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Research article

Sweet potato production efficiency in Nigeria: Application of data envelopment analysis

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Abstract: This study examined Sweet Potato (SwP) production efficiency in Nigeria. A multi-stage sampling technique was employed in selecting 93 SwP farms in February, 2016. Data on farm and farmers' characteristics, input and output quantities and prices, constraints to SwP production among others were collected using pre-tested, well-structured questionnaire. The data were analysed with descriptive statistics, Data Envelopment Analysis (DEA) and Tobit regression. The results of the analysis revealed that the mean Technical Efficiency (TE), Allocative Efficiency (AE), Economic Efficiency (EE) under Constant Return to Scale (CRS) assumption were 0.685, 0.445 and 0.301 respectively. On the other hand, the TE, AE and EE under Variable Return to Scale (VRS) assumption were 0.783, 0.604 and 0.467 respectively. The Scale Efficiency (SE) was found to be 0.877. The results indicate that access to credit increased TE of farms by 3.5%. Regular training of SwP farmers increased their AE by 10.5% and EE by 16.6%. Access to credit by farmers decreased SE of farms under CRS and VRS by 1.9% respectively. Labour shortage, poor access to improved technology and infestation by insect pests were the three most important constraints limiting SwP production in the study area. Therefore, improving the efficiency of SwP production will require policies that will see to regular training of farmers by extension agents and other stakeholders and enhancement of rural farmers' access to credit.

Keywords: efficiency; sweet potato farms; production constraints; DEA; Nigeria

1. Introduction

Nigeria is an agrarian country, hence, its economic growth and development heavily relies on the functioning of the agricultural sector of which the crop sub-sector plays a vital role. Agricultural sector contributed 22% to the nation's GDP, while the crop sub-sector's contribution stood at 20% in 2014 [1]. About 36.4% of the work force in the country is directly employed by the sector. The crop sub-sector involves the production of cash and food crops, notable among the food crops are cereals, legumes, root and tubers. Some of the root and tuber crops been cultivated by farmers in the country include: Cassava, yam and sweet potato. The global ranking of the SwP producing counties showed Nigeria to be the largest producer in Africa, and the second largest producer in the world after China in 2014 [2]. The total production was put at 3.92 metric tonnes with about 2% increase compare to 2013, but has the potential yield estimated at 7 metric tonnes [1].

Sweet potato has numerous potential benefits and uses. It requires fewer inputs and less labour than other crops such as cereals, more productive, and adaptable to marginal growing conditions (e.g., drought and poor soil) [3]. Sweet potato is an important food and feed crop in sub-Sahara Africa (SSA) and ranks fourth after maize, bananas, and cassava [2]. It serves as cash crop and is one of the most popular food crops which serve as food security promoting root crop in sub-Sahara Africa specifically, and the world at large. The importance of the crop in national and household food security coupled with health and livelihoods of poor farming households in Nigeria cannot be over-emphasized. In Kwara State, the crop plays particularly important role in cultural practices of the peoples' traditions at the beginning of harvest [4].

Despite the numerous potential uses and benefits of sweet potato in Nigeria, the production of the crop is below the nation's potential. Sweet potato has a yield potential of 20–50 tonnes per hectare wet weight in the tropics [5]. Farmers in SSA however produce below 10 tonnes per hectare wet weight on the average [6], while farmers in Nigeria recorded one of the world's lowest average potato yields of less than 3.1 tonnes per hectare. In the United States of America and Japan, yields of 22.8 and 21.7 tonnes per hectare were recorded respectively [2]. The low yields in Nigeria were due to quality of planting materials (vines), high labour costs, biotic and abiotic constraints. As opined by Fawole, the low productivity recorded in SwP farms is traceable to inefficiency in resource use [7]. Previous studies on sweet potato farms in the country focused on adaptability and productivity, value addition as well as processing [7,8]. The study by Adeyonu et al. on efficiency of SwP farms focused on TE [8]. To the best of researchers' knowledge, Adugna's research is the only study that focused on efficiencies (TE, AE, EE and SE) of sweet potato farms [9]. Hence, this study examined the efficiency (TE, AE, EE and SE) of SwP production using DEA and the constraints threatening production in Nigeria.

