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PERFORMANCE ASSESSMENT IN NIGERIA'S PEASANT AGRICULTURE: AN APPLICATION OF DATA ENVELOPMENT ANALYSIS ON RICE PRODUCERS IN CROSS RIVER STATE, NIGERIA

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ABSTRACT

The paper investigated the performance of swamp rice producers in Cross River State, Nigeria, in terms of their productive efficiency, using the non-parametric data envelopment analysis (DEA) approach to frontier estimation. Results show that the efficiency levels of rice producers in the region are generally above 65%, on average, under the assumption of variable returns to scale (VRS), thus indicating substantial levels of inefficiency. Of the 95 farmers sampled, 14 were fully technically efficient, while 4 each were fully allocatively and economically efficient (in the VRS sense), thus providing a benchmark for which the inefficient producers could emulate. Allocative inefficiency was the major source of overall inefficiency, while the key cause of technical inefficiency was the problem of sub-optimal scale. Among others, the study recommends that the problem of sub-optimal scale could be addressed by increasing farm sizes of the 77 farms operating at sub-optimal scale to an average of about 0.4 hectares, while that of allocative inefficiency could be alleviated by providing rice producers in the region with information on the cost-minimizing input mixes of their best-practice peers to enable them become fully allocatively efficient.

KEY WORDS: Benchmarking, Efficiency, Best-practice, DEA model, Rice

INTRODUCTION

Performance assessment in agriculture is necessary if productivity growth, brought about by technological change and efficiency improvement, must be sustained. It has been widely recognised that high and sustained levels of agricultural growth, largely driven by productivity growth are vital in a nation's economic growth. This is even more important in a peasant agriculture where technological change contributes very little or nothing to increased productivity, thus placing efficiency improvement at the core of efforts to foster productivity growth in agriculture.

According to Schultz (1964), although peasants in traditional agrarian societies are poor, they were efficient in allocating their resources, implying that given their state of technology, they are able to produce the highest attainable level of output by an efficient combination of the resources at their disposal. The broad question which arises is whether this hypothesis is true for peasant rice farmers in Cross River State, given that recent empirical evidence for some parts of Nigeria suggest that rice farmers are inefficient in resource use (Eremie, 1986; Olagoke, 1991; Onyenweaku, 1994; Onyenweaku, Agu and Obasi, 2000; Ohajianya and Onyenweaku, 2001 and 2002; Onyenweaku and Ohajianya, 2007).

In this paper, the performance of rice producers is assessed by measuring their efficiency using Data Envelopment Analysis (DEA)[1]. Strictly speaking, assessing performance in the context of DEA involves benchmarking, which is a procedure for improving performance by identifying best practice, measuring performance against best practice and then forming benchmarking partnerships between best practice (peers) and non-best practice enterprises so that the latter can identify and eliminate their less efficient practices (Jaforullah and Whiteman, 1999). This implies that by using the results of the DEA model, it is possible to work out what is required by inefficient farms to become efficient. This is possible because of the level of details on individual farms that the DEA methodology provides when compared with the widely used parametric production frontier method of estimating farm efficiency. Consequently, in the framework of peasant agriculture, the productivity of farmers could be enhanced through improvement in their efficiency levels by emulating identified best practices from their peers at the efficient frontier through benchmarking partnerships.

Considering the importance[2] of rice as a food security crop and a potential export commodity in Nigeria given the country's comparative resource advantage in its production, this novel study[3], being the

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first to use DEA to assess the performance of rice farmers in Nigeria, to our knowledge, will attempt to address the following (and other ancillary) research issues: what is the level of technical, allocative and economic efficiency of rice producers in Cross River State? What is the major source of technical and overall inefficiency in rice production in Cross River State? Are rice producers in Cross River State producing mostly at optimal, sub-optimal or supra-optimal scale?

Given empirical answers to the issues raised above and other incidental ones, it would be possible to assure that rice producers operate at the best practice frontier which implies producing at optimal scale. This would eliminate or at least reduce scale inefficiency granted that results, would among other things, indicate the output maximizing input quantities that would eliminate inefficiencies. To achieve this, however, would require better information dissemination and education among inefficient producers of their best practice peers.

The sequence of this paper is, by design, simple and self-contained. In what follows, the analytical framework, broadly inspired by Coelli (1996) is presented, with explicit specifications of the mathematical programming models. Next, is a description of the data and empirical procedures. This is then followed by the results of the empirical exercise and discussion. The final section concludes the paper proffering policy implications and directions for further research.

