MODELLING THE TECHNICAL EFFICIENCY OF RICE PRODUCTION IN NIGERIA

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ABSTRACT

Rice botanically known as Oryza sativa has become a household food item in Nigeria, prompting the adoption of measures to ensure self-sufficiency in its production thus the need to analyse its production efficiency. This study employed data drawn from selected Nigerian states which included 168 rice farms within a Cobb-Douglas stochastic production frontier framework. The technical efficiency mean value obtained implied that on average, rice farmers obtained only 63% of the optimal output from inputs used in the production process. This therefore suggests that when inputs are efficiently utilized, technical inefficiency should be 37%. Empirical results more specifically revealed a considerable need for increased efficiency to complement rice supply shortfalls. The study suggested among other policy thrusts the need to assist rice farmers with adequate finance in order to increase production efficiency.

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1. Introduction

Attaining stable food supply is a key determinant of growth in any economy. The Sustainable Development Goals (SDGs) recognize the importance of food sustainability as an important goal since a society which lacks basic feeding capacity is an enclave of economic vices: unemployment, poverty, insecurity, resource underutilization, and other economic challenges with no exception to Nigeria. In recent years, the Nigerian government has been promoting programmes that are geared towards guaranteeing food security; rice (*Oryza sativa*) is one of the items on the front burner.

Rice is becoming an important crop produce in Nigeria owing to availability of arable land and other environmental factors favourable to its cultivation. Due to increased availability (for instance, 6.3 million and 6.07 million tonnes was cultivated in 2015 and 2016 respectively), rice has become a regular meal in Nigeria. Households consume it locally and industries use its by-products in producing industrial outputs such as rice flour. In order to achieve food sufficiency in the product and increase its market value, several policies have been adapted aimed at stimulating indigenous farmers (Efayena, Olele and Buzugbe, 2018). Government intervention is becoming increasingly important since both rice production and consumption have been on the increase in Nigeria. However, imbalances are found in production and consumption equilibrium, with supply of rice falling short of demand, resulting in increased rice importation to eradicate imbalances (Olaf et al., 2003). Thus, there is a need to examine efficiency in the production of rice in Nigeria.

Although previous studies by Ogundele and Okoruwa (2006), Akintayo and Rahji (2016), and Ayedun and Adeniyi (2019) all focused on technical efficiency of rice production in Nigeria, their scopes were somewhat limited to a few states and regions. For instance, the study by Ogundele and Okoruwa (2006) focused on four states in Nigeria; Ayedun and Adeniyi (2019) centred on Benue and Nassarawa; Akintayo and Rahji (2016) and Kadiri et al. (2014) targeted the North Central region and the Niger Delta respectively. There is thus a need to extend the scope of such studies in order to capture states across all geopolitical zones in Nigeria. This will make for easy and holistic comparison and policy recommendations. The importance of such a study cannot be overemphasized, especially in view of the recent border closure and increase in the import duty on rice. This action implies that local rice farmers can reap more benefits as long as the production process is efficient.

Thus, the main thrust of this study is to empirically investigate the technical efficiency in the production of rice in selected rice-producing states in Nigeria. Since local production of rice is adjudged an imperfect substitute for foreign rice due to its relatively low quality compared with imported rice, it is imperative to examine how technically efficient rice production is in Nigeria.

2. Literature Review

Several empirical studies have been done in developing economies on the rice production process and its efficiency (Saysay, Gabagambi, Mlay & Minde, 2018; Lema, Tessema & Abebe, 2017; Mailena, Shamsudin, Radam & Latief, 2014; Ataboh, Umeh & Tsue, 2014; Erhabor & Ahmadu, 2013). In particular, Ayedun and Adeniyi (2019) examined rice production efficiency among 408 peasant farmers sampled from Benue and Nasarawa states in North Central Nigeria. A stochastic frontier analysis established a 61% technical efficiency mean which implied 39% inefficiency in the production process. In another instance, Linh, Lee, Peng and Chung (2017) adopted the data envelopment analysis (DEA) in estimating technical efficiency among 200 rice farmers in Vietnam (Dong Thap province). The study showed a high scale and technical efficiency, although a decreasing returns to scale was observed among a larger proportion of the farmers.