Conceptual/theoretical framework and literature review

Efficiency is a concept in economics that is greatly used in managerial and production economics. Efficiency can be defined as the largest amount of ratios of weighted outputs to weighted inputs subject to the condition that similar ratios for every Decision Making Unit (DMU) are less than or equal to one [10]. It then follows that the efficiency of each DMU is relative to the ratio of output to input of the most efficient firm. Economic Efficiency in agriculture implies getting the maximum amount of output per hectare of land cultivated or per animal, with the least cost of production in terms of manpower and other inputs [11]. Generally, economic efficiency can be separated into two distinct types-TE and AE [12]. A firm (farm) that is not 100% efficient technically will find it difficult to be efficient in resource allocation [12].

Technical efficiency in agriculture is a term which refers to the capacity of a farm to either produce the maximum amount of output(s) from the given level of inputs, or to produce the given level of output(s) from the minimum amount of inputs for the given technology. Allocative efficiency is a measure of the extent to which the farm's marginal value product can be equated with the marginal costs. It considers inputs utilization by the enterprise (farm) in relation to their current prices in the market. The AE, just like the TE, becomes relevant if the objective of the farm is to maximize its profits or to minimize its costs. Scale efficiency on the other hand is defined as the most efficient scale of operation when the objective is to maximize mean productivity.

Efficiency analysis involves two techniques which are the parametric Stochastic Frontier Analysis (SFA) and non-parametric DEA. The SFA was developed to provide a coherent principles to analyze efficiency [13–15]. The imposition of a deterministic functional form (Translog, Cobb-Douglass, etc.) on a production or a cost frontier will make it parametric. The assumption here is that any difference between the calculated function and the observation is as a result of farm's inefficiency and some random errors out of the farmer's control. The DEA method was initiated by Farrell [12] and Charnes et al. [16] re-formulated it to a mathematical programming problem. In DEA, no postulations about the functional forms relating inputs and outputs are required and the farm's inefficiency is derived solely from the difference between the calculated function and the observation (frontier technology). Also, DEA method can be used for production system that has to do with multiple inputs and multiple outputs, and it can estimate all the associations between inputs and outputs (TE, AE, EE and SE) simultaneously [17].

However, employing DEA method in measuring farm's efficiency requires that choice be made between two options. The first of the options is to choose between Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). Constant Returns to Scale assumes that all DMUs are operating at the optimal scale, implying that it is possible for big and small farms to reach the same level of productivity. The CRS assumption has been criticized in that in reality it is not likely that all big and small farms will reach the same level of productivity in developing countries because the farms are heterogeneous in nature. Variable Return to Scale is superior to CRS due to its ability to estimate the efficiency scores (TE, AE and EE) with no regard to SE effects [18]. A little wonder Banker et al. suggested an adoption of VRS DEA model over CRS DEA model [19]. Also, VRS DEA is common in agricultural production. The second option is to choose between input-based DEA and output-based DEA. The focus of the input-based DEA model is to produce the same amount of output(s) by using fewer inputs, and its output-based counterpart focuses on using the same amount of inputs to produce maximum output(s). Choosing between the two models will be a function of availability of resources, hence, the choice will vary from region to region and country to country.

A number of studies have employed CRS DEA and VRS DEA to measure efficiency of farms [20–23]. Also, Begum et al. and Shrestha et al. used input-based approach and the choice was justified based on the fact that the studies were done in developing countries [21,23]. To the best knowledge of researchers, little or nothing is known about SwP production efficiency utilizing DEA.

Hence, this study used input-based CRS DEA model and VRS DEA model to evaluate SwP production efficiency in Nigeria been a developing country.

2. Materials and methods

2.1. The study area and data collection

The study was conducted in Kwara State being the second largest producer of SwP in the country after Plateau State. The state is made up of 16 Local Government Areas (LGAs). The total population of the State was 2,365,353 in 2006 out of which farmers accounted for about 80% [1,24]. Offa and Oyun LGAs were purposively selected because about 70% of the SwP farms in the state were found in the LGAs [24]. Following this was a random selection of 10 farming communities from each of the selected LGAs, resulting into 20 communities. The enumerators worked with village heads to compile the list of commercial sweet potato farming households, from where 112 were randomly selected at the third stage. However, only 93 (83%) of the questionnaire had required information that were useful for this study. Information on socio-economic characteristics of farmers, quantities and cost of farm inputs (land, labour, fertilizer, pesticides, planting materials (vines)) etc., quantity and prices of outputs (SwP roots and vines), as well as constraints associated with SwP production were collected from sweet potato farmers during the 2014/2015 planting season.