ANALYTICAL FRAMEWORK

Following Coelli (1996), both constant returns to scale (CRS) and variable returns to scale (VRS) input-orientated[4] models were pursued. By means of these models, we estimated technical, allocative and economic efficiency. Furthermore, we decomposed economic inefficiency into it technical and allocative components. Beyond these, technical efficiency was decomposed into its ‗scale' and ‗pure' components, thus providing us with an understanding of the major source of technical inefficiency. Finally, we estimated allocative efficiency by first estimating a cost minimizing DEA model rather than a revenue maximizing DEA model (both of which would lead to a measure of overall or economic efficiency) since we are dealing with a single output and multiple inputs in the current study.

Model Specification

Technical Efficiency

Constant Returns to Scale (CRS) Model

Consider a situation where there are data on *K* inputs used in rice production and *M* output on each of the *N* rice producers or decision management units (DMUs). For the i-th rice farmer, we represent these by the vectors x_i and y_i respectively. The *K x N* input matrix, *X*, and the *M x N* output matrix, *Y*, represent the data of all the *N* rice farmers. Using the duality (see, Coelli, 1996) in linear programming, we can straightforwardly write the envelopment problem in the form:

$$Min_{\theta,\lambda}\theta$$

Subject to $-y_i + Y\lambda \geq 0$;

$$\theta x_i - X\lambda \geq 0;$$

$$\lambda \geq 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where: θ is a scalar and λ is an *N x 1* vector of constants. The value of θ obtained will be the technical efficiency score for the i-th rice farmer. It will satisfy $\theta \leq 1$ with a value of 1 indicating a point on the frontier and hence a technically efficient rice farmer. Note that the linear programming problem must be solved *N* times, once for each rice farmer in the sample. A value of θ is then obtained for each farmer.

Assume our four input ($X_1\, X_2\, X_3\, X_4$) and one output (*Y*) case, for the rice farmer number 1, we could re-write equation (1) as:

$$Min_{\theta,\lambda}\theta,$$

Subject to
$$\begin{aligned}
&-y_1 + (y_1\lambda_1 + y_2\lambda_2 + \ldots + y_{95}\lambda_{95}) \geq 0,\\
&\theta X_{11} - (X_{11}\lambda_1 + X_{12}\lambda_2 + \ldots + X_{195}\lambda_{95}) \geq 0,\\
&\theta X_{21} - (X_{21}\lambda_1 + X_{22}\lambda_2 + \ldots + X_{295}\lambda_{95}) \geq 0,\\
&\theta X_{31} - (X_{31}\lambda_1 + X_{32}\lambda_2 + \ldots + X_{395}\lambda_{95}) \geq 0,\\
&\theta X_{41} - (X_{41}\lambda_1 + X_{42}\lambda_2 + \ldots + X_{495}\lambda_{195}) \geq 0,\\
&\lambda \geq 0
\end{aligned} \quad \ldots\ldots\ldots\ldots \quad (2)$$

Where: $\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4, \ldots, \lambda_{95})$

Variable Returns to Scale (VRS) Model

We specify an input-orientated (VRS) model for technical efficiency to enable us decompose technical efficiency into its ‗pure' and ‗scale' components. In doing this, we modify the constant returns to scale (CRS) linear programming problem to account for variable returns to scale (VRS) by adding the convexity constraint: $N1^{'}\lambda = 1$ to equation (1) to provide:

$$Min_{\theta,\lambda}\theta$$

Subject to $-y_i + Y\lambda \geq 0$;

$$\theta x_i - X\lambda \geq 0;$$
$$N1^{'}\lambda = 1;$$
$$\lambda \geq 0$$ é ...é ... (3)

Where: *N1* is an *N x 1* vector of ones. This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the constant returns to scale (CRS) conical hull, and thus provides technical efficiency scores which are greater than or equal to those obtained using the CRS model. Given our four-input and one-output case, for rice farmer number 1, we can re-write equation (3) as:

$$Min_{\theta,\lambda}\theta,$$

Subject to
$$\begin{aligned}
&-y_1 + (y_1\lambda_1 + y_2\lambda_2 + \ldots + y_{95}\lambda_{95}) \geq 0,\\
&\theta X_{11} - (X_{11}\lambda_1 + X_{12}\lambda_2 + \ldots + X_{195}\lambda_{95}) \geq 0,\\
&\theta X_{21} - (X_{21}\lambda_1 + X_{22}\lambda_2 + \ldots + X_{295}\lambda_{95}) \geq 0,\\
&\theta X_{31} - (X_{31}\lambda_1 + X_{32}\lambda_2 + \ldots + X_{395}\lambda_{95}) \geq 0,\\
&\theta X_{41} - (X_{41}\lambda_1 + X_{42}\lambda_2 + \ldots + X_{495}\lambda_{95}) \geq 0,\\
&N1'\lambda = 1\\
&\lambda \geq 0
\end{aligned}$$ é é é é é é é é ...é é é é é (4)

Where: $\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4, \ldots, \lambda_{95})$

