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APPLICATION OF DATA ENVELOPMENT ANALYSIS FOR TECHNICAL EFFICIENCY OF SMALLHOLDER PEARL MILLET FARMERS IN KANO STATE, NIGERIA

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Abstract

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In northern Nigeria, pearl millet is a traditional crop, both in terms of production and consumption. However, performance of pearl millet among smallholder farmers has either stagnated or progressed at a very slow pace, placing the average yield for this vital crop at 1-1.5 t/ha as against the potential yields of 2.5-4 t/ha. Low productivity reflects the possibility of inefficiency among farmers. Thus, evaluating differences in technical efficiencies (TEs) of pearl millet cultivating farmers and the sources of technical inefficiencies, the findings of this study are expected to be beneficial to policy makers and pearl millet farmers as well. Using Data Envelopment Analysis (DEA) and Ordinary Least Square (OLS) model, this study aims to investigate the extent of TE and its determinants of 256 randomly selected pearl millet farmers in Kano state, during 2013/2014 period of crop cultivation. Based on input-oriented and VRS, the empirical result indicated that the average value of TE was found to be 81%. This implies that pearl millet farmers operate at 81% level of TE which means total inputs could be saved by 19% without sacrificing any yield if all farmers were efficient as 62 benchmark farmers identified by DEA. The major slacks were in seed, followed by agrochemicals, labour and fertilizer use. The findings relating to return-to-scale in pearl millet farms in the study area showed that the predominant form of scale efficiency is increasing returns-to-scale (69.14%). The result of OLS regression analysis indicates that age of farmers, credit, education, experience; farm size, household size and type of seed planted have a significant and positive effect on the TE of pearl millet production.

Key words: technical efficiency; pearl millet; data envelopment analysis; ordinary least square regression

Introduction

Pearl millet is an annual grass in the family *Panacea* that is believed to have originated from western tropical Africa about 3000 years ago (FAO, 2008). It spreads throughout eastern and southern Africa, some parts of America and Australia. According to Factfish (2014), Pearl millet is known as one of the most essential cereals globally. It is an important staple food crop to about 500 million people in arid and semi-arid zones of Asia and Africa, who utilizes more than 90% global production of the crop. Pearl Millet is known to have health benefits like inhibitive effect on cardio vascular diseases, cancer, and blood pressure (Gupta et al., 2012). Pearl millet is also a good source of green fodder and an energy provider which gives superior nutritional benefits laden with minerals, proteins and vitamins. In the same token the millet straw is one of the most important building materials for granaries and fencing, and also used as feed to cattle

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during the dry season. Reports by United States Department of Agriculture (USDA, 2014) indicated that the current estimated World annual millet production is 29.9 million tons (55% Africa, 43.5% Asian and 1.5% from the other four continents). In Nigeria and particularly in the North-Western region, pearl millet is a traditional crop, both in terms of production and consumption and it is very important staple crop for over 40% of the populace. Nigeria has become increasingly important in the production of the crop, accounting for 14% of average annual global production within the period 1992-1994 as compared to only 9% in the 1979-1981 periods. The average annual millet production in Nigeria during 2005 to 2010 was about 6.28 million tons, which ranked the country as the second largest world millet producer after India. However, reports by Food and Agriculture Organization Corporate Statistical Database (FAOSTAT, 2015) indicated that Nigeria lost its position to Niger, China and Mali during 2011 to 2014, by dropping to 5th position in the World with average annual production of 1.21 million tons, representing only 4.9% of the total world production. Despite its importance in terms of food provision and economic gains, millet in Nigeria is still faced with numerous problems which resulted to low productivity, in spite of an expanding production area. The national average yield per hectare declined from 1.5 tons per hectare in 1981-1985 to 0.45 tons in 2011, 0.96 tons in 2012 and 0.88 in 2014 against the potential of 2.0-3.5 tons/ha (FAOSTAT, 2015).