2.2. Analytical techniques

Descriptive statistics, DEA and Tobit regression models were employed to analyse the data gathered for the study. Descriptive statistics were used to analyse farmers' and farms' characteristics as well as production constraints. DEA was used to analyse EE, TE, and AE from where the SE was computed. The relationships between farmers' and farms' characteristics with sweet potato production efficiency were analysed using Tobit regression models. While the descriptive statistics and Tobit regression were analysed with the aid of STATA 11 statistical package, DEAP version 2.1 statistical package was employed in analyzing DEA [18].

2.2.1. Data envelopment analysis

This study examined the efficiency of SwP farms under both the CRS and VRS. The CRS shows the total TE score by solving the linear programming (LP) based DEA model shown in Eq 1 [16]. Suppose the n single output production units (SwP farms) referred to as DMUs made use of multiple inputs, m in the production of output (SwP). Assume Y_i is the output, X_i is the vector of inputs matrix (m × 1), Y is the vector of output matrix (1 × n), and X is the (m × n) input matrix of DMUs where n = 93. Then, the constrained optimization problem in the LP DEA can be stated as:

$$\min_{\theta_i^{CRS}\,\lambda} \theta_i^{CRS} \text{; subject to: } Y_i \leq Y\lambda,\ \theta_i^{CRS} X_i \geq X\lambda, \lambda \geq 0 \tag{1}$$

Where scalar θ_i^{CRS} is the TE value of the ith DMU under the CRS and λ is an (n × 1) vector of the weights attached to each efficient DMU. In order to derive the TE value for each of the DMUs', a separate linear programming constrained optimization problem was solved. In CRS assumption, any DMU with $\theta^{CRS} = 1$ and ≤ 1 respectively is said to be on the frontier and technically efficient, and below the frontier and technically inefficient. The technically efficient production cost of the ith DMU is stated as: $P_i'(\theta_i^{CRS}X_i)$, where P_i is the vector of input price.

In order to obtain the overall EE, under the CRS assumption, the DEA LP constrained optimization problem was solved as shown in Eq 2.

$$\min_{X_i^*\lambda} P_i' X_i^*; \text{subject to: } Y_i \leq Y\lambda, X_i^* \geq X\lambda, \lambda \geq 0 \tag{2}$$

where the cost minimization objective or economically efficient input vector for the ith DMU is X_i^*, and its price P_i, and the output level, Y_i. The total EE value for the ith farm was calculated as the ratio of the least cost to the actual cost using equation III, where EE = 1 implies economically efficient, and EE < 1 signifies economically inefficient.

$$EE_i = \frac{P_i' X_i^*}{P_i' X_i} \tag{3}$$

Furthermore, the AE index is generated as shown in Eq 3.

$$AE_i = \frac{EE_i}{\theta_i^{CRS}} = \frac{P_i^i X_i^*}{P_i'(\theta_i^{CRS} X_i)} \tag{4}$$

where AE = 1 means that the DMU is allocatively efficient, and AE < 1 implies the highest amount of cost that the technically efficient DMU could save by using the least cost strategy [15].

Solving a VRS DEA model was required to disaggregate the overall TE into its parts namely: The Pure Technical Efficiency (PTE) and the SE [23]. This can be done by imposing another constraint, $\sum_{j=1}^{n} \lambda_j = 1$ on Eq 1 [20]. The process of separating scale effect from the TE gives rise to PTE from the VRS DEA. Hence, the TE score under VRS is stated as (θ_i^{VRS}) and the technically efficient production cost of ith DMU under the VRS is equal to $P_i'(\theta_i^{VRS}X_i)$. The SE was derived by employing Eq 5 as follows:

$$SE_i = \frac{\theta_i^{CRS}}{\theta_i^{VRS}} \tag{5}$$

where SE = 1 suggests that the DMU is scale efficient, and SE < 1 suggests it is scale inefficient (implying that the DMU could increase productivity by adjusting its scale of operation). Inefficiency in the scale of operation could be the outcome of one of increasing returns to scale or decreasing returns to scale, and can be calculated by solving: The Non-Increasing Returns to Scale (NIRS) or the Non-Decreasing Returns to Scale (NDRS). While the (NIRS) is given as: $\sum_{j=1}^{n} \lambda_j \leq 1$, the (NDRS) is stated as: $\sum_{já=1}^{n} \lambda_j \geq 1$.

