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Application of Data Envelopment Analysis to Evaluate Farm Resource Management of Nigerian Farmers

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ABSTRACT The present study applied the cost approach constant returns to scale and variable returns to scale data envelopment analysis models to evaluate farm resource management of Nigerian farmers using 393 rural farmers in Benue State. Scale efficiency among the respondents varied substantially ranging between 0.002 and 1.00, with a mean scale efficiency of 0.70. The study showed that some of the decision-making units have scale inefficiency, suggesting that the decision-making units are not all operating at the optimal scale. Most of the respondents operated very far away from the efficiency frontier. The overall technical inefficiency among the respondents resulted more by scale inefficiency compared to pure technical inefficiency. Allocative inefficiency is worse than technical inefficiency, implying that the low level of overall economic efficiency is the result of higher cost (allocative) inefficiency and scale inefficiency (operating at less than optimal scale size). Solving allocation and scale problems is critical for improving farm resource use efficiency of Nigerian farmers.

INTRODUCTION

The performance of the Nigerian farmers in this study was evaluated in terms of the productivity and efficiency of the farmers. Production efficiency means attainment of a production goal without waste (Ajibefun and Daramola 2003). Efficiency is concerned with relative performance of the processes used in transforming given input into output (Ohajianya and Onyeweaku 2001).

The measurement of efficiency is important because it is a success indicator and performance measure by which production units are evaluated. Furthermore, the ability to quantify efficiency provides decision makers with a control mechanism with which to monitor the performance of the production system or units.

Production efficiency can be measured technically, allocatively and economically. These three measures of production efficiency give general overview of the farmer's overall performance in resource utilization in the production process. Technical efficiency is the ability of a farmer to produce on the maximum possible frontier. A production process may be technically inefficient, in the sense that it fails to produce maximum output from a given bundle of inputs. Technical inefficiency results in an equi-proportionate over-utilization of inputs (Hazarika and Subramanian 1999).

Allocative efficiency is the farmer's ability to produce a given level of output using the cost minimizing input ratios. Invariably, a farm is considered to be allocatively efficient in the use of a given factor if the farm is able to equate the marginal value product (MVP) of the factor to the factor price (P). A production process may be allocatively inefficient in the sense that the marginal revenue product (MRP) of input might not be equal to the marginal cost of that input. Allocative inefficiency results in utilization of inputs in the wrong proportions, given input prices.

Economic efficiency is the farmer's ability to produce a predetermined quantity of output at minimum cost given the available technology. Economic efficiency is the ability of farmer to maximize profit (Adeniji 1988; Ohajianya and Onyenweaku 2001). Economic efficiency is the product of technical and allocative efficiency. It indicates the costs per unit of output for a firm which perfectly attains both technical and price efficiencies. Technical and allocative efficiencies are necessary and, when they occur together, are sufficient conditions for achieving economic efficiency (Yotopoulous and Lau 1973).

This study uses the cost approach constant returns to scale and variable returns to scale data

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envelopment analysis models. The cost approach data envelopment analysis model has the advantage of allowing simultaneous estimation of the technical efficiency, allocative efficiency and economic efficiency of individuals (Coelli 1996). The use of the variable returns to scale specification permits the calculation of technical efficiency devoid of scale efficiency effects (Coelli 1996). The data envelopment analysis (DEA) model offers a flexible approach with a considerable scope for the use of diverse data (real and monetary) (Ready et al. 2004). Furthermore, DEA is deterministic and permits the choice between the constant return to scale (CRTS) specifications and the variable return to scale (VRTS) specifications depending on whether all decision making units (DMU's) are operating at the optimal scale and otherwise respectively.

Using multiple stage data envelopment analysis model, Gorman and Ruggiero (2008) evaluated the US state police performance. They found that most states are technically efficient, but nearly half are operating at less than optimal scale size. Using a variant of data envelopment analysis, slack based measure (SBM), Kuah et al. (2010) assessed quality management efficiency. They observed that data envelopment analysis is suitable to measure quality management efficiency and give improvement suggestion to the inefficient quality management.