In addressing this problem of low productivity of pearl millet, various efforts have been made by different governments and NGOs. Yet, this problem lingers, there is still reported unevenness in production between the expected average potential yields of 2.0-3.5 tons/ha and the actual average yields of 1.25 tons/ha. This was very much lesser than the expected yield obtainable in other places, which brings down the country's yield in world ranking to 30th in the 1999-2010 and 60th during the period of 2011-2014 (FAOSTAT, 2015). Since increased productivity has direct correlation with technical efficiency, this low productivity reflected the possibility of inefficiency among pearl millet farmers in the study area. Usually, inefficiency is believed to have stemmed from the use of inadequate, over dependence on unimproved technologies, poor farm management, and poor understanding of efficient agricultural practices. Improved efficiency and productivity influence agriculture and production of food directly by increasing the available source of food and indirectly by raising income of the farmers. Increased productivity through efficiency of farming have been declared by Gallup et al., (1997) as the way to enhance the opportunities of subsistence farmers to produce more, which could subsequently lead to increase in food security and income levels of the farmers in particular and the country in general. In this light, the present study is therefore conducted to analyze the TE of pearl millet production in North-western Nigeria.

Literature Review

Generally, relative efficiency indices are estimated using two common methods. These are the parametric or stochastic frontier analysis (SFA) and the nonparametric or data envelopment analysis (DEA). SFA undertakes a functional relationship between inputs and outputs, and it employs statistical techniques to estimate parameters of the production function. According to Coelli (1995), one distinguished feature associated with the stochastic model specification of SFA is that, it permits for hypothesis testing. However, the downside of SFA technique is that it imposes specific assumptions on both the functional form of the frontier and the distribution of the error term. Unlike SFA, DEA uses linear programming techniques to construct a piecewise frontier of the data. Being a nonparametric in nature, DEA does not need any assumptions about functional form or distribution type, and therefore attributes all deviations from production frontier to inefficiency, because it is deterministic in nature (Coelli, 1995). DEA approach places less structure on the shape of an efficient frontier, which is considered as a remarkable feature of nonparametric frontier techniques over parametric measures.

This study made use of DEA models to calculate TE under the assumption of constant returns to scale (CRS) and variable returns to scale (VRS). Färe 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 TE 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 TE and does not attribute inefficiencies to differences in scale (Färe et al., 1985). As the VRS assumption advocates that not all farms are operating at optimum scale and the assumption of CRS assumes that farmers are scale efficient. This infers that if there is a difference in efficiency under both assumptions (CRS & VRS) then scale inefficiencies exist. DEA-VRS proposed by Banker et al. (1984) was used in this research, because in this study we expected the return to scale (RTS) to vary or be variable. 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).

Despite the tremendous importance and utility of pearl millet to over 40% of the populace in northern Nigeria, it is implausible to apprehend that there are very scanty studies conducted on efficiency of pearl millet in Nigeria and none was discovered that used frontier approaches (DEA or SFA). However, with regard to DEA application, the approach 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 analyze the TE, AE, EE and SE of rice cultivation in Bangladesh; Murthy et al. (2009) used DEA to study the TE and SE of tomato farmers in Karnataka, India; Javed et al. (2010) used DEA to measure the TE of rice-wheat system in Punjab region of Pakistan; Ogunniyi and Oladejo (2011) employed DEA methodology in the estimation of TE Tomato production in Nigeria; Koc et al. (2011) determined the TE of second maize crop growing farms in East Mediterranean in Turkey; Dube and Guveya (2012) studied the TE of Smallholder Out-grower Tea Farming in Chipinge District of Zimbabwe using DEA technique; Baležentis (2012) applied DEA to estimate TE and expansion of Lithuanian family farms; Using DEA, Nan Wutyi et al. (2013) analyzed farm level TE and socioeconomic determinants of rain-fed rice production in Myanmar; Iliyasu and Mohamed (2016) used two-stage DEA in evaluation of contextual factors influencing the TE of freshwater pond culture systems in Peninsular Malaysia.

Theoretical Framework

The theoretical framework on efficiency by Farell (1957), Battesse (1992) and Coelli (1996) was 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 designates TE (Figure 1).

$$TE = OZ/OK \tag{1}$$
$$AE = OA/OZ^* \tag{2}$$
$$EE = OZ/OK \text{ X } OA/OZ= OA/OK \tag{3}$$