The stochastic frontier (SF) model was employed in the study by Djomo, Odoemenem and Biam (2016) to evaluate the technical efficiency of small-scale rice farmers in Cameroon (West Region). Farm size and volume of labour were found to positively stimulate rice production. The study also found inefficiency in fertilizer utilization and credit, prompting policy recommendations in these areas of interest.

On their part, Akintayo and Rahji (2016) in north central Nigeria, measured farmers' technical efficiency in paddy production. The SF production approach was adopted to ascertain technical efficiency among 151 rice farmers selected using the multi-stage sampling technique. Empirical results clearly showed that farm size, fertilizers (quantity) and labour significantly influenced rice output. The obtained technical efficiency average measures were relatively low for the sampled farms.

The survey data of 15 Indonesian provinces was employed by Unggul, Purwono, Haryanto and Primanthi (2015) in investigating efficiency (technical) of producing rice in a frontier production framework. The empirical results confirmed a wide variation in efficiency among the sampled provinces, with income, access to credit and land size being the major production efficiency determinants. In a study in Cambodia, Sokvibol, Li and Pich (2016) investigated the rice production process with respect to efficiency (technical) using a SF production model. Employing a 4-year survey data, the study found that investment in farming equipment, farm size, and fertilizers significantly influenced rice production. Kadiri et al. (2014) examined the production of rice in Nigeria, focusing on the Niger Delta. A multistage sampling technique with an SF production function was adopted among 300 farmers to determine their production efficiency. The econometric results obtained showed that the production was technically inefficient. Thus, recommendations geared toward stimulating rice production in the Niger Delta were proffered.

On their part, Khai and Yabe (2011) employed a dataset of Vietnamese rice farmers to ascertain their technical efficiency. Data from the 2005/2006 VHLSS (Vietnam Household Living Standards Survey) was employed and was analysed adapting the SF analysis method in the Cobb-Douglas (CD) framework. Estimates proved that agricultural policies advocated by the government had not improved the farmers' efficiency since a technical efficiency of 81.6% was obtained from the data. Ogundele and Okoruwa (2006) investigated technical efficiency differentials in rice varieties. This was with a goal to ascertaining which variety (traditional versus improved rice) could be efficiently produced in Nigeria. A total of 302 farmers from four major rice-producing states in Nigeria were sampled using multistage random sampling, comprising 160 traditional rice variety producers and 142 hybrid variety producers. The size of arable land used for cultivation was found to be the main determinant of increased rice output, while the utilization of critical inputs (for instance herbicides and fertilizers) was below the recommended quantity given the available farm size.

Dhungana, Nuthall and Nartea (2004) examined the efficiency (technical) in rice production in Nepal. Both the Tobit and deterministic models were adopted to capture inefficiency effects and efficiency (technical) respectively.

The intensity of combining resources like seed, labour, mechanical equipment and fertilizer was found to determine differences in rice production efficiency. Employing non-parametric methods (deterministic and Tobit models), Krasachat (2003) established that on the average overall efficiency (technical) in processing rice was relatively low in Thailand and that the resource land determines such efficiency level. The study by Xu and Jeffrey (1998) adequately captured the differences in efficiency (technical) in the cultivation of hybrid and conventional rice varieties. This was achieved in a SF model with dual decomposition. The resulting model showed a significant difference in rice production using the conventional farming technique and producing hybrid rice.

Drawing from the findings of the above studies, modelling the existing levels of efficiency of rice production will help policymakers develop viable policy options. In Nigeria in particular, rice production is central to the agricultural sector because it is one of the staple foods widely consumed across the population distribution. Therefore, rice production efficiency is a critical factor in the national effort to promote food security.

However, periodic vicissitudes in the rice market environment relating to inputs and outputs along with improvements in technology of rice production, have spurred rice farmers to regularly adjust farming techniques to achieve efficiency (Efayena et al., 2018). Therefore, studies connected with rice farm efficiency are essential and useful to both farmers and policy makers.