Allocative and Economic Efficiency

To estimate allocative efficiency, we used data on prices of inputs in addition to input quantities as well as output quantities to first estimate a cost minimization DEA to get the cost efficiency scores. Then, together with technical efficiency scores obtained from the input-oriented DEA model in equation (1), we then calculated our allocative efficiency values for each of the rice farmers. We specify the cost minimization DEA thus:

$$Min\lambda, x_i^{*} w_i^{'},$$

Subject to
$$\begin{aligned}
&-y_i + Y\lambda \geq 0,\\
&x_1^{*} - X\lambda \geq 0,\\
&N1^{'}\lambda = 1,\\
&\lambda \geq 0
\end{aligned}$$ é .é é é é é .(5)

Where: w_i is a vector of input prices for the *i-th* rice farmer and x_i^{*} (which is calculated by linear programming) is the cost minimising vector of input quantities for the *i-th* rice farmer, given the input prices w_i and output levels y_i. The total cost efficiency (CE) or economic efficiency of the *i-th* rice farmer was calculated as:

$$CE = \frac{w_i^{'} x_i^{*}}{w_i x_i}$$ é é é é é é é é é é é é é ..é é é é é é é é é é é é é é é .é é ...(6)

Equation (6) implies the ratio of minimum cost to observed cost. We can thus calculate allocative efficiency (AE) for the *i-th* farmer as:

$$AE_i = \frac{CE_i}{TE_i}$$ é é é é é é é é é é é ..é .(7)

Since $CE = TE * AE$ é .é é é ....(8)

Scale Efficiency, Pure Technical Efficiency and Returns to Scale

To obtain scale efficiencies and evaluate returns to scale, we decomposed technical efficiency scores estimated form CRS DEA into two components, one due to scale inefficiency and the other due to ‱pureò technical inefficiency by calculating the difference between technical efficiency scores from the CRS and VRS DEA. Thus, if there was a difference in the two technical efficiency scores for a particular rice farmer, then this would indicate that the farmer has scale inefficiency.

Technically speaking, the VRS technical efficiency scores are the pure technical efficiency scores and as stated earlier because the VRS model is more flexible and envelops the data in a tighter way than the CRS model, the

VRS technical efficiency score is equal to or greater than the CRS or õoverallö technical efficiency score. Thus, the scale efficiency (SE) of the i-th farmer is given as:

$$SE_i = \frac{TE_{i,CRS}}{TE_{i,VRS}} \quad \text{é é} \quad (9)$$

Where SE = 1 implies scale efficiency or constant returns to scale or optimal scale and SE<1 indicates scale inefficiency.

However, scale inefficiency can be due to the existence of either increasing or decreasing returns to scale. This may be determined by calculating an additional DEA problem with non-increasing returns to scale (NIRS) imposed. Thus, we implemented this by re-writing the model in equation (4), replacing the *N1'λ=1* restriction with *N1'λ≤1*. Thus, the NIRS DEA model was specified as:

$$Min_{\theta,\lambda}\theta$$

Subject to $-y_i + Y\lambda \geq 0$;

$$\theta x_i - X\lambda \geq 0;$$

$$N1'\lambda \leq 1;$$

$$\lambda \geq 0 \quad \text{é .é é ...} \quad (10)$$

If the NIRS technical efficiency score is unequal to the VRS technical efficiency score, it indicates that increasing returns to scale exist for the farmer, implying that the farmer is operating at sub-optimal scale. On the other hand, if the NIRS technical efficiency and the VRS technical efficiency scores are equal, then decreasing returns to scale apply, indicating that the farmer is operating at supra-optimal scale.

The estimations were carried out with the aid of Data Envelopment Analysis Programme (DEAP) Version 2.1. The summary results are presented in section 4.

Data Description and Empirical Procedures

The study made use of primary farm-level data from a survey of 100 swamp rice farmers in Cross River State based on their 2005 production activities. A multi-stage sampling technique was adopted for study. The first stage involved the purposive selection of Obubra Local Government Area (LGA) of the State out of about four LGAs that are major rice cultivators in the State. The reason is the proximity and cost of carrying out the field work. In the second stage, ten villages were randomly selected from a list of major rice growing communities in the LGA. Lastly, ten rice farmers were also randomly selected from each of the ten selected villages, thus making a total of 100 rice farmers for the study. More LGAs would have been covered but the cost implication is high since there was no grant for the study.

The data were collected via a structured questionnaire administered to the farmers as well as from direct observation/field measurement. Of the 100 farmers sampled, data on 5 farmers were not complete. Thus, data on 95 farmers were used in the analysis. Data on the socioeconomic characteristics of swamp rice farmers, quantities of inputs used, output quantities, as well as, input costs and output price, were collected. The study assumes that all rice producers in the study area were faced with the same input and output prices.