In Nigeria, several studies have been conducted on the analysis of farm efficiency. For example, Ajibefun (2002), using the stochastic frontier production function, analysed policy issues in technical efficiency of Nigerian small scale farmers. Ater and Umeh (2003) applied a stochastic frontier production function to analyse poverty reduction among dry season Fadama enterprises in Nigeria. Ajibefun and Daramola (2003) applied stochastic frontier production function and cost function for the analysis of determinants of technical and allocative efficiency of micro-enterprises in Nigeria. Asogwa et al. (2007) applied stochastic frontier production function for technical efficiency analysis of Nigerian cassava farmers as a guide for food security policy. Asogwa et al. (2011) applied stochastic frontier production function and cost function for technical and allocative efficiency analysis of Nigerian rural farmers and its implication for poverty reduction. Of all these studies, none has focused on the application of DEA for the analysis of farm efficiency. The CRTS assumption is only appropriate when all DMU's are operating at an optimal scale. Imperfect competition, constraints on finance, etc. may cause a DMU to be not operating at optimal scale. Banker et al. (1984) suggested an extension of the CRTS DEA model to account for variable returns to scale (VRTS) situations. The use of the CRTS specification when not all DMU's are operating at the optimal scale will result in measures of technical efficiency (TE) which are confounded by scale efficiencies (SE). The use of the VRTS specification will permit the calculation of TE devoid of these SE effects. The focus of this paper therefore, is to develop a model to evaluate farmers' resource management **(**efficiency) by using Data Envelopment Analysis (DEA).

Objectives of the Study

The broad objective of this study is to develop a model to evaluate farmers' resource management efficiency by using Data Envelopment Analysis (DEA). The specific objectives of the study are to:

i. evaluate the technical efficiency levels of Nigerian farmers;
ii. evaluate the allocative efficiency levels of Nigerian farmers;
iii. evaluate the overall economic efficiency levels of Nigerian farmers; and
iv. evaluate the scale efficiency levels of Nigerian farmers.

Statement of Hypothesis

The following hypothesis was stated and tested:

i. there is no significant difference between the constant return to scale (CRTS) and variable return to scale (VRTS) efficiency scores among the Nigerian farmers.

METHODOLOGY

The Study Area

For this study, farm level data were collected on 393 rural farmers in Benue State. Benue State is one of the 36 states of Nigeria located in the North-Central part of Nigeria. The State has 23 Local Government Areas, and its Headquarters is Makurdi. Located between Longitudes 6^0 35'E and 10^0E and between Latitudes $6^0$30'N and

$8^0 10$'N. The State has abundant land estimated to be 5.09 million hectares. This represents 5.4 percent of the national land mass. Arable land in the State is estimated to be 3.8 million hectares (BENKAD 1998). This State is predominantly rural with an estimated 75 percent of the population engaged in rain-fed subsistence agriculture. The state is made up of 413,159 farm families (BNARDA 1998). These farm families are mainly rural. Farming is the major occupation of Benue State indigenes. Popularly known as the "Food Basket" of the Nation, the State has a lot of land resources. For example cereal crops like rice, sorghum and millet are produced in abundance. Roots and tubers produced include yams, cassava, cocoyam and sweet potato. Oil seed crops include pigeon pea, soybeans and groundnuts, while tree crops include citrus, mango, oil palm, guava, cashew, cocoa and *Avengia spp*.

Sampling Technique

The multistage simple random sampling technique was used to select the farmers for the study. Benue State is divided into three (3) agricultural zones: Zone A, Zone B and Zone C. Zone A and Zone B are made up of seven local government areas each while Zone C is made up of nine local government areas. Using a constant fraction of 45%, three local government areas were randomly selected from Zone A and Zone B while four local government areas were randomly selected from zone C under the guide of Benue State Agricultural and Rural Development Programme workers in Benue State Agricultural and Rural Development Agency (BNARDA). From each of the selected local government areas, one rural community was randomly selected. Finally, from each community, households were randomly selected on the basis of the community's population size using a constant sampling fraction of 1% so as to make the sampling design to be self-weighting and hence avoid sampling bias (Eboh 2009). Based on the foregoing, 393 farming households were randomly selected from the rural communities selected for the study.

Data Collection

Data were obtained through the use of structured questionnaire, copies of which were administered to the selected 393 farm households in Benue State, Nigeria. Production resources were categorized into five groups: land, labour, seed, fertilizer and pesticide. Land was measured in hectares, human labour was measured in man-days (for family and hired labour), seed was measured in kilogrammes, fertilizer was measured in kilogrammes and pesticide was measured in litres. The unit prices of the resources were measured in Naira.

Data Analysis

The data collected were analysed using the Data Envelopment Analysis Programme (DEAP). Both the constant returns to scale (CRTS) and variable returns to scale (VRTS) DEA models were used for data analsis. Furthermore, t-test was used to test the null hypothesis.