3. Methodology

3.1 Theoretical framework

In the production process, given input factors, market price and a constant output scale, the technical efficiency of producing a given amount of product is the proportion of minimum cost to actual cost expressed as a percentage (Jondrow, Knox, Materov & Schmidt, 1982). It can be expressed as:

$$E(u_i|\varepsilon_i) = \frac{\delta_u\delta_v}{\delta}\left[\frac{f(\frac{\varepsilon_j}{\delta})}{1-f(\frac{\varepsilon_j}{\delta})} - \frac{\varepsilon_j\lambda}{\delta}\right] \tag{1}$$

where:

$\lambda = \sigma_u^2/\sigma_v^2;\ \sigma^2 = \sigma_v^2 + \sigma_u^2$

f = standard normal density

F = cumulative distribution function.

Specifically, given that y_{it} is the actual output level and y_{it}^* is the output at the stochastic frontier, technical efficiency is the distance between these two variables. It can be aptly expressed as:

$$TE_{it} = \frac{y_{it}}{y_{it}^*} \exp(-U_{it}) \tag{2}$$

where:

$$U_{it} = \eta_t U_i;\ \eta_t = \exp[-\eta(t-T)]$$

The parameter η_t gives a measure of technical efficiency changes over a period of time. Technical efficiency loss declines, increases or remains constant when the parameter $\eta>0$, $\eta<0$, or $\eta = 0$ respectively. The variable T captures technological progress in the process.

3.2 Model specification

Drawing from the theoretical framework, rice production can be captured in a production frontier since it is a multi-input and single-output production model. This can be expressed as:

$$Y_i = f(X_{ij}; \alpha) + \varepsilon_i \tag{3}$$

where: Y_i is farm i output; X_{ij} = vector of farm i inputs; ε is the error term which is given as ω_i-η_i. Note that η_i captures technical inefficiency; $\eta_i \geq 0$; ω_i and η_i are assumed to be independent.

The error term component, *vi* is a two-sided ($-\infty<\omega_i<\infty$) normally distributed random error ($\omega \sim N\ [0,\delta^2_\omega]$) which captures factors that are exogenously determined, including hazards (natural/man-made), pest invasion, unfavourable weather conditions, and others; measurement errors, and other statistical noise (Coelli, Rao, O'Donnell & Battese, 2005).

Observed output to potential output ratio of farm *i* in equation (2) denotes the technical efficiency of farm i. Hence technical efficiency denoted by TE_i is given by:

$$TE_i = \exp(-u_i) \tag{4}$$

In specifying the technical efficiency model, the Cobb-Douglas (C-D) production function was adopted owing to its advantages over other conventional models (for example, convenience and simplicity). The production form of C-D stochastic production frontier is given as:

$$Qty_i = \delta_0 + \delta_1 Land + \delta_2 Seed + \delta_3 Fertilizer + \delta_4 Pesticides + \delta_5 Labour + \delta_6 Machinery + v_i + u_i \tag{5}$$

Table 1 provides a description of the specified variables in equation (5):

Table 1. Description of variables

Variable	Description
Qty	Total rice output of the farmer in kilogram per hectare (kg/ha)
Land	Farm size (hectares)
Seed	Quantity of seeds planted in kilogram per hectare (kg/ha)
Fertilizers	Quantity of fertilizers applied per hectare (kg/ha)
Pesticides	Quantity of pesticides used in kilogram per hectare (kg/ha)
Labour	Labour used per hectare (man days)
Machinery	Machinery used per hectare (h ha-1)
v_1	Random errors which are assumed to be independently and identically distributed
u_1	Non-negative random variable associated with technical inefficiency of production
δ_1	Parameters to be estimated

Source: Survey data, 2021

3.3 Technique of estimation

The study adopted the maximum likelihood estimation (MLE) method (Kumbhakar and Lovell, 2003). The technique provides the estimators of the explanatory variables and variance parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ *and* $\gamma = \sigma_v^2/[\sigma_v^2 + \sigma_u^2]$. This method hinges on the assumptions of random error term, v_{it} ~

$iidN(0, \sigma_v^2)$, and non-negative error term which is expressed as $u_{it} \sim iidN^+(\mu, \sigma_u^2)$.