One output and four inputs were pursued in the empirical approach. The four inputs are land, labour, fertilizer and seed. The inputs costs and output price plus their respective units of measure are shown in Table 1 while Table 2 shows the socioeconomic characteristics of the sampled farmers.

Table 1: Inputs Costs, Output Price and Units of Measure in Swamp Rice Production

Variable	Quantities					Prices
	Unit	Mean	Min	Max	S. Deviation	**Naira per unit**
Rice output	Kilograms	1037.684	200	3500	711.415	**20**
Farm size	Hectares	0.286	0.06	0.95	0.175	**2000**
Labour	Man days	42.281	16.41	127.35	22.895	**250**
Seeds	Kilograms	33.896	7.5	112.5	20.817	**30**
Fertilizer	**Kilograms**	**15.315**	**0**	**150**	**33.460**	**40**

Source: Compiled from field data

Farm size, that is the area cultivated to swamp rice by the farmer, was measured using the builderøs measuring tape of 100 metres length. In any given field, a standard measurement for a plot was taken and then multiplied by the number of plots that made up the field to arrive at the total size of the field. The total area in square metres was then converted to hectares by using 10000 as denominator. To ease measurement, a plot was taken as 14.5m x 14.5m or 201.25m^2. It should be noted that most of the land area for swamp rice cultivation was rented and the cost of land was the rental value of land that prevailed at the time.

Labour was measured in man days, and was used in all farm operations: nursery preparation, land clearing, puddling, fertilizer application, transplanting, weeding, bird scaring and harvesting of rice paddy. The labour input from women and children was converted to man equivalent using the adjustment factor of 0.67 and 0.33 respectively, for women and children following Upton (1996). Lastly, own labour (family labour), hired labour and exchange labour were all aggregated to make up the labour input.

Seeds used for nursery preparation were measured in a wash-hand basin, which weighs five kilograms on a weighing scale when filled with rice seeds. The quantity of seeds planted by each farmer was determined by multiplying the number of wash-hand basins of rice seeds planted by five kilograms. Farmers sampled for the study were persuaded to measure their seeds on wash hand basins before nursery preparation, to enable estimation of the quantity of seed planted per farmer.

All farmers who applied fertilizer on their rice farms used nitrogen-phosphorus-potassium fertilizer (N.P.K 15:15:15). This was the only type that was available and affordable.

Table 2 shows the socioeconomic characteristics of swamp rice farmers in Cross River State. The age composition of the sampled farmers shows that 36% of them fall within the age bracket of 36 and 45 years. Beyond this, the table further reveals that a total of 88% of the farmers are within the age range of 18 to 45 years. This indicates that most of the rice farmers are within the active age bracket. The gender distribution of the respondents shows that 95% of the farmers are males while only 5% are women, meaning that rice production in the region is dominated by men. In terms of educational attainment, the data on the table show that 37% of the farmers have attained secondary level education, while 29% and 17% have attained primary and tertiary level education respectively. Only 17% of them had no formal education at all. Farmersô level of education has implication on their efficiency/productivity. 70% of the sampled farmers had family sizes ranging between 6 and 10 persons. It has been hypothesized that farmers with large family sizes often use them to supplement hired labour, thereby reducing costs and increasing productivity. The farm size distribution shows that 92% of the sampled farmersô farms were very small - ranging between 0.05 and 0.5 hectare. No farmer had up to 1 hectare cultivated to rice. Generally, this might affect scale efficiency. Considering fertilizer usage, only 21% of the farmers applied fertilizer while the rest of them did not. This might be an indication of weak technology transfer/adoption in the area, among other reasons.

Table 2: Socioeconomic Characteristics of Swamp Rice Farmers in Cross River State

Variable	Frequency	Percentage
Age (Years)		
18-25	17	**18**
26-35	32	**34**
36-45	34	**36**
Above 45	12	**12**
Total	**95**	**100**
Sex		
Male	90	**95**
Female	5	**5**
Total	**95**	**100**
Educational Status		
No formal education	16	**17**
Primary education	28	**29**
Secondary education	35	**37**
Higher education	16	**17**
Total	**95**	**100**
Family Size		
2-5	14	**14**
6-10	66	**70**
>10	15	**16**
Total	**95**	**100**
Farm Size		
0.05-0.50	87	**92**
0.51-0.99	8	**8**
1 and above	0	**0**
Total	**95**	**100**
Fertilizer Usage		
Users	20	**21**

Non-users	75	**79**
Total	**95**	**100**

Source: Compiled from field data

RESULTS AND DISCUSSION

The results of the DEA for swamp rice farmers in Cross River State are summarised in tables 3 to 5. Table 3 shows the technical, allocative and economic efficiency measures for the rice farmers. The estimated mean technical efficiency for the sampled rice farmers is 84.50% and 92.40%, respectively, for constant returns to scale and variable returns to scale DEA models. The results indicate that 8 out of the 95 farms in the sample were fully technically efficient under the constant returns to scale assumption while 14 were fully efficient in the variable returns to scale model. The estimated mean allocative efficiency scores were 65.40% for constant returns to scale and 81.13% for variable returns to scale model, while the mean economic efficiency scores estimated from the DEA frontier for both constant and variable returns to scale models were 55.50% and 75.03% respectively. Clearly, the analyses reveal significant inefficiencies in swamp rice production in Cross River State. In particular, inefficiencies were higher under the constant returns to scale assumption because it is more restrictive in practice than the variable returns to scale assumption.