2.2.2. Tobit regression analysis

Following the derivation of the efficiencies using the DEA model, Tobit regression model was employed to determine the factors influencing SwP farms' efficiencies [25]. The model, also known as censored regression model is widely used in the occasions when the dependent variable is censored from either above or below. Since the DMUs efficiency scores obtained range between 0 and 1, applying an OLS model on such an instance will yield biased estimates. Researches on efficiency has widely adopted this technique [26,27]. The empirical specification for the Tobit model is:

$$E_i^* = \beta_0 + \sum_{m=1}^{M} \beta_m G_{im} + \varepsilon_i, \qquad \varepsilon_i \backsim \mathrm{ind}(0, \sigma^2) \tag{6}$$

$$E_i = 1 \; if \; E_i^* \geq 1E_{i,}, \quad E_i = E_i^* \; if \; 0 \leq E_i^* \leq 1, \qquad E_i = 0 \; if \; E_i^* \leq 0$$

where E_i^* is a hidden variable which is the efficiency value for the ith DMU that is showed in association to the observed variable E_i derived from DEA model, β_0 and β_m are vectors of parameters to be estimated, G_{im} are independent variables (farms' and farmers' characteristics and institutional factors) and ε_i is an independently and normally distributed error term with zero mean and constant variance.

Statistical diagnostic tests were performed on the models to check for multicollinearity as well as heteroscedasticity [23] status among the variables. These became necessary to ascertain non-violation of the assumptions of multiple regression. Variance Inflation Factor (VIF) test was performed to determine multicollinearity status. The specification of VIF test for each independent variable (G_i) is as follows:

$$VIF \; = (1 - R_i^2)^{-1} \tag{7}$$

where R_i^2 is the coefficient of determination when G_i is regressed on the remaining independent variables of the model. A VIF value of above 10 suggests the presence of multicollinearity [28]. The mean VIF was found to be 1.52 and ranged between 1.05–2.28, implying absence of multicollinearity. Breusch-Pagan/Cook-Weisberg test was conducted on the data to ascertain the presence of heteroscedasticity. The estimated value stood at 0.02 and 0.8795 for Chi square 1 and Prob > Chi square 2 respectively, indicating the absence of heteroskedasticity [29].

2.2.3. Constraints

Information on production constraints encountered on SwP farms were collected using a five-point Likert-type scale. Ten questions on production constraints generated were from literature and researchers' personal field experience. Each of the farmers interviewed was asked to rate the level of importance of each constraints to his/her SwP production on a five-point Likert-type scale (1 = not at all important; 5 = extremely important).

3. Results and discussions

3.1. Descriptive statistics of the variables used in the study

The summary of variables analysed using descriptive statistics in this study is presented in Table 1. The results showed that the mean SwP output in the study area stood at 3.93 tonnes/hectare, while the average farm land cultivated was found to be 1.69 hectares. The farm land cultivated compares well with the national average size of 2.0 hectares. The use of improved vine variety was not popular in the study area as only about 32% of the farmers made use of it. The majority of the farmers owned the land they cultivated, about 26% of the farmers were females, more than half did not have access to credit and also belonged to farmers' cooperative society. The mean age and experience in farming of the farmers were about 49 years and 22 years respectively, which implied that they were quite experienced and belonged to active labour force. The result on age distribution of respondents confirms International Labour Organization's (ILO's) report that economically productive person in a population is within the age of 49 years [30]. Farmers' average years of schooling stood at about 10 and a minority of them (29%) had been exposed to entrepreneurial training in the last 5 years.

Table 1. Descriptive statistics.