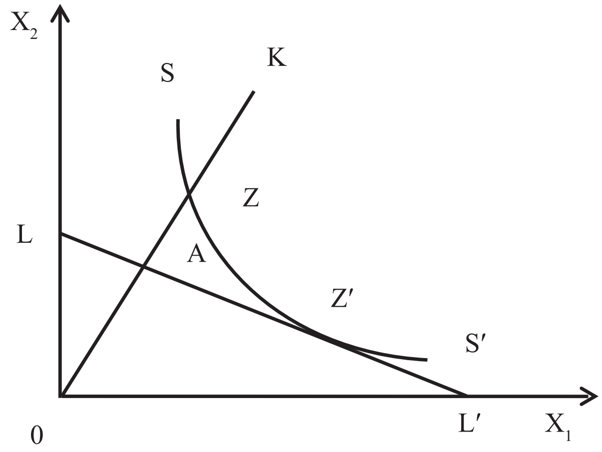

Fig. 1. Input-Oriented Measure for Technical, Allocative and Economic Efficiencies
Source: Farell (1957); Coelli et al. (1998)

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 TE. Thus, AE and EE efficiencies 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.

Materials and Methods

The Study Area

The study was undertaken in Kano state of Northwestern Nigeria. Kano State is considered as an agricultural and commercial state, and it is located on 12°37′ N, 9°29′ E, 9°33′ S, and 7°43′ W (Olofin et al., 2008). It has a daily mean temperature of 30°C to 33°C during March to May and has the lowest temperature of 10°C during the months of September to February. The state characterized by uni-modal rainfall pattern with a mean annual rainfall of 600 mm (Mignouna et al., 2013). Kano State has an estimated total land mass of 20 760 Square kilometers, with 1 754 200 hectares of agricultural land and 75 000 hectares of grazing land and forest vegetation. The state has a total of 44 Local Government Areas (L.G.As) and projected population of 13 383 682 people (NPC, 2006). Kano State is well-known for the production of groundnuts, rice, pearl millet, sorghum, maize, vegetables as well as for its huge solid mineral deposits. Kano is the most widely irrigated state in the country and has cultivable land over 3 million hectares (Oyewole and Ojeleye, 2015).

Sources and Method of Data Collection

The study made use of both primary and secondary data. Primary data was collected with the aid of structured questionnaire from cross sections of independent pearl millet farmers in the study area. Secondary data and other relevant information were gathered from conference papers, journals, publications from government and NGOs, internet, text books and thesis.

Sampling technique and sample size

A structured questionnaire study was conducted during 2013/2014 production season to collect data from a cross-section of pearl millet farmers in Kano State of the North-eastern, Nigeria. Well trained and experienced extension officers were employed to collect information on inputs, outputs produced and socioeconomic characteristics of pearl millet farmers in the study area. Random sampling technique was used to obtained data with the aid of a structured questionnaire. Kano state was purposively selected based on the high concentration of pearl millet farmers in the northwest region.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) method was used in this paper in order to obtain efficiency scores of pearl millet production in Kano state of Nigeria (Table 1). DEA was solely used for the analysis of TE because it has the capability to integrate technical parameters that might not be captured by parametric production efficiency techniques and its ability of tackling multiple inputs and outputs (Coelli et al., 2005).

The efficiency of a firm is calculated based on the 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 is adopted to calculate TE in this paper. This technique is selected because in agricultural production farmers have more control on their inputs than output (Coelli et al., 2005).

Table 1
Summary statistics for variables used in the DEA and OLS analyses

Variable	Unit	Min	Mean	Max	S.D.
Output	Kilogram	494.64	1159.69	2460.24	224.00
Chemicals	Litre	0.38	1.63	7.00	1.01
Seed	Kilogram	5.00	30.50	107.14	14.92
Labour	Man-days	13.65	36.76	107.25	12.44
Manure	Ox-cart	3.50	14.76	45.00	5.74
Fertilizer	Kilogram	33.33	95.27	312.00	38.84
Age	Years	20.00	37.91	77.00	12.94
Credit	Dummy	0.00	0.28	1.00	0.45
Agrochemicals	Dummy	0.00	0.40	1.00	0.50
Cooperative	Dummy	0.00	0.35	1.00	0.48
Education	Years	0.00	10.30	18.00	5.64
Experience	Years	1.00	10.04	32.00	7.14
Extension	Dummy	0.00	0.25	1.00	0.43
Household size	Number	1.00	10.00	31.00	6.29
Type of Seed	Dummy	0.00	0.71	1.00	0.46

Source: Field Survey, 2015

TE for N DMUs can be evaluated using an input-oriented measure as solution to linear programming (Coelli et al., 1998; Koc et al., 2011):

$$\begin{aligned} &\textit{Minimize} && \theta, \lambda^{\theta} \\ &\textit{Subject to:} && -y_i + Y\lambda \geq 0 \\ & && x_i - X\lambda \geq 0;\ NI'\lambda = 1;\ \lambda \geq 0 \end{aligned} \tag{4}$$

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.