Technical efficiency results imply that rice farmers in the region could reduce the use of all inputs by an average of 15.5% and 7.6% (under CRS and VRS models, respectively) without a reduction in their output. Allocatively, since we assumed in our DEA estimations that cost minimization is the basis on which the farmersô allocation decision are taken, we thus define allocative efficiency as the proportion by which the costs of the levels of inputs on a farm can be reduced without any loss in output. Consequently, the estimated allocative efficiency scores of 65.40% and 81.13% (for CRS and VRS assumptions) suggest that on average the farmers could reduce their costs by 34.60% and 18.87% respectively, by choosing a more cost-efficient input mix, without any loss in output. In fact, these results suggest that allocative inefficiency was higher in rice production in the area than technical inefficiency.

Furthermore, the average level of Farrellôs overall (economic) efficiency is 55.50% under constant returns to scale and 75.03% assuming variable returns to scale. This means, in principle, that the sample rice farms can potentially reduce their overall cost of rice production, on average, by 44.50% and 24.97% for CRS and VRS respectively and still achieve the existing level of output. The measures of relative allocative and technical efficiency provide evidence as to the source of economic inefficiency (deviations from overall cost-minimising behaviour). Undoubtedly, many rice farms in the sample employed the ówrongô input mix, given input prices, such that, on average, their costs were 34.60% and 18.87% higher than the cost minimising level under the two scale assumptions (CRS and VRS), respectively. Nonetheless, as has been noted earlier, farms have the potential to reduce their physical input, on average, by 15.5% and 7.6%, under the two scale assumptions, respectively and still produce the same level of rice output.

We note also from table 3 that the number of technically, allocatively and economically efficient farms were 14, 4 and 4 respectively under the variable returns to scale assumption. This indicates that not all of the technically efficient firms were allocatively or economically efficient, because of using inappropriate cost-minimizing input quantities. For instance, while farmer 2 (from the sample of 95 farmers) was technically efficient, he was not allocatively/economically efficient because he used 0.25 hectares of farmland instead of 0.546 hectares; 84.9 mandays of labour instead of 65.667 mandays; 75 kilograms of seed in place of 65kilograms and 0 kilograms of fertilizer instead of 82.353kilograms.

From the above discussion, and granted that overall (economic) efficiency is made up of technical and allocative efficiency, we thus summarise the sources of economic inefficiency for both models in figures 1 and 2. For the constant returns to scale model, the average relative economic efficiency score was 55.50%, implying that economic inefficiency was 44.50%. This is then decomposed into its technical and allocative inefficiency components. We find that technical inefficiency contributes 15.5% while allocative inefficiency contributes 34.60%. Following the same logic, the mean overall efficiency in the variable returns to scale model was 75.03%, suggesting that overall inefficiency was 24.97%. Of this figure, 7.6% was due to technical inefficiency while 18.87% was due to allocative inefficiency. It is evident and noteworthy that allocative inefficiency contributed more to overall inefficiency. This shows that many of the sampled farmers were not able to equate marginal value product of inputs to their prices.

TABLE 3: Frequency Distributions of Technical, Allocative and Economic Efficiency Measures in both Constant Returns Scale (CRS) and Variable Returns to Scale (VRS) Input Orientations.

Efficiency Class (%)	Technical Efficiency		Allocative Efficiency		Economic Efficiency	
	CRS	VRS	CRS	VRS	CRS	**VRS**
= 100	8	14	1	4	1	**4**
90 - < 100	27	47	-	15	-	**7**
80 - < 90	31	31	-	31	-	**13**
70 - < 80	20	3	11	35	7	**39**
60 - < 70	8	-	69	9	18	**26**
50 - < 60	-	-	10	1	46	**5**
40 - < 50	1	-	4	-	16	**1**
< 40	-	-	-	-	7	**-**
Mean (%)	84.50	92.40	65.40	81.13	55.50	**75.03**
Standard Deviation (%)	10.82	6.13	6.81	9.81	10.58	**11.07**
Minimum (%)	44.40	70.70	42.00	51.10	24.90	**47.60**
Maximum (%)	**100**	**100**	**100**	**100**	**100**	**100**