3.4 Data sources and measurement

A total of 168 rice farms were sampled from 14 states [Benue (BEN), Kogi (KOG), Kwara (KWA), Nasarawa (NAS), Niger (NIG), Plateau (PLA), Kaduna (KAD), Ekiti (EKI), Taraba (TAR), Anambra (ANA), Edo (EDO), Abia (ABI), Ogun (OGU) and Bauchi (BAU)] in Nigeria. Data on inputs and output of rice production (see table 2) were obtained using a well-structured questionnaire administered to selected farmers in the study states. The survey was carried out during the planting season (mid-March to mid-April) and harvesting season (mid-September to October) with the assistance of field officers.

4. Results and Discussion

4.1 Descriptive statistics

The statistics in table 2 show that the average cultivated land was 2,721 Ha and the average number of rice seeds per hectare was 17 Kg ha^{-1}. An average of 69 Kg ha^{-1} and 173 Kg ha^{-1} of fertilizers and pesticides were utilized.

Table 2. Descriptive statistics

	N	Mean	Standard deviation	Min.	Max
Land (ha)	168	2721	1685	397	13700
Seed (kg ha^{-1})	168	17	11	6	100
Fertilizers (kg ha^{-1})	168	69	56	9	350
Pesticides (kg ha^{-1})	168	173	207	4	1650
Labour (man days)	168	25	12	9	109
Machinery (h ha^{-1})	168	733	519	12	3461
Output ((kg ha^{-1})	168	1304	729	182	5300

Source: Author's compilation (2021).

As seen from table 2, units of rice harvested per hectare averaged 1,304kg. In addition, on the average, rice farmers utilized 69kg of fertilizer input per hectare of arable land. The average labour employed was 25 man days per hectare.

4.2 Aggregated analysis

Table 3 shows the estimates of the specified econometric model.

Table 3. Maximum Likelihood Estimates of the Parameters of Cobb-Douglas Stochastic Frontier Production Function for Rice Production

Variables	Coefficient	Standard Error	t-ratio
Constant	3.6531	1.3534	2.6992$^{\psi}$
Ln (land)	-0.4249	0.2408	-1.7642$^{\omega}$
Ln (seed)	0.0574	0.0158	3.6217$^{\varphi}$
Ln (fertilizers)	0.0685	0.0235	2.9105$^{\psi}$
Ln (pesticides)	0.3920	1.1800	2.1774$^{\psi}$
Ln (labour)	-0.7538	0.2330	-3.2351$^{\varphi}$
Ln (machinery)	2.5271	1.3048	1.9367$^{\omega}$
Variance measures			
Sigma-square (σ^2)	6.8492	2.1578	3.1741$^{\varphi}$
Gamma (γ)	0.9218	0.2263	4.0734$^{\varphi}$
Lamda (λ)	5.3916	1.5243	3.5370$^{\varphi}$
Log likelihood function	-102.6277		

1%, 5% and 10% significance levels are denoted by φ, ψ, ω respectively.
Source: Authors' compilation (2021).

The estimated coefficients were positive for seeds, fertilizer, pesticides and machinery inputs. The positive coefficients of these input variables suggest that an increase in the quantities of these inputs would result in an upsurge in rice production.

Conversely, labour and land exert strong negative correlations with rice output. This can be seen in the coefficient of land input. Rice output is observed to decrease by 0.4249kg units with a unit increase in land input. This is possibly caused by the high cost of acquiring additional hectares of land for production. This finding contrasted with those of Surendra (2016) and Micah and Musa (2015), but agreed with that of Oumarou and Zhou (2016). Increasing labour led to a decrease in rice output to the tune of 0.7538kg. This calls into question the quality of labour input available, corroborating the findings of Sokvibol et al. (2016). With regard to a unit increase in fertilizer input, rice output increased by 0.0685kg. This is consistent with the findings of Oumarou and Zhou (2016) and Sibiko et al. (2013).

The sigma squared (σ^2), indication of goodness of fit was found to be statistically significant at 5% level. This showed the goodness of fit of the survey data from states as well as the model specified. The estimated value of gamma (γ) was 0.9218, which indicates that technical inefficiency accounts for over 92% of the total variation in rice output. Differently put, 92% of the observed disparities among rice farmers can be attributed to the variation in technical efficiency. The variance ratio [lamda (λ = 5.3916)] parameter showed that variation in rice output or production is caused by differences in farming techniques and practices adopted by farmers. The estimated variance parameter sigma square (σ^2 = 6.8492) was significantly different from zero at 1% probability level implying that the inefficiency impacts are random and stochastic. The viability of individual unit technical efficiency is imperative for policymaking. Table 4 depicts the individual technical efficiency of the sampled population.