Ordinary Least Square (OLS) Regression explaining the determinants of TE

It is well known that after having applied DEA techniques to estimate TE in the first stage, most researchers used Tobit regression model to investigate its determinants in the second-stage. However, Since TE 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 and Natarajan, 2008). It was argued by Banker and Natarajan (2008); McDonald (2009) that the most appropriate method to use in this situation is the application of OLS regression technique, which is believed to produce better results in the second stage DEA than using the Tobit regression model. John and Kuosmanen (2012) added that the OLS regression of the DEA–TE scores on the contextual variables provides a statistically consistent estimator of the coefficients under more general assumptions. The OLS approach is also found to be significantly more reliable than both the single-stage and double-stage procedures used in SFA model (Iliyasu and Mohamed, 2015; Iliyasu et al., 2016). Therefore, in order to understand the determinants of TE, this study concurred with Banker and Natarajan (2008); McDonald (2009); John and Kuosmanen (2012). Among others, the OLS method has also been adopted by Bozoğlu et al. (2007); Kibirige (2014); Iliyasu and Mohamed (2015); Iliyasu et al. (2016); Iliyasu and Mohamed (2016) in their respective studies. The model is expressed as:

$$\begin{aligned} TE_{VRS} = {} & \alpha_o + \alpha_{1Age} + a_{2Agrochemicals} + \alpha_{3Cooperative} + \alpha_{4Crtedi} + \\ & + \alpha_{5Education} + a_{6Experience} + \alpha_{7Extension} + \alpha_{8Farmsize} + \\ & + a_{9Householdsize+\mathrm{Seedtype}} + \mu \end{aligned} \tag{5}$$

where: TE_{VRS} represents VRS measure of technical efficiency

Age = age of the farmer (years)

Agrochemicals = Agrochemicals (1 = used agrochemicals, 0 = otherwise)

Cooperative = Cooperative membership (member = 1, otherwise = 0)

Credit = Access to credit (Access = 1, otherwise = 0)

Education = educational level of farmers (years)

Experience = Farming experience (years)

Extension = contact with extension agent (Dummy)

Farm size = Farm size (hectare)

Household size = Household size (numbers of persons)

Seed Type = Type of seed planted (Improved = 1, Recycled = 0)

α_1-α_9 are the scalar parameters to be estimated

α_o = constant

Results and Discussion

Farm level technical efficiencies

Results of the input-oriented DEA analysis using the computer program DEA 2.1, developed by Coelli (1996) are presented in Table 2. The results indicate overall technical efficiency (TE_{CRS}) ranges from 33 to 100% with an average of 70% and standard deviation of 0.148. Pure technical efficiency (TE_{VRS}) across the 256 pearl millet farmers was, on average 81% ranging from 43% to 100% with a standard deviation of 0.150. The SE index for the 256 samples ranges from 44% to 100% with a sample mean and standard deviation of 87% and 0.129 respectively.

Table 2
Distribution of DEA technical efficiency scores

Efficiency Index	TEcrs	TEvrs	SE
31-40	1	0	0
41-50	18	3	2
51-60	47	19	7
61-70	82	50	31
71-80	49	64	31
81-90	25	32	42
91-99	14	25	103
1.00	20	63	40
Total	256	256	256
Min (%)	33	43	44
Max (%)	100	100	100
Mean (%)	70	81	87
Std. Dev.	0.148	0.150	0.129

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

The results indicate that on average, pearl millet farmers were 19% inefficient (100-81). This means that the sampled farmers can reduce using inputs in pearl millet production, on average, by 19%, and achieve the same level of output with the existing technology. In other words, sampled pearl millet farmers can evaluate up to 81% of used inputs through improved management. The results are also positive as they suggest that the pearl millet farms have the potential to reach the production frontier through increasing levels of technical and scale efficiency. This result is not at variance with the theory that the VRS frontier is more elastic and envelops the data in a tighter way than the CRS frontier. Only twenty (7.81%) pearl millet farmers were efficient in terms of CRS and sixty three (24.61%) farms were fully efficient under the VRS model. The TE scores under CRS are equal to, or less than those calculated under the VRS DEA model. This relationship is used to obtain the measure of SE. Scale inefficiency (13%) may occur due to an operation below the optimal scale, as a result of the fact that a 69.14% of pearl millet farmers operate at increased returns to scale.