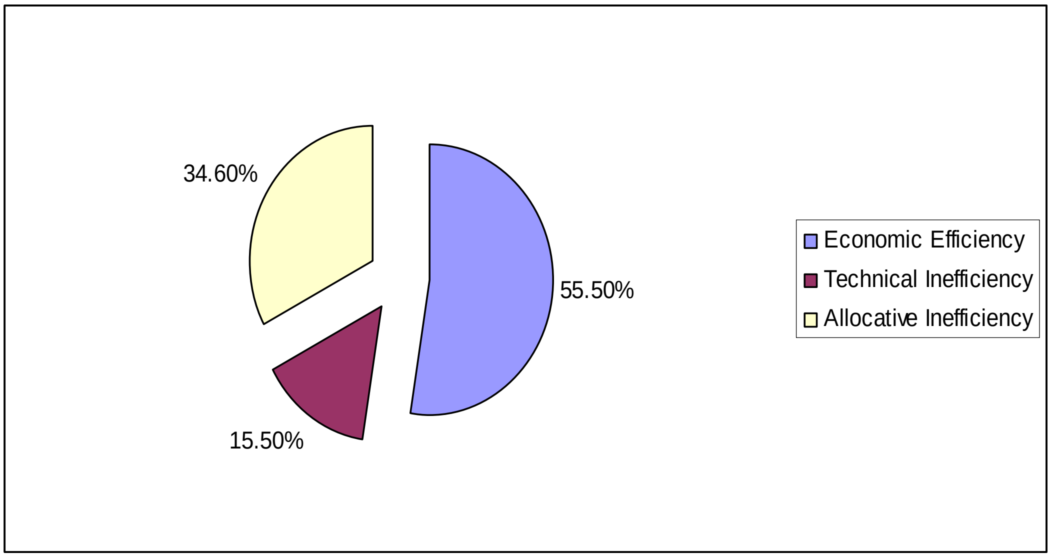

Figure 1: Sources economic inefficiency in rice farms in Cross River State (CRS)

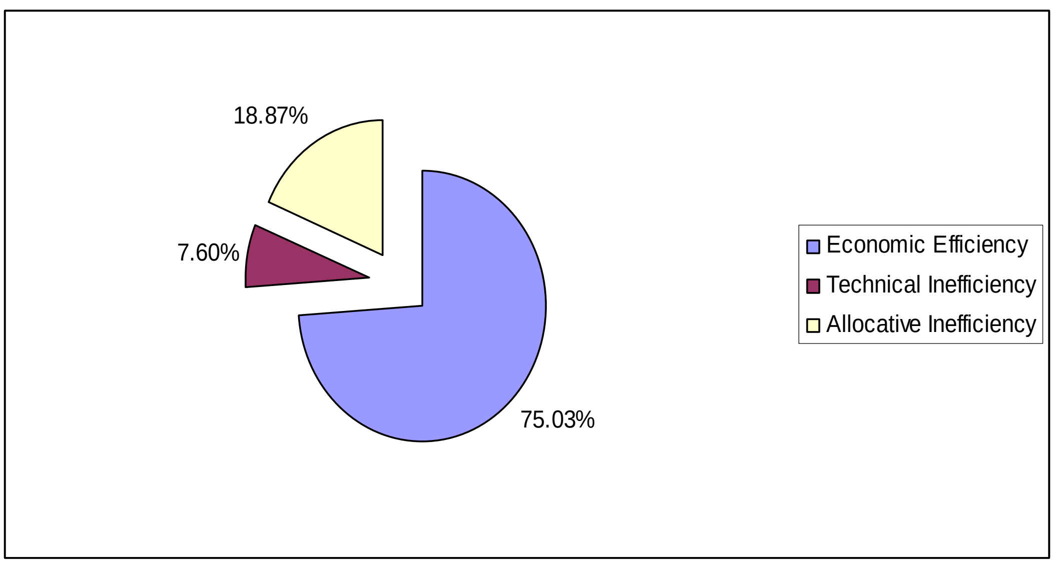

Figure 2: Sources economic inefficiency in rice farms in Cross River State (VRS)

To analyse the sources of technical inefficiency, we turn to the results in Tables 4 and 5, showing overall, scale and pure technical efficiency indexes, as well as scale efficiency components. The estimated mean overall technical efficiency score for the sampled farmers is 84.5%, while the estimated average scale and pure technical efficiency were 91.2% and 92.4% respectively. This implies that the average level of overall technical inefficiency was 15.5%, made up of 8.8% scale inefficiency and 7.6% pure technical inefficiency, as shown in figure 1. A technical interpretation of these results is that rice farmers can, on average, reduce their inputs by about 15.5% by operating at optimal scales and by eliminating pure technical inefficiencies through the adoption of the best practices of efficient rice farms, without a reduction in their output levels.