Model Specification

Data Envelopment Analysis (DEA): Before presenting the model, the relevant concepts are presented below:

Overall Technical Efficiency (OTE): This is related to a given farm operating in constant return to scale (CRTS). Overall technically efficient farms fall on the frontier. The overall technical efficiency can be disaggregated into two measures *viz*., pure technical efficiency and scale efficiency.

Pure Technical Efficiency (PTE): This concept arises when a given farm is operating under variable returns to scale (VRTS). A decision-making unit (farm) which is identified as technically not efficient on CRTS frontier can become technically efficient, if it falls on the VRTS frontier. This unit falling on VRTS frontier is technically efficient.

Scale Efficiency (SE): A decision–making unit is said to be scale efficient if it operates under constant returns to scale.

Input Congestion: This implies overutilization of resources. This is found in variable returns to scale.

The DEA Model

Given the CRTS assumption, the best way to introduce DEA is via the *ratio* form. For each decision-making unit (DMU) one would like to obtain a measure of the ratio of all outputs over all inputs, such as $u'y_i/v'x_i$, where u is an Mx1 vector of output weights and v is a Kx1 vector of input weights. To select optimal weights one specifies the mathematical programming problem:

$\max_{u,v} (u'y_i/v'x_i)$,
st $u'y_j/v'y_j \leq 1$, j=1,2,…, N,
$u, v \geq 0$ .... (1)

This involves finding values for u and v, such that the efficiency measure of the i-th DMU is maximized, subject to the constraint that all efficiency measures must be less than or equal to one. One problem with this particular ratio formulation is that it has an infinite number of solutions. To avoid this one can impose the constraint $v'x_i = 1$, which provides:

$\max_{ì,v} (ì'y_i)$,
st $v'x_i = 1$,
$\mu'y_j - v'x_j \leq 0$, j =1,2, …,N,
$\mu, v \geq 0$, ... (2)

where the notation change from u and v to μ and v reflects the transformation. This form is known as the *multiplier* form of the linear programming problem.

Using the duality in linear programming, one can derive an equivalent *envelopment* form of this problem:

$\min_{\theta,\lambda} \theta$,
st $-y_i + Y\lambda \geq 0$,
$\theta x_i - X\lambda \geq 0$,
$\lambda \geq 0$, ... (3)

where θ is a scalar and λ is a N x1 vector of constants. This envelopment form involves fewer constraints than the multiplier form (K + M < N + 1), and hence is generally the preferred from to solve. The value of θ obtained will be the efficiency score of the i-th DMU. It will satisfy θ ≤ 1, with a value of 1 indicating a point on the frontier and hence a technically efficient DMU, according to the Farrell (1957) definition. Note that the linear programming problem must be solved N times, once for each DMU in the sample. A value of é is then obtained for each DMU.

The CRTS linear programming problem can be easily modified to account for VRTS by adding the convexity constraint: N1'λ=1 to (3) to provide:

$\min_{\theta,ë} \theta$,
st $-y_i + Y\lambda \geq 0$,
$\theta x_i - X\lambda \geq 0$,
$N1'\lambda=1$
$\lambda \geq 0$, ... (4)

where θ is a scalar and λ is a N x1 vector of constants, whereas N1 is an Nx1 vector of ones. The value of θ obtained will be the efficiency score of the i-th Decision Making Unit (DMU). It will satisfy θ ≤ 1, with a value of 1 indicating a point on the frontier and hence a technically efficient DMU, according to the Farrell (1957) definition.

One would then run the following cost minimization Data Envelopment Analysis:

$\text{Min}_{\lambda,xi^*} w_{i2} x_i^*$
st $-y_i + Y\lambda \geq 0$,
$x_i^* - Xë \geq 0$,
$N1'\lambda=1$
$\lambda \geq 0$, ... (5)

where w_i is a vector of input prices for the i-th DMU and x_i^* (which is calculated by the LP) is the cost minimizing vector of input quantities for the i-th DMU, given the input prices w_i and the output levels y_i. The total cost efficiency (CE) or economic efficiency of the i-th DMU would be calculated as:

$CE = w_{i2} x_i^* / w_{i2} x_i$ .... (6)

That is, the ratio of minimum cost to observed cost. One can then calculate the allocative efficiency residually as:

AE = CE/TE .... (7)

Note that the product of technical efficiency and allocative efficiency provides the overall economic efficiency. Note that all three measures are bound by zero and one.