The CRS assumption is appropriate when all farms are operating at an optimal scale. However, unfair competition, government regulations, financial constraints etc., may cause a firm not to operate at optimal scale (Coelli et al., 2005). The use of CRS specification when not all firms are operating at the optimal scale, results in measures of TE that are confounded by SE. The use of the VRS specification permits the calculation of TE devoid of these SE effects. Otherwise, as shown in both Table 2 and Figure 1, SE is higher than VRS TE. This indicates that the cause of inefficiency is a certain amount of product which cannot be produced using the minimum inputs.

Excess Input Use

The mean input slacks and excess input usage proportions were estimated and shown in Table 3. A slack indicates excess (leftover) of an input. A farmer can reduce costs on an input by the quantity of slack without decreasing existing output. The highest slacks (excess) were in manure, followed by seed, agrochemicals, labour and fertilizer use. Manure costs of the sampled pearl millet farms could be reduced by 26.53%, seed and agrochemicals used by 26.00% and 24.64%, respectively, while sustaining the same levels of yield. Extra input savings are also presented in Table 3. Being the pearl millet farmers operating on small scale, with larger family size per household and combining livestock alongside crops farming which make manure and family labour cheaply available in the farms could be the reason for excess fertilizer, manure and labour usage.

For the inefficient farms, the inadequacies could have been caused by either misallocation of resources or inappropriate scale. The 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 (Alemdar and Oren, 2006). Since we have obtained relatively high scale efficiencies (mean SE=87%) in this study, it can be concluded that inefficiencies emanate largely from to improper use of resources.

Returns to Scale (RTS)

Table 4 contains the fractions of pearl millet farmers that were operating at optimal (CRS), sub-optimal (IRS), and super- optimal (DRS) levels. Out of the 256 farmers in this study, 26 (10.16%) were found to be operating at the optimum scale (CRS). While, 177 (69.14%) and 53 (20.70%) were operating at sub-optimal (IRS) and super-optimal (DRS) scales, respectively. The implication of this result is that if the scale of 177 farms increase by 30.86% and the scale of 53 farms decrease by 79.30%, efficiency of pearl millet in the study can be increased. An average of 2.91hectares was cultivating by farmers operating at the optimum scale and producing 1409.58 kg/ha of millet grain, releasing an average gross returns of $ 536.75/ha. For the sampled pearl millet famers experiencing IRS, they farmed an average of 2.08 hectares and produced 1108.82 kg/ha of pearl millet, generating an average gross returns of $ 406.46/ha. Farmers who were found to be exhibiting DRS, on average were cultivating 4.05 hectares of land and getting 1293.74 kg of pearl millet output, making a mean gross returns of $ 475.60/ha. The mean output at the optimal scale is larger than that at the super-optimal, followed by that of suboptimal scale for the sampled pearl millet farms. However, farms under optimal scale used smaller average farm size than those operating at super-optimal scale.

Table 3
Estimated input slacks from DEA Model

Input	Min. Slack	Max. slack	Mean Slack	Std. Dev.	Average input	Excess input used (%)
Farm size	0.00	1.95	0.15	0.29	2.57	5.84
Fertilizer	0.00	180.48	11.53	26.03	86.87	13.27
Manure	0.00	59.52	3.82	8.64	14.40	26.53
Labour	0.00	87.56	4.91	11.59	34.00	14.44
Seed	0.00	120.66	7.28	14.08	28.00	26.00
Agrochemicals	0.00	2.91	0.34	0.63	1.38	24.64

Source: Field Survey, 2015

Table 4
Characteristics of farms with respect to returns to scale scores

Characteristics	No. of farmers	% of Farmers	Mean farm size used (ha)	Yield (kg/ha)	AGR
Sub-Optimal (IRS)	177	69	2.08	1108.82	406.46
Optimal (CRS)	26	10	2.91	1409.58	536.75
Super-Optimal (DRS)	53	21	4.05	1293.74	475.60