Variables	n = 93			
	Mean	Std. dev.	Min.	Max.
Output/Ha (Tonnes)	3.934	1.363	2	12
Farm size (Ha)	1.689	1.139	0.4	8
Labour/Ha (Man-days)	2.439	1.500	1	12.5
Vines/Ha (Kg)	93.555	21.713	62	221
Fertilizer/Ha (Kg)	78.896	97.361	0	285.7
Pesticides/Ha (Liters)	1.621	0.395	1	3
Types of vines	0.355	0.545	0	3
Farm ownership	0.828	0.379	0	1
Sex	0.731	0.446	0	1
Age (Years)	48.570	10.661	28	71
Education (Years)	9.810	5.319	0	16
Experience in farming (Years)	22.183	9.852	5	52
Access to credit	0.484	0.502	0	1
Distance to nearest market (Km)	3.985	2.047	1	8
Membership of cooperative society	0.570	0.500	0	1
Participation in Entrepreneurial Training	0.710	0.456	0	1

Note: Source: Survey results, 2018.

3.2. Efficiency measurement

The frequency distribution and mean of the efficiency estimates from the DEA analysis are shown in Table 2. The estimated efficiency scores ranged between 0.127 and 1.000 for TE, AE, EE and SE. The high variability in the scores necessitated the clustering of the scores into five categories which are: <0.60, 0.60–0.69, 0.70–0.79, 0.80–0.89 and >0.89 to show their position in relation to the maximum efficiency of 1. The results indicate that there is substantial inefficiencies in SwP production in the study area under CRS and VRS assumptions, which implied that most of the technologies farmers are using are inefficient. Hence, there is a real need for many of the farmers to adopt improve technologies so as to reduce inefficiencies. The mean TE, AE and EE values were lower under the CRS than under the VRS assumption, which are in consonance with the submissions of Murthy et al., Begum et al. and Shrestha et al. [20,21,23].

The computed mean TE were 0.685 and 0.783 under CRS and VRS assumptions respectively, less than 35% of SwP farms under the CRS assumption and 14% SwP farms under the VRS assumption showed efficiency values of less than 0.6. The efficiency scores of 22.6% and 17.2% of the farms under CRS procedure and VRS procedure respectively stood at between 0.60–0.69. Just about 16% of farms under CRS method and about a quarter of the farms under the VRS method had efficiency score of over 0.89. The calculated mean AE score was found to be 0.445 and 0.604 under CRS and VRS procedures respectively. The majority of the SwP farms (86%) under CRS and over 64% under VRS attained efficiency level of less than 0.60, while as low as 8.6% and 14% farms under CRS and VRS method respectively achieved between 0.60 and 0.69 levels of efficiency. A mere 1.1% of the farms under both assumptions derived efficiency score of between 0.80 and 0.89, while just 1.1% and 4.3% of the farms respectively under CRS method and VRS method attained efficiency level of more than 0.89.

Furthermore, the estimated mean EE score of 0.310 under CRS approach and 0.467 under VRS approach were lower than the highest efficiency level of 1. This is an indication that high inefficiency exist in SwP production in the study area. Farms in the study area can therefore improve on their production management by considerably reducing the costs of variable inputs while maintaining the output level. The result is in agreement with that of [31]. A majority of the SwP farms (over 94% under CRS assumption and more than three-quarter under VRS assumption) achieved efficiency scores of below 0.60 while very few farms (about 1% under CRS approach and about 4% under VRS approach) exhibited efficiency scores of more than 0.89. The mean SE stood at 0.877, implying that 12.3% of the costs of producing SwP given the existing technology, can be avoided by adjusting the scale of operation. More than 50% of the farms studied achieved SE value of more than 0.89, few of the farms had the least efficiency value of below 0.60, while the remaining 39.8% obtained efficiency scores of between 0.60 and 0.89.

Table 2. Efficiency estimate from DEA (CRS and VRS) models.

