19	12.67	
Trading	19	12.67	
Civil Service	17	11.33	
Others	2	1.33	
Total	**150**	**100**	
Farming Experience			**21.1**
1-10	21	14.0	
11-20	66	44.0	
21-30	39	26.0	
Above 30	24	16.0	
Total	**150**	**100**	

Source: Field Survey, 2019

Table 2. Distribution of DEA technical efficiency scores

Efficiency Index	TEcrs	TEvrs	SE
≤0.4	25	21	27
0.41-0.50	27	11	16
0.51-0.60	44	30	20
0.61-0.70	10	41	8
0.71-0.80	11	10	23
0.81-0.90	9	7	12
0.91-0.99	8	8	30
1.0	16	22	14
Mean	0.56	0.69	0.74

TEcrs: – Overall Technical Effi ciency Score,, TEvrs: – Pure Technical Efficiency Score, SE: – Scale Efficiency

Table 3. Characteristics of farms with respect to returns to scale scores

Characteristics	No of farmers	% of farmers
IRS	86	57.33
CRS	26	17.33
DRS	38	25.33

IRS = Increasing return to scale
CRS = Constant return to scale
DRS = Decreasing return to scale

Determinants of Technical Efficiency among maize-based Agroforestry Farmers

Table 4 shows factors that influence technical efficiency among maize-based agroforestry farmers in the study area. The factors that were significant at 5% level were age, education, farming experience, farm size and access to extension services. The results revealed that technical efficiency increases significantly with age of the farmers. This implies that older farmers were more technically efficient in their production when compared to younger farmers. This may not be unconnected to the fact that farming experience of a farmer increases with age as well as resources empowerment which usually lead to increase in efficiency. Likewise, the coefficient of access to extension services is significant and positively related to technical efficiency. In other words, an increase in farmers' access to extension services will also lead to an increase in technical efficiency level of such farmers.

In addition the coefficient of farmers' level of education was found to be positively and significantly related to technical efficiency. This implies that farmers with more years of schooling are more technically efficient than farmers with less years of education or no education. It could therefore be inferred that farmers who are educated are expected to have a better understanding of modern technologies and easily implement the technologies. They also tend to have better managerial expertise, and therefore they are likely to be more efficient than uneducated farmers. This corroborates findings by Javed et al. (2010) where they posited that education plays a significant role in farmers understanding and implementation

Table 4. Result of OLS regression model for efficiency scores

Variable	Coefficient	SE	t-value	p-value
Age	1.021	0.418	2.442	0.032*
Household Size	1.765	1.662	1.062	0.101
Agrochemicals	0.549	0.706	0.777	0.295
Education	1.031	0.133	7.752	0.011*
Cooperative	0.108	1.023	0.106	0.637
Farming Experience	2.001	0.402	4.978	0.030*
Access to Credit	1.052	2.077	0.506	0.432
Seed quantity	0.145	0.122	1.189	0.092
Farm Size	-1.201	0.124	-9.685	0.002*
Extension Access	0.334	0.022	15.182	0.007*
Constant	2.887	0.124	23.282	0.000

Source: STATA 12 Outputs

of modern technologies for improved production. Furthermore, the positive and significant coefficient of farming experience shows that as farmer's farming experience increases, their level of technical efficiency also increases. This can therefore be related to the fact that farmers who spent more years in farming, ceteris paribus, are expected to have a better understanding, skills and knowledge of farming practices than those with fewer years and this leads to higher efficiency. This corroborates studies by Lubadde et al. (2016); Iliyasu and Mohamed (2016) and Mukhtar et al. (2018) that increased farming experience enhances the efficiency of farmers.

Findings also showed that the coefficient of farm size was significantly but negatively related to technical efficiency of farmers in the study area. The implication of this is that small farm-sized farmers are more technically efficient than those with larger farm size. The reason for this may not be unrelated to the fact that farmers with small farm holdings tend to use land more judiciously than large farm holding farmers due to the limited land available to them.

Conclusion and Recommendation

This study employed the use of DEA frontier approach to assess the technical efficiency of maize-based agroforestry farmers in Oyo State, Nigeria. Data used for the study was collected through the administration of one hundred and fifty copies of structured questionnaire .The results show that technical efficiency (VRS) was estimated to be 69%, suggesting that maize-based agroforestry farmers in the study area could reduce the existing level of inputs by 31% and can still achieve the same level of output produced. In addition, the regression results also showed that age, education, farming experience, farm size and access to extension services contribute significantly to the variations observed in the technical efficiencies of the farmers. In view of this, it is recommended that extension services should be intensified among the farmers in the study area so as to educate and enlighten the farmers on appropriate and right inputs combination in order to ensure efficiency in their production.

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