AGR = Average Gross Return

Results of Regression Diagnostics

Regression diagnostics were carried out for the linear model to ensure that the collected data have met the assumption underlying OLS regression and results are presented in Tables 5 and 6. The data was tested for the presence of multicollinearity. It is expected that no single regressor should be linearly correlated with another regressor. Tolerance value (1/VIF) and variance inflation factor (VIF) were used to assess the incidence of multicollinearity. The tests showed that none of the VIF or tolerance value illustrates any serious multicollinearity. In fact, according Greene (2012) and Gujarati and Porter (2009), VIF value greater than 10 or tolerance value (1/VIF) of less than 0.1 indicate serious multicollinearity. Hence, average VIF and 1/VIF values of 1.44 and 0.71 (Table 5), implies the absence of multicollinearity problem in the data set. In addition, the correlation matrix results in the same table also revealed weak relationships among the explanatory variables.

Secondly, heteroscedasticity test was carried out on the data. Heteroscedasticity is a violation of one of the requirements of OLS in which errors variance is not constant (Gujarati and Gujarati 2009). The Breusch-Pagan-Godfrey test for heteroscedasticity was applied. The test, as shown in the same Table 5, was insignificant with p-value of 0.054 ($p>0.05$), suggesting that the null hypothesis the there is no heteroscedasticity (random terms have constant variance) is failed to be rejected. The Ramsey reset test for functional form specification was also conducted and the result showed insignificant values of t-statistic and F-statistic with $p=0.994$ ($p>0.05$) and $p=0.994$ ($p>0.05$), respectively, which means that the null hypothesis that the model is appropriately specified is failed to be rejected. The final assumption of OLS which is optional is the normality of error terms or residuals. This assumption states that, conditional upon the explanatory variables, the errors are normally distributed. The normality assumption was checked using a Jaque-bera test, and result produces insignificant p-value of 0.114 ($p>0.05$), indicating that the residuals exhibit normal pattern (Table 6). In the light of the above results, it is concluded that the data met all the OLS assumptions and hence fit for analysis.

Factors affecting VRS-DEA technical efficiency

Selected factors which are presumed to have effects on VRS-DEA TE of pearl millet farmers in the study areas were examined and shown in Table 7. Using OLS technique, the previously obtained farm specific TE_{VRS} scores

Table 5
Multicollinearity Tests using Pearson correlation matrix, Tolerance and variance inflation factor

	Age	Agrochem	Credit	Cooperative	Education	Experience	Extension	Farm size	HHsize	SeedType
Age	1									
Agrochem	-0.243	1								
Credit	0.229	-0.173	1							
Cooperative	0.015	0.050	0.127	1						
Education	0.143	-0.153	0.288	0.127	1					
Experience	0.044	-0.241	0.264	0.146	0.361	1				
Extension	0.282	-0.019	0.447	0.205	0.393	0.281	1			
Farm size	-0.128	0.596	-0.131	0.032	-0.093	-0.177	0.025	1		
HHsize	0.151	-0.105	0.318	0.131	0.255	0.188	0.261	-0.052	1	
Seed Type	0.549	-0.079	0.257	0.109	0.278	0.149	0.383	0.007	0.292	
VIF	1.58	1.71	1.39	1.07	1.35	1.28	1.57	1.57	1.21	1.67
1/ VIF	0.63	0.58	0.72	0.93	0.74	0.78	0.64	0.64	0.83	0.60

Source: Field Survey, 2015
Average VIF and 1/VIF are 1.44 and 0.71, respectively

Table 6
Results of Diagnostic tests for the OLS regression model

Diagnostic test statistics	Test-Statistics	P-value	Decision Rule
Heteroscedasticity test	Breusch-Pagan-Godfrey	0.054	Fail to reject H_0
Functional Form Specification	Ramsey RESET Test	0.994	Fail to reject H_0
Normality Test	Jaque-Bera	0.062	Fail to reject H_0