Efficiency score	n = 93			
	TE	AE	EE	SE
<0.60	34.4 (14.0)	86.0 (64.5)	94.6 (75.3)	5.4
0.60–0.69	22.6 (17.2)	8.6 (14.0)	1.1 (17.2)	10.7
0.70–0.79	15.1 (24.7)	3.2 (16.1)	1.1 (2.2)	15.1
0.80–0.89	11.8 (18.3)	1.1 (1.1)	2.2 (1.1)	14.0
>0.89	16.1 (25.8)	1.1 (4.3)	1.1 (4.3)	54.8
Mean	0.685 (0.783)	0.445 (0.604)	0.310 (0.467)	0.877
Standard error	1.558	1.868	1.748	1.456

*Note: Figures in parenthesis and SE values are under VRS DEA and the standard errors are the same for CRS and VRS models. Source: Survey results, 2018.

3.3. Type of returns to scale of SwP farms

Type of returns to scale of farms is presented in Table 3. The result shows that the majority of the farms (about 59%) operate under IRS, implying that 59% of them had the potential to increase production by reducing the inputs costs. The result concurs with that of Adugna et al. but in sharp disagreement with that of Tiku et al. [9,32]. Almost 31% of the farms fell in the region of DRS, implying that it is possible for this proportion of farms to increase their TE by lowering their levels of production. Only nearly 10% of the farms operate under CRS, implying that they operated under optimum production scale.

Table 3. Type of returns to scale of farms.

Type of returns to scale	Frequency	Percentage	Mean output	Output range
Constant returns to scale	9	9.68	5.512	2.40–12.00
Decreasing returns to scale	29	31.18	3.904	2.25–6.50
Increasing returns to scale	55	59.14	3.75	2.00–6.75
Total	93	100		

Note: Source: Survey results, 2018.

3.4. Factors influencing SwP production efficiency

The results of the factors influencing SwP production efficiency is presented in Table 4. As shown in the Table, the diagnostic statistics showed that the independent variables used in the model have good explanatory power. Age of farmers contribute significantly and positively to TE in SwP production at ($P < 0.10$). The positive influence of age on level of TE indicates that as farmers grow older and gain more experience in SwP, they tend to be knowledgeable about utilization of inputs more efficiently. The result is in conformity with Tiku et al., but in sharp disagreement with Otunaiya et al. [33,31]. The sex of the farmer had negative significant influence on farms' AE and EE at ($P < 0.1$), implying that female farmers were more allocatively and economically efficient than male farmers. This may be due to the fact that females were more prudent with resources than their male counterparts. This result is in consonant with the submission of Shrestha et al. but deviates from that of Tiku et al. [23,33].

The result of the analysis also showed that education and farms' TE are positively related at ($P < 0.10$). This may be because educated farmers had acquired better skills which were utilized in accessing information and proper planning of their farms better than their less educated ones. Begum et al. and Oluwatayo et al. obtained similar result [21,34]. Entrepreneurial training received by farmers' had direct significant association with SwP farms' AE and EE at (($P < 0.05$ and $P < 0.10$) level of significance with coefficients of 0.11 and 0.17 respectively. Training programs expose farmers to modern farming techniques as well as marketing activities. Credit access significantly increased TE with coefficient of 0.04 at ($P < 0.05$) and decreased SE with coefficient of 0.02 at ($P < 0.01$). In the case of TE, it could be that the farmers had access to credit which enabled them to get needed inputs for optimum yield. The result is in line with the findings of Shrestha et al. and Khan and Ali [23,35]. The inverse association between credit access and SE may not be unconnected with the fact that large scale farmers did not depend on credit to finance their farming operations. The result is consistent with that of Shrestha [23]. Indirect significant relationship exists between market distance and TE at ($P < 0.10$), implying that increasing the market distance will lower TE of SwP farms. Farmers rely on market for the purchase of various farm inputs and also sales of their outputs.

The results of standardized coefficients of the independent variables are shown in Table 5. Factors capable of improving EE of SwP production are ranked in the order of importance using their beta values. The value was higher for sex, vine type, training, credit access, education, value addition status, market distance, farming experience and age. The vine type, value addition status and farming experience though not significant in Tobit regression, are capable of improving efficiency of SwP farms in the study area.

Table 4. Tobit regression analysis of factors influencing efficiency in SwP production.

