



Bioscene

Bioscene

Volume- 22 Number- 02

ISSN: 1539-2422 (P) 2055-1583 (O)

www.explorebioscene.com

Driving Efficiency in Rice Farming: A Data Envelopment Analysis of Key Factors in Delta State, Nigeria

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Abstract: This study estimated the efficiency of rice farmers in Delta State, Nigeria, and also identified the key factors influencing their performance. It adopted a survey design. A multistage sampling technique was used to select the respondents. Primary data was collected from the farmers using a well-structured questionnaire. Data Envelopment Analysis (DEA), Ordinary Least Squares regression (OLS) and Tobit regression model were used to realize the objectives. The results show that 43.1% of farmers, fall in the moderate-efficiency range ($TE = 0.61-0.80$), with a mean TE of 0.73, 30.2% fall within the high-efficiency range ($TE \geq 0.81$) with a mean TE score of 0.92. Meanwhile, 26.7% of the farmers are classified as severely inefficient ($TE \leq 0.60$), with a mean TE of 0.48. The OLS regression analysis reveals that farm size, level of education, access to credit, extension contact, irrigation use and cooperative membership have positive and significant effects, while fertilizer application has a negative and significant impact on rice farming efficiency in the State. The model explains 57.2% of the variation ($R^2 = 0.572$), with an F-statistics of 29.84 ($p < 0.001$), indicating strong overall fit. The constraints faced by these farmers include high cost of inputs (28.9%), limited access to credit (22.2%), poor irrigation infrastructure (17.8%), pest and disease infestation (13%), and lack of modern farming equipment (11%). This study recommends policy interventions to enhance rice farming. Key suggestions include: subsidies for quality inputs, increased extension services, and promotion of machinery adoption through cooperatives or leasing schemes.

Keywords: Rice Farming, Efficiency, Data Envelopment Analysis, Tobit Regression, Ordinary Least Squares (OLS)

Introduction:

The agricultural sector is a vital component of the Nigerian economy, accounting for approximately 24% of the country's Gross Domestic Product (GDP) and employing about 70% of the labor force (National Bureau of Statistics, 2020). Rice is one of the most widely consumed staple foods in Nigeria, with the country being one of the largest consumers of rice in Africa (Food and Agriculture Organization, 2019). Delta State, located in the Southern part of Nigeria, is one of

the major rice-producing states in the country, with a significant number of rice farmers operating in the State (Delta State Ministry of Agriculture, 2020). Despite the significance of the agriculture sector and the rice sub-sector in particular, Nigerian rice farmers face numerous challenges that affect their efficiency and productivity. Some of the challenges include inadequate access to credit, poor agricultural extension services, lack of modern farming technologies, and inadequate irrigation facilities (Ogunleye, 2017; Ajiboye, 2018). These challenges have resulted in low productivity and efficiency to rice farmers in Nigeria, with the country's rice yield per hectare being one of the lowest in the world (FAO, 2019). The concept of efficiency in agriculture refers to the ability of farmers to produce the maximum output possible from the resources available to them (Coelliet al., 2005). Efficiency is a critical factor in agricultural production, as it determines the productivity and competitiveness of farmers in the market (Bravo-Ureta et al., 2007). There are several factors that can influence the efficiency of rice farmers, including farm size, education level, access to credit, agricultural extension services, and irrigation facilities (Ali et al., 2018; Khan et al., 2019).

Data Envelopment Analysis (DEA) is a non-parametric method that is widely used to measure the efficiency of decision-making units (DMUs) such as farms (Charnes et al., 1978). It is an important tool for analyzing the efficiency of rice farmers, as it can help to identify the factors that are influencing their efficiency and provide insights into how they can improve their productivity (Coelliet al., 2005). A number of studies has been conducted to examine the efficiency of rice farmers in various parts of the world including Nigeria. (Ogunleye, 2017; Ajiboye, 2018). In Nigeria, several studies have been conducted to analyze the efficiency of rice farmers using DEA. In 2017, Ogunleye evaluates the efficiency of rice farmers in Ogun State and operated within an efficiency level of 0.63. Ajiboye (2018) also used DEA to analyze the efficiency of rice farmers in Kwara State, Nigeria, and found that the average technical efficiency of the farmers was 0.56. However, there is a need for more studies to be conducted in other parts of the country, including Delta State, to provide more insights into the factors that are influencing the efficiency of rice farmers. The specific objectives of the study are to; evaluate the technical efficiency of rice farmers in Delta State, determine key factors influencing the efficiency of rice farmers in Delta State; analyze the effects of socio economic and institutional factors on the efficiency of rice farmers in Delta State and identify constraints affecting the efficiency of rice farms in the study area.

DEA is a powerful tool that helps in assessing the performance and efficiency of decision-making units, such as farms, by comparing the input resources they use to the outputs they produce. In the context of rice farming, DEA can identify the most efficient farmers, highlight areas for improvement, and provide insights into how resources can be better allocated to maximize productivity. This

analysis is crucial for enhancing agricultural practices and boosting the overall output in Delta State. The study identify the key factors influencing their performance. It aims to offer valuable insights into strategies for enhancing the productivity and market competitiveness of these farmers. Additionally, the study will contribute to the existing body of literature on rice farming efficiency in Nigeria and provide policymakers with evidence-based information to guide the development of effective policies and programs that support improved efficiency in the sector. This work contributes to the understanding of the factor affecting the technical efficiency of rice farmers Delta State Nigeria.

Material and Methods

Description of the Study Site

Delta State is located in the South-South geopolitical zone of Nigeria, bounded by Edo State to the North, Anambra State to the East, Bayelsa State to the Southeast, and the Atlantic Ocean to the South. Geographically, it lies between latitude 5°00'N and 6°30'N and longitude 5°00'E and 6°45'E. The State is characterized by a diverse landscape, including coastal plains, mangrove swamps, freshwater wetlands, and upland regions shaped by the Niger River and its tributaries (National Bureau of Statistics, 2021). Delta State experiences a tropical climate with two distinct seasons: the rainy season (March to October) and the dry season (November to February). Annual rainfall ranges from 1,500 mm to 2,500 mm, accompanied by high relative humidity and average temperatures between 25°C and 32°C (Nigerian Meteorological Agency (NiMet]) 2020). These climatic conditions, coupled with fertile alluvial soils and extensive water resources, provide a favorable environment for agricultural activities, especially rice farming and the cultivation of other staple crops such as cassava, maize, and vegetables (Onoja & Achike, 2020). The study area within Delta State benefits from this conducive agro-ecological environment, making it a productive zone for rice farming and other agricultural ventures.



Fig 1. Map of Delta State Showing the Study Area (NPC2006)