Calculation of Scale Efficiency

Many studies have decomposed the technical efficiency (TE) scores obtained from a CRTS DEA into two components, one due to scale inefficiency and one due to "pure" technical inefficiency. This may be done by conducting both a CRTS and a VRTS DEA upon the same data. If there is difference in the two TE scores for a particular DMU, then this indicates that the DMU has scale inefficiency (SE). The scale inefficiency can be calculated from the difference between the VRTS TE score and the CRTS TE score. Thus,

$TE_{I,\,CRTS} = TE_{I,\,VRTS} \times SE_I$ .... (8)

RESULTS AND DISCUSSION

Efficiency Estimates from the Data Envelopment Analysis Programme

The result in Table 1 shows that majority of the respondents (46.31%) operated within a technical efficiency range of 0.50 and less than 0.90. The implication of this result is that majority of the respondents are not technically efficient in the use of production resources. This can result to an equi-proportionate over utilization of inputs (input congestion), and hence low productivity, low output and low income.

Table 1: Percentage distribution of the respondents by technical efficiency estimates

Efficiency estimate	*Frequency*	*Percentage*
0.01<0.10	0	0.00
0.10<0.50	55	13.99
0.50<0.90	182	46.31
≥0.90	156	39.69
Minimum efficiency	0.292	
Maximum efficiency	1.00	
Mean efficiency	0.774	

Source: Field Survey, 2009.

Furthermore, technical efficiency among the respondents varied substantially ranging between 0.292 and 1.00, with a mean technical efficiency of 0.774 (Table 1). This result suggests that the farmers are not utilizing their production resources efficiently, indicating that they are not obtaining maximal output from their given quantum of inputs. In other words, technical efficiency among the respondents can be increased by 22.6 percent through better use of available production resources, given the current state of technology. This would enable the farmers obtain maximum output from their given quantum of inputs, and hence increase their farm incomes thereby reducing poverty. This validates claim by Asogwa *et al*. (2011) that Nigerian rural farmers are not obtain maximum output from their given quantum of inputs.

Majority of the respondents (32.32%) operated within an allocative efficiency range of 0.0001 and less than 0.001 (Table 2). The implication of this result is that majority of the respondents are not allocatively efficient in the use of production resources. This can result to the utilization of inputs in the wrong proportions, given input prices, and hence higher costs of input combination and reduced return to capital.

Furthermore, allocative efficiency among the respondents varied widely ranging between 0.0001 and 0.869, with a mean allocative efficiency of 0.149 (Table 2). This result suggests that the farmers are not able to equate the marginal value product (MVP) of the factor to the factor price (P) as they allocate the factors of production for production, indicating that they are utilizing the inputs in the wrong proportions, given input prices. In order words, 85.1 percent of resources are inefficiently allocated relative to the best-practiced farms producing the same output and facing the same technology in the study area. This implies that allocative efficiency among the respondents could be increased by 85.1 percent in the area through better utilization of resources in optimal proportions given their respective prices and given the current state of technology. This would enable the farmers equate the marginal revenue product (MRP) of input to the marginal cost of the input thereby improving farm income, and hence reduction of poverty. This agrees with the findings of Asogwa et al. (2011) that Nigerian rural farmers are not utilizing production inputs in the optimal proportions, given input prices.

Table 2: Percentage distribution of the respondents by allocative efficiency estimates

Efficiency estimate	*Frequency*	*Percentage*
0.0001<0.001	127	32.32
0.001<0.01	125	31.81
0.01<0.10	29	7.38
0.10<0.50	61	15.52
0.50<0.90	51	12.98
Minimum efficiency	0.0001	
Maximum efficiency	0.869	
Mean efficiency	0.149	

Source: Field Survey, 2009.

Majority of the respondents (37.66%) operated within an economic efficiency range of 0.0001 and less than 0.001 (Table 3). The implication of this result is that majority of the respondents are not economically efficient in the use of production resources. This can result to higher costs per unit of output for a farm firm and hence the inability of the farmer to maximize profit.