Source: Field Survey, 2015

were regressed against the selected farmers' socio-economic characteristics in order to identify sources of inefficiencies among the farms. The estimates showed that technical efficiency (TE) increases with age of pearl millet farmers and is significant at 5% level of probability. This implies that aged farmers were more technically efficient in pearl millet production. This can be attributed to the fact that farming experience of a household increases with age as well as resources empowerment which usually lead to increase in TE. Coefficient of access credit is significant and positively associated with TE. That is, increase access to credit increases TE level of the pearl millet farmers. According to Desai and Mellor (1993) explained that farm credit boosts diversification of agricultural systems that stabilize and possibly improve farm productivity, if it is appropriately extended, managed and utilized. Maseatile (2011); Butler and Cornaggia (2011) and Tleubayev et al. (2017) reported comparable results in Lesotho, U.S.A. and Kazakhstan, respectively.

The estimated coefficient of farmers' level of education was found to be positively and significantly associated with TE at 1% level, meaning that farmers who more years of schooling are more technically efficient. This suggests that farmers who are educated are expected to have a better understanding of modern technologies and easily implement the technologies which every often also tend to have better managerial expertise, and therefore they are likely to be more efficient than uneducated farmers. This relationship is the findings of many researchers, few among which include Coelli et al. (1998); Murthy et al. (2009) and Javed et al. (2010). The positive coefficient of farming experience indicates that as farmer's farming experience increases TE also increases. This result can be attributed to the fact that farmers who spent more years in farming occupation all things being equal, are expected to have a better understanding, skills and knowledge of farming practices which lead to higher efficiency. This result is in line with earlier studies by Bhatt and Bhat (2014); Lubadde et al. (2016); Iliyasu and Mohamed (2016).

The coefficient of farm size devoted for pearl millet cultivation was found to have a negative and significant influence on TE at 1% level. This means that smaller farms are more technically efficient than those with larger farm sizes. The possible reason for this result is that farmers cultivating smaller land area tend to use land more industriously and combine their resources better. This to a certain extent minimizes loss in the level of soil fertility which in turn makes them more efficient. This is conformity with findings of Coelli and Battese (1996); Masterson (2007) and Bhatt and Bhat (2014). The household size variable is positively related to technical efficiency and statistically significant only at 1%. This means farmers with large family size are more technically efficient. This is probably because farmers that

Table 7
Result of OLS regression model for efficiency scores

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	0.567	0.027	20.689	0.000
Age	0.001	0.000	2.299	0.022
Agrochemicals	0.005	0.004	1.323	0.187
Cooperative	0.003	0.011	0.251	0.802
Credit	0.088	0.013	6.885	0.000
Education	0.131	0.012	10.592	0.000
Experience	0.005	0.001	6.218	0.000
Extension	0.003	0.013	0.207	0.836
Farm Size	-0.014	0.005	-2.906	0.000
Household Size	0.003	0.001	4.083	0.000
Seed type	0.068	0.015	4.479	0.000

Source: Field Survey, 2015

have large household size tend to endeavor to obtain higher output in order to meet their subsistence necessities. Furthermore, large household size has labour endowment required to implement farm management decisions. The findings are consistent with Bhatt and Bhat (2014) and Lubadde et al. (2016). In this study, coefficient of type of seed planted by farmers was found to be positive and statistically significant at 1% level. This implies that planting improved pearl millet seeds have positive effect on TE. According Kibirige (2014), the type of seeds planted by farmers has a positive relationship with farm efficiency, since it has been established that improved technologies affect productivity positively.

Conclusion and Recommendation

In this study, DEA frontier approach was applied to investigate the TE of pearl millet farmers in Kano state, Nigeria. Using comprehensive data collected through structured questionnaire during 2013/2014 cultivation season, for 256 randomly selected pearl millet farms, measures of TE were estimated. The results indicate that VRS technical efficiency was estimated at 81%, suggesting that pearl millet farmers in the study could reduce the existing level of inputs by 19% and still achieve the same level of output produced. The greatest excesses were detected in manure, seed, agrochemicals, labour and fertilizer use. These excesses negatively influence TEs of pearl millet production in the study. Apart from the wrong inputs use, OLS regression results also showed that age, credit, education, experience, farm size, household size and type of seed contribute significantly to the explanation of TE. Based on the above results, it is recommended that extension services should be primed as to educate the farmers on appropriate and right inputs combination which ensure efficiency in production of pearl millet.

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