Although there may not be any significant difference between inefficiency scores due to farm size and inefficiency due to management, it is clear that the major source of technical inefficiency in rice production in the region is scale inefficiency (and subsequently decreasing returns to scale or increasing returns to scale) and thus, technical inefficiency in rice farms in Cross River State can mostly be eliminated through the elimination of scale inefficiency. Furthermore, the results in Table 4 indicate that the number of efficient farms under the constant returns to scale (overall technical efficiency), variable returns to scale (pure technical efficiency) and scale efficiency assumptions were 8, 14 and 8 respectively.

TABLE 4: Overall Technical, Scale and Pure Technical Efficiency Scores

	Overall Technical Efficiency	**Scale Efficiency**	**Pure Technical Efficiency**
Mean (%)	84.50	91.20	**92.40**
Standard Deviation (%)	10.82	8.63	**6.13**
Minimum	44.40	56.20	**70.70**
Maximum	100	100	**100**
Number of Efficient Farms	**8**	**8**	**14**

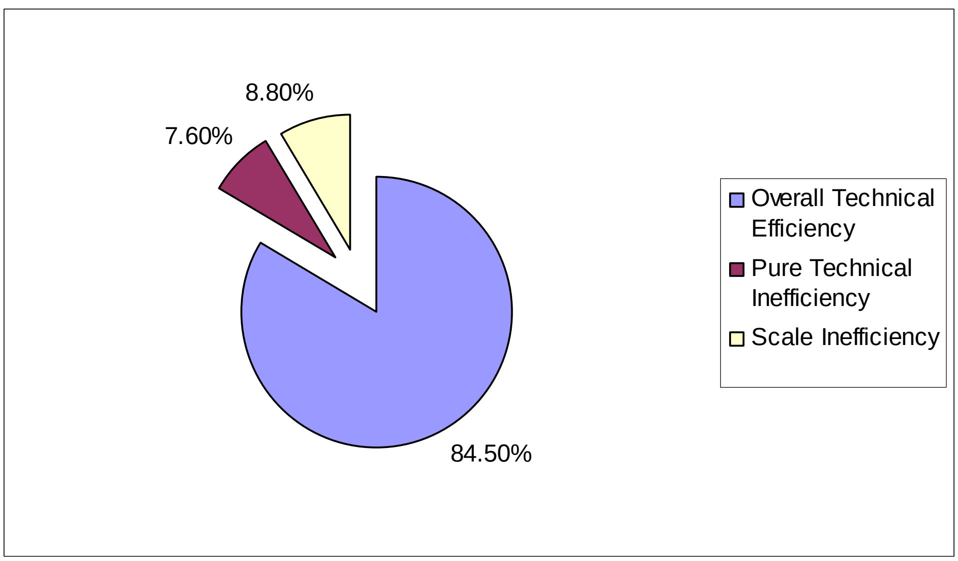

Figure 3: Efficiency of input use in rice farms in Cross River State

Next we shed more light on the scale efficiency in rice farms in Cross River State as we discuss the results summarised in Table 5 and Figure 2. The DEA results for the respective rice farms indicate that, out of the 95 rice farms, only 8.42% or 8 farms were operating at optimal scale (constant returns to scale), 10.53% or 10 farms operated above optimal scale (that is exhibited decreasing returns to scale) and 81.05% or 77 farms operated below optimal scale (that is increasing returns to scale). These results are very informative. Undoubtedly, the largest increase in technical efficiency could be achieved by addressing the problem of sub-optimal scale given that the largest proportion of rice farms are characterised by it. From Table 5, it has been shown that eliminating sub-optimal scale would increase the overall technical efficiency of 77 rice farms by an average of 9.68% from 81.51% to 91.19%. On the other hand, eliminating supra-optimal scale would only increase the overall technical efficiency of the 10 rice farms by an average of 0.92% that is from 94.75% to 95.67%. Obviously, this shows that policy efforts to improve productive efficiency of rice farmers must encourage trends towards larger rice farms rather than the reverse.

Further empirical evidence shows that on average, the optimal size of sampled rice farms was 0.395 hectares. This suggests that the 77 rice farms operating at sub-optimal scale were below their optimal size by an average of 0.159 hectares. In contrast, the results also indicate that the 10 farms that were operating at supra-optimal scale exceeded their optimal size by an average of 0.222 hectares (see table 5).