Table 4. Frequency Distribution of Technical Efficiency for Rice Farming

Efficiency	Scores	Percentage
1.00	-	
0.90-1.00	21	12.5
0.80-0.90	32	19
0.70-0.80	27	16.1
0.60-0.70	46	27.4
0.50-0.60	23	13.7
0.40-0.50	8	4.8
0<0.40	11	6.5
Mean	0.6319	
Minimum	0.1625	
Maximum	0.8747	
Standard deviation	0.1628	

Source: Authors' compilation (2021).

A cursory look at table 4 shows that none of the rice farms had a fully efficient production process, since 0.8747 was the highest efficiency score and 0.1625 was the lowest. The mean technical efficiency (63.19%) implies that there are opportunities to increase the volume of rice production by 36.81%.

4.3 States analysis

In order to carry out a holistic appraisal, the study analysed technical efficiency in the individual states sampled. The results are presented in tables 5A and 5B.

Table 5A. Maximum Likelihood Estimates of the Parameters of Cobb-Douglas Stochastic Frontier Production Function for Rice Production in Selected States

Explanatory Variable	BEN	KOG	KWA	NAS	NIG	PLA	KAD
Constant	3.128**	2.9412***	3.0036**	3.9188**	1.4911***	3.2441***	1.9903**
	(1.2032)	(2.9583)	(1.1083)	(1.4525)	(0.3844)	(0.8382)	(0.6935)
Ln (land)	0.4126**	0.7663**	0.6101***	0.9967**	0.5321**	0.7043***	0.6811**
	(0.1443)	(0.3090)	(0.0897)	(0.3547).	(0.2558)	(0.1334)	(0.2874)
Ln (seed)	-0.1321***	0.3619**	-0.1760***	-0.0048**	0.1361**	0.6453	0.1194**
	(0.0358)	(0.1297)	(0.0442)	(0.0024)	(0.0474)	(0.5926)	(0.0435)
Ln (fertilizers)	0.0016***	-0.0102***	0.1287**	0.0083**	0.1437***	-0.3164**	0.7342
	(0.0004)	(0.0027)	(0.0471)	(0.0033)	(0.0156)	(0.1194)	(0.5170)
Ln (pesticides)	0.1343	0.4193**	0.1175**	0.6211***	0.7508**	0.6222**	-0.5753***
	(0.1017)	(0.1698)	(0.0454)	(0.0754)	(0.2933)	(0.2279)	(0.1504)
Ln (labour)	0.0371**	0.0013***	-0.6991**	0.0117	0.0038**	0.0019**	0.0026**
	(0.0133)	(0.0003)	(0.3345)	(0.0095)	(0.0015)	(0.0008)	(0.0009)
Ln (machinery)	0.0035**	-0.4717	0.9273**	0.4359***	0.0074**	0.1026***	0.0017**
	(0.0013)	(0.6836)	(0.3553)	(0.0832)	(0.0030)	(0.0161)	(0.0006)
Variance measures							
Sigma-square(σ^2)	0.1019***	0.4661**	0.1160***	0.2623**	0.6220***	0.1089**	0.5317**
	(0.0276)	(0.2343)	(0.0299)	(0.1255)	(0.1300)	(0.0444)	(0.1991)
Gamma (γ)	0.6818***	0.7431**	0.8291**	0.7122**	0.9948***	0.8991**	0.7116**
	(0.1391)	(0.2847)	(0.3015)	(0.2695)	(0.2565)	(0.4540)	(0.2514)
Log likelihood function	-104.031	-33.6729	-106.441	-118.6381	-103.177	-116.041	-97.2417

Note: 1%, 5% and 10% significance levels are denoted by ***, **, * respectively. Figures in parentheses are standard errors of estimates.
Source: Authors' compilation (2021).