Furthermore, economic efficiency among the respondents varied widely ranging between 0.0001 and 0.869, with a mean economic efficiency of 0.128 (Table 3). This result suggests that the farmers in the study area are not able to minimize the cost of production. In other words, 87.2 percent of production costs were wasted relative to the best practiced farms producing the same output and facing the same technology in the study area. The implication is that overall economic efficiency among the respondents could be increased by 87.2 percent in the area through the reduction in production costs that would occur if production were to occur at the allocatively and technically efficient point given the current state of technology. This would enable the farmers to minimize production costs, and hence maximize income and profit and consequently reduction of poverty. This agrees with the observation of Asogwa et al. (2011) that Nigerian rural farmers do not produce at the allocatively and technically efficient point given the current state of technology.

Table 3: Percentage distribution of the respondents by economic efficiency estimates

Efficiency estimate	*Frequency*	*Percentage*
0.0001<0.001	148	37.66
0.001<0.01	105	26.72
0.01<0.10	48	12.21
0.10<0.50	52	13.23
0.50<0.90	40	10.18
Minimum efficiency	0.0001	37.66
Maximum efficiency	0.869	
Mean efficiency	0.128	

Source: Field Survey, 2009.

Majority of the respondents (33.59%) operated within a scale efficiency range of 0.50 and less than 0.90 (Table 4). The implication of this result is that majority of the respondents are not scale efficient.

Furthermore, scale efficiency among the respondents varied substantially ranging between 0.002 and 1.00, with a mean scale efficiency of 0.70 (Table 4). This result suggests that the farmers are operating in less than optimal scale size. In other words, scale efficiency among the respondents can be increased by 30.14 percent by operating in optimal scale size, given the current state of technology. This would enable the farmers operate in optimal scale size, and hence increase their farm productivity and incomes thereby reducing poverty. This result is in consonance with that of Gorman and Ruggiero (2008) who found that nearly half of the DMUs studied were operating at less than optimal scale size.

Table 5 presents the summary statistics of efficiency measures under CRTS specifications and VRTS specifications. The result of a t-test shows that there is a significant difference between the two groups (CRTS specifications and VRTS specifications) of efficiency scores at 5 percent

Table 4: Percentage distribution of the respondents by scale efficiency estimates

Efficiency estimate	*Frequency*	*Percentage*
0.001 < 0.01	55	13.99
0.01 < 0.10	37	9.15
0.10 < 0.50	57	14.50
0.50 < 0.90	132	33.59
≥ 0.90	112	28.50
Minimum efficiency	0.001374	
Maximum efficiency	1.00	
Mean efficiency	0.69862	

Source: Field Survey, 2009.

level of significance (Table 6). This indicates that some of the decision-making units have scale inefficiency, suggesting that the decision-making units are not all operating at the optimal scale.

Table 5: Summary Statistics of Different Efficiency Measures for the Benue Rural Farmers

Variable	*Minimum efficiency*	*Maximum efficiency*	*Mean efficiency*
OTE	0.001	1.00	0.551
PTE	0.292	1.00	0.774
SE	0.001374	1.00	0.69862
OAE	0.0001	0.897	0.097
PAE	0.0001	0.869	0.149
OEE	0.0001	0.750	0.058
PEE	0.0001	0.869	0.128

Source: Field Survey, 2009.

Table 6: T-test of no significant difference between the CRTS and VRTS efficiency scores among Benue rural farmers

	VRTS	*CRTS*
Mean	0.777955357	0.557933036
Hypothesized mean difference	0	
Degree of freedom	446	
t Statistics	8.93	
t Critical	1.97	
Decision	Reject H_0	

Source: Field Survey, 2009.
*Critical value is significant at 1% level of significance (two-tail).

The average level of overall technical efficiency (OTE), pure technical efficiency (PTE) and scale efficiency is estimated at 55.1 percent, 77.4 percent and 69.86 percent respectively. The average level of overall allocative efficiency (OAE) and overall economic efficiency (OEE) is estimated at 9.7 percent and 5.8 percent respectively. The corresponding figure for the pure allocative efficiency (PAE) and pure economic efficiency (PEE) is estimated at 14.9 percent and

12.8 percent respectively. These results generally highlight the relative inefficiency that characterizes the farmers in the study area. The overall technical inefficiency among the respondents resulted more by scale inefficiency compared to pure technical inefficiency. The results further indicate that allocative inefficiency is worse than technical inefficiency, which implies that the low level of overall economic efficiency is the result of higher cost (allocative) inefficiency and scale inefficiency (that is, operating at less than optimal scale size). This suggests that solving allocation and scale problems is critical for improving farm resource management (efficiency) of Nigerian farmers. This corroborates Kuah et al. (2010) who observed that data envelopment analysis is suitable to measure DMU's efficiency and give improvement suggestion to the inefficient DMU.