TABLE 5: Technical and Scale Efficiency of Rice Producers in Cross River State

	Optimal Scale	Supra-optimal Scale	Sub-optimal Scale
Number	8	10	**77**
Area (Ha)			
Average	0.395	0.617	**0.236**
Minimum	0.170	0.420	**0.060**
Maximum	0.670	0.950	**0.630**
Average Measure of Technical Efficiency (%)			
Overall Technical Efficiency	100	94.75	**81.51**
Pure Technical Efficiency	**100**	**95.67**	**91.19**

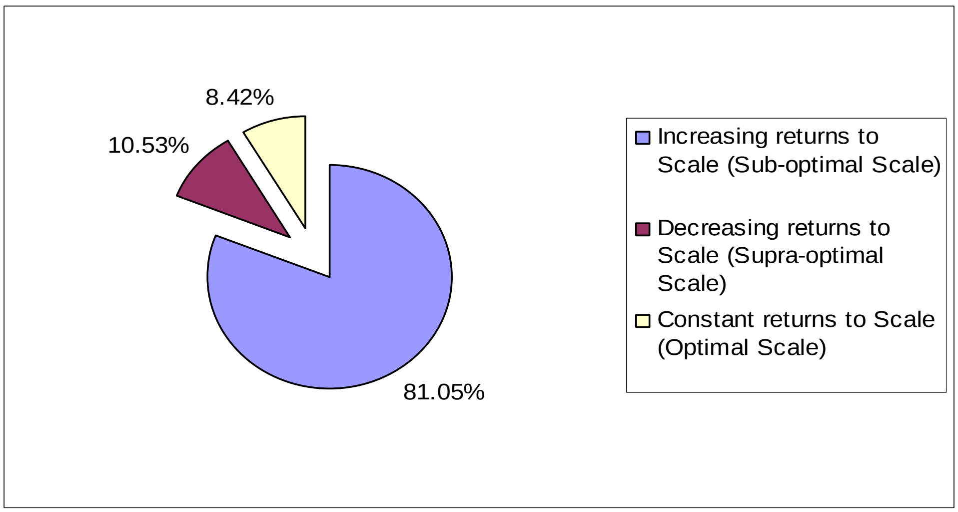

Figure 4: Scale efficiency of rice farms in Cross River State

CONCLUSIONS AND POLICY IMPLICATIONS

This paper has investigated the performance of swamp rice producers in Cross River State, Nigeria, in terms of their productive efficiency, using the non-parametric DEA approach to frontier estimation. The results of the analyses answer the research questions that were raised, sufficiently well. The study has shown that the (technical, allocative and overall) efficiency levels of rice producers in the region are generally above 65%, on average, under the assumption of VRS, thus indicating substantial levels of inefficiency. The study also indicates that, of the sampled farmers, 14 were fully technically efficient, while 4 each were fully allocatively and economically efficient (in the VRS sense), therefore providing a benchmark for which the inefficient producers could emulate.

The decomposition of economic inefficiency into its technical and allocative components revealed that allocative inefficiency was the major source of overall inefficiency. Furthermore, technical inefficiency was decomposed into its ñpureò and ñscaleò components, and the results indicated higher scale inefficiency compared with pure technical inefficiency. Scale inefficiency, on its part, was further analysed in terms of its three components: constant returns to scale, increasing returns to scale and decreasing returns to scale, and the results revealed that the major source of technical inefficiency in swamp rice production in the State was the problem of increasing returns to scale (sub-optimal scale).

From the findings of this study, the policy implications are very clear. In addressing the problem of inefficiency, we bear in mind that overall inefficiency stems from a combination of technical and allocative inefficiency, thus, we begin with the implications of technical inefficiency results. The major source of technical inefficiency was the problem of sub-optimal scale, thus technical efficiency could be enhanced by increasing farm sizes of the 77 farms operating at sub-optimal scale to an average of about 0.4 hectares. One way of achieving this is by consolidation of existing holdings, perhaps by forming rice producer cooperatives; producing in small groups of two or three farmers depending on the initial size of their holdings. With regards to the problem of pure technical inefficiency (arising from poor management practices), farmer education on good management or best practice is inevitable. In this case, inefficient farmers can emulate management style of the fully efficient or best-practice farmers on the DEA frontier in order to be "purely" technically efficient themselves. All of these allusions, however, require education of the farmers of existing best-practice from efficient peers by extension personnel, who in turn need be equipped with informed knowledge on research findings, such as these, regarding rice producers in the area.

Allocative inefficiency contributed more to overall inefficiency signalling excessive costs on inputs used, implying that the input mix of rice producers in the study was not consistent with cost minimization. Thus, the farmers did not equalize marginal returns with true factor market prices. However, in a strict sense, most of the farmers failed to use the cost-minimizing input quantities and thus were allocatively inefficient. Consequently, rice producers should be provided with information on the cost-minimizing input mixes to enable them become fully allocatively efficient. This comes as part of DEA estimation output and is probably one of the major advantages of DEA over parametric frontier estimation. The above recommendations if implemented would eliminate or at best substantially reduce overall inefficiency in swamp rice production in the State.

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