Table 5B. Maximum Likelihood Estimates of the Parameters of Cobb-Douglas Stochastic Frontier Production Function for Rice Production in Selected States

Explanatory Variable	EKI	TAR	ANA	EDO	ABI	OGU	BAU
Constant	3.4217***	2.6994***	4.0331**	3.2148***	1.1691**	3.8241***	1.9367***
	(0.4068)	(0.9640)	(1.5380)	(0.3682)	(0.4115)	(0.8171)	(0.3535)
Ln (land)	0.9807**	0.2374**	0.7291***	0.4260**	0.1165**	0.7803***	0.5417**
	(0.3313)	(0.1188)	(0.1137)	(0.1725).	(0.0416)	(0.1346)	(0.2291)
Ln (seed)	0.0016***	-0.0422**	0.2718**	0.7181**	0.9902***	0.1734**	0.0751**
	(0.0003)	(0.0167)	(0.1125)	(0.3629)	(0.1495)	(0.0872)	(0.0317)
Ln (fertilizers)	0.9817**	0.6180**	-0.0427**	0.9271***	0.4579**	0.5034	-0.2138**
	(0.4719)	(0.2958)	(0.0214)	(0.1228)	(0.1708)	(0.4059)	(0.0911)
Ln (pesticides)	0.2408**	-0.0081**	0.2124***	0.1764**	-0.0225**	0.0089**	0.0601***
	(0.0848)	(0.0041)	(0.0218)	(0.0887)	(0.0085)	(0.0036)	(0.0079)
Ln (labour)	0. 0179**	-0.0107***	0.0329**	0.0361**	-0.2168**	0.9702**	0.0504***
	(0.0069)	(0.0013)	(0.0122)	(0.0126)	(0.1085)	(0.3901)	(0.0056)
Ln (machinery)	0.1912***	0.9375**	0.0119**	-0.0041**	0.0290***	-0.6566**	0.0342***
	(0.0211)	(0.3811)	(0.0061)	(0.0015)	(0.0033)	(0.2498)	(0.0048)
Variance measures							
Sigma-square(σ^2)	0.1026***	0.1699**	0.1440**	0.5666**	0.0176**	0.1117***	0.8201**
	(0.0067)	(0.0688)	(0.0517)	(0.2225)	(0.0738)	(0.0239)	(0.3304)
Gamma (γ)	0.9509**	0.8361**	0.7315**	0.8134***	0.9478**	0.7216**	0. 6406***
	(0.3508)	(0.3119)	(0.3661)	(0.1018)	(0.3811)	(0.3047)	(0.1025)
Log likelihood function	-109.6331	-136.8417	-104.1368	-131.2061	-103.7639	-157.1482	-120.5317

Note: 1%, 5% and 10% significance levels are denoted by ***, **, * respectively. Figures in parentheses are standard errors of estimates.
Source: Authors' compilation (2021).

From tables 5A and 5B, the coefficients of land variable across the states were positive and significant, which implies that there is a possibility of increasing rice production by increasing the size of farming land. Other than Benue, Kwara, Nasarawa and Taraba, other states in the sample had positive and significant coefficients of seeds. This implies that other than the aforementioned states, rice productivity can be boosted in the other states through improvement and increase in the amount of seeds planted. Fertilizers were not found to stimulate rice productivity in Kogi, Plateau, Anambra and Bauchi. In terms of pesticides application, rice production was not boosted in Kaduna, Taraba and Abia.

The results also show that while an increase in labour will not significantly increase rice productivity in Kwara, Taraba and Abia, machinery adoption in rice production will increase productivity in Benue, Kwara, Nasarawa, Niger, Plateau, Kaduna, Ekiti, Taraba, Anambra, Abia and Bauchi. Niger State and Bauchi State had the highest and least gamma (γ) values. For Niger State, this implies that a large variation in rice output in the state was due to technical efficiencies.

The frequency distribution and descriptive statistics of technical efficiency at the state level are presented in table 6. The results clearly indicate that more states had technical efficiencies in rice production, lying between 0.60 and 0.70, showing a cluster of technical efficiencies within that region. The distribution of technical efficiencies presented in table 6 shows that there is a huge gap between the most technically-efficient and the least technically-efficient state.

The mean technical efficiencies across the states show that there are ample opportunities to increase rice productivity through well-coordinated strategies. Therefore, in the short run, rice production can be improved through the adaptation of technical synergy. This will increase the gross margin of rice production, reduce costs incurred in the production process, as well as increase profitability.