Variables	TE	AE	EE	SE
Constant	0.909 (0.107)***	0.436 (0.150)***	0.429 (0.270)***	1.010(0.100)***
Age	0.003 (0.002)*	−0.003 (0.003)	−0.003(0.005)	0.003(0.002)
Sex	−0.542 (0.037)	−0.0836 (0.050)*	−0.162(0.085)*	−0.009(0.035)
Education	0.005 (0.003)*	0.003 (0.004)	0.002(0.008)	0.001(0.003)
Training	−0.014 (0.034)	0.105 (0.050)**	0.166(0.097)*	−0.035(0.032)
Vine type	0.027 (0.039)	0.032 (0.054)	0.048(0.098)	−0.012(0.037)
Credit Access	0.035 (0.016)**	0.059 (0.045)	0.077(0.085)	−0.019(0.006)***
Value addition status	0.005 (0.033)	0.032 (0.023)	0.010(0.043)	−0.011(0.015)
Market distance	−0.014 (0.007)*	0.002 (0.010)	0.026(0.019)	0.005(0.007)
Farming experience	0.003 (0.002)	0.005 (0.003)	0.001(0.006)	0.001(0.002)
Sigma	0.139(0.010)	0.176(0.019)	0.244(0.043)	0.130(0.010)
Log likelihood	49.630	10.533	24.160	51.451
LR	15.07	22.72	18.83	17.30

*Note: *, ** and *** represent 10%, 5% and 1% respectively, figures in parenthesis are the standard errors. Source: Survey results, 2018.

Table 5. Standardized coefficients of explanatory variables on economic efficiency in SwP production.

Variables	Beta value	Rank
Age	0.005	9
Sex	−0.305	1
Education	0.088	5
Training	0.126	3
Vine type	0.137	2
Credit access	0.093	4
Value addition status	0.079	6
Market distance	−0.076	7
Farming experience	0.019	8

Note: Source: Survey results, 2018.

3.5. Constraints in SwP production

Constraints in SwP production is presented in Table 6. As presented in the table, the most important constraint in SwP production is labour shortage, which could be responsible for some of the inefficiencies obtained in SwP farms. Farming in the country is still characterized by hoe and cutlass that relied heavily on human labour. However, a sizable number of abled persons in most parts of the country including Kwara State have abandoned farming for transport business with motorcycle which provides them with a relatively stable daily wage. This has resulted into shortage of farm labour in the study area. Poor access to improved technology is the second most important production constraint on SwP farms as reported by the farmers. Most of the farmers relied on crude implements such as cutlass and hoe for the associated farming activities and the use of improved vine for planting was not popular among them. The third most important constraint is poor yield. This may also be connected to the use of crude implements and local type of vines among other factors. Similar result was obtained by Okonya et al. [36]. Insect pests ranked fourth of the production constraints. Low access to credit was the fifth important constraint in SwP production. This may be due to the fact that farmers found it difficult to meet the conditions set out by most of the formal credit sources and some informal sources before they could access loan. The result is similar to that of Fuglie [37]. Diseases are the next important constraint involved in SwP production and this may affect the yield of the crop, and hence, level of efficiency. Other important production constraints were bad roads, low price of output, lack of processing facilities and high transport cost.

Table 6. Constraints farmers faced in SwP production.

Constraints	Mean value	Rank
Insect pests	3.52	4th
Diseases	2.66	6th
Labour shortage	4.43	1st
Poor access to improved technology	4.20	2nd
Lack of processing facilities	2.98	9th
Low price	2.32	8th
Poor yield	3.87	3rd
High transport cost	2.01	10th
Bad roads	2.54	7th
Low access to credit	2.19	5th

*Note: Source: Survey results, 2018.

4. Conclusions

The results of the analysis of efficiency of sweet potato farms revealed that the farms were not efficient in the use of resources. The efficiency scores obtained under VRS were higher than those under CRS. Farmers' and institutional characteristics influenced the TE, AE, EE and SE of the farms differently. While farmers' level of education had direct relationship with farms' TE only, entrepreneurial training received had direct influence on both AE and EE. Access to credit influenced farms' TE positively, but had a negative effect on farms' SE. Also, TE of SwP farms was negatively influenced by distance to the nearest market. Labour shortage, poor access to improved technology and infestation by insect pests were the three most important constraints limiting SwP production in the study area. This study suggests regular training of SwP farmers by extension agents and other stakeholders as well as enhancement of their access to credit.

Conflict of interest

The authors declare no conflict of interest.

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