The effect of a marginal increase in technical, scale and allocative efficiency on total economic efficiency could be substantial. Any improvement in agricultural productivity would lead to increase in returns to the households from agricultural activity. Such increase in household incomes would lead to rapid poverty reduction.

CONCLUSION

The study showed that some of the decision-making units have scale inefficiency, suggesting that the decision-making units are not all operating at the optimal scale. Most of the respondents operated very far away from the efficiency frontier. The overall technical inefficiency among the respondents resulted more by scale inefficiency compared to pure technical inefficiency. Allocative inefficiency is worse than technical inefficiency, implying that the low level of overall economic efficiency is the result of higher cost (allocative) inefficiency and scale inefficiency (operating at less than optimal scale size). Solving allocation and scale problems is critical for improving farm resource management of Nigerian farmers.

REFERENCES

Adeniji JP 1988. Farm size and resource use efficiency in small-scale agricultural production: the case of rice farms in Kwara State of Nigeria. *Agricultural Journal*, 23(2): 51-62.

Ajibefun IA 2002. Analysis of policy issues in technical efficiency of small scale farmers using the stochastic frontier production function: With application to Nigerian Farmers. *Paper Prepared for Presentation at the International Farm Management Association Congress*, Wageningen, Netherland, July 2002, 8 pp.

Ajibefun IA, Daramola AG 2003. Determinants of Technical and Allocative Efficiency of Micro-Enterprises: Firm-level Evidence from Nigeria. *African Development Bank*, pp. 353-395.

Asogwa BC, Umeh JC, Ater PI 2007. Technical Efficiency Analysis of Nigerian Cassava Farmers: A Guide for Food Security Policy. In: Consolidation of Growth and Development of Agricultural Sector. *Proceedings of the 9th Annual National Conference of the Nigerian Association of Agricultural Economists (NAAE)* held at 100 Seater Theatre, Abubakar Tafawa Balewa University, Bauchi, 5 – 8 November, 2007, pp 2-10.

Asogwa BC, Ihemeje JC, Ezihe JAC 2011. Technical and allocative efficiency analysis of Nigerian rural farmers: Implication for poverty reduction. *Agricultural Journal*, 6(5): 243-251.

Ater PI, Umeh JC 2003. A stochastic frontier production function for poverty reduction analysis: The World Bank Assisted Dry Season Fadama Enterprises in Benue State, Nigeria. *Journal of Economic and Social Research*, 3(3): 7-15.

Bankers RD, Charnes A, Cooper WW 1984. Some Models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30: 1078-1092.

BENKAD 1998a. Diagnostic Survey of Roots and Tubers in Benue State. Consultancy Report by BENKAD Consultants for BNARDA, 35 pp.

BNARDA 1998b. Crops Area and Yield Survey, Report by Benue Agricultural and Rural Development Authority (BNARDA), 35 pp.

Coelli TJ 1996. *A Guide to DEAP Version 2.1: A Data Envelopment Analysis (Computer) Programme*. Center for Efficiency and Productivity Analysis. Department of Econometrics, University of New England Armidale, NSW, 2351, Austtralia, 50 pp.

Eboh EC 2009. *Social and Economic Research: Principles and Methods.* 2nd Edition. Enugu, Nigeria: African Institute for Applied Economics.

Gorman MF, Ruggiero J 2008. Evaluating US state police performance using data envelopment analysis. *International Journal of Production Economics*, 113(2): 1031-1037.

Kuah C T, Wong KY, Behrouzi F 2010. Application of data envelopment analysis to assess quality management efficiency. In: Academic Science Research. *Proceedings of the 6th International Conference of the World Academy of Science*, Engineering and Technology, Singapore, August 25 – 27, 2010, Issue 69, pp. 49-54.

Ohajianya DO, Onyenweaku EC 2001. Gender and relative efficiency in rice production systems in Ebonyi State, Nigeria: A Profit function analysis. *Journal of Sustainable Agriculture and Environment,* 3(2): 384 – 393.

Reddy SS, Ram PR, Sastry TVN, Devi IB 2004. *Agricultural Economics*. New Delhi: Oxford and IBH Publishing Co. Pvt. Ltd.

Yotopoulous PA, Lau LJ 1973. Test of relative economic efficiency: same further results. *American Journal of Economic Review*, 63 (1): 214-225.