Table 6. Frequency Distribution and Descriptive Statistics of Technical Efficiencies for Rice Production in Selected States

Efficiency	No of States (%)													
	BEN	KOG	KWA	NAS	NIG	PLA	KAD	EKI	TAR	ANA	EDO	ABI	OGU	BAU
1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
0.90-1.00		2(16.7)					1(6.7)	2(16.7)	2(12.5)	-	2(18.2)	-	1(7.7)	2(20)
0.80-0.90	2(9.5)	2(16.7)	1(11.1)	-	1(9.1)	1(10)	2(13.3)	1(8.3)	1(6.2)	1(16.7)	1(9.1)	1(10)	3(23.1)	1(10)
0.70-0.80	1(4.8)	1(8.3)	1(11.1)	1(8.3)	2(22.2)	1(10)	2(13.3)	2(16.7)	1(6.2)	1(16.7)	1(9.1)	2(20)	2(15.4)	1(10)
0.60-0.70	9(42.8)	3(25)	3(33.3)	5(41.7)	3(33.3)		6(40)	3(25)	4(25)	2(22.2)	3(27.2)	3(30)	4(30.7)	3(30
0.50-0.60	3(14.3)	1(8.3)	2(22.2)	1(8.3)	1(9.1)	1(10)	1(6.7)	1(8.3)	2(12.5)	1(16.7)	1(9.1)	1(10)	1(7.7)	2(20)
0.40-0.50	5(23.8)	1(8.3)	1(11.1)	1(8.3)	1(9.1)		2(13.3)	1(8.3)	3(18.8)	-	2(18.2)	1(10)	1(7.7)	-
0<-0.40	1(4.8)	2(16.7)	1(11.1)	2(16.7)	2(22.2)	1(10)	1(6.7)	2(16.7)	3(18.8)	1(16.7)	1(9.1)	2(20)	1(7.7)	1(10)
Total	21(100)	12(100)	9(100)	12(100)	11(100)	10(100)	15(100)	12(100)	16(100)	6(100)	11(100)	10(100)	13(100)	10(100)
Mean	0.5731	0.4117	0.4619	0.3345	0.4051	0.5546	0.4873	0.3991	0.4435	0.5157	0.3006	0.4813	0.5661	0.4236
Minimum	0.1131	0.1753	0.1624	0.1353	0.1881	0.1741	0.1686	0.1208	0.1616	0.1822	0.1573	0.1457	0.1618	0.1829
Maximum	0.8556	0.7204	0.7511	0.6335	0.5918	0.8362	0.7011	0.6631	0.8114	0.6240	0.8706	0.7822	0.6632	0.8109
Std. dev.	0.1631	0.1604	0.2071	0.2113	0.1668	0.1733	0.2036	0.1773	0.1560	0.1591	0.2001	0.1647	0.2511	0.1538

Source: Authors' compilation (2021).

5. Conclusion and Recommendations

This study focused on the efficiency (technical) process in the production of rice in Nigeria. The study employed data from 168 rice farms across 14 states in Nigeria, spanning all the geopolitical zones. The study clearly showed the existence of widespread technical inefficiency in rice production among the sampled farms. Specifically, the study found that in spite of substantial utilization of inputs (for example, fertilizers and pesticides), efficiency was relatively low. The study also showed that since rice production is highly labour intensive in Nigeria, enhancing productivity of labour is primordial to improvement in rice production. Thus, the utilization of labour-saving technologies and other inputs which will result in enhanced efficiency in rice production is advocated. In terms of productivity costs, there is urgent need for increased and improved productivity of rice through a more efficient process. This can be achieved through a re-orientation of the management process in rice production, from cultivation through harvesting, processing and marketing of the product.

In addition, government policies should be targeted at reducing and/or subsidizing the prices of inputs in rice production such as pesticides, fertilizers, machinery and hybrid seeds. Government assistance in land acquisition may also help in improving the efficiency of land as that could lead to reduction in the cost of acquiring land and thus engender efficiency. Also, financial assistance programmes geared specifically at the rice sub-sector will act to stimulate increased private sector involvement in rice production, since financial constraints, particularly related to input procurement may deter participation in the rice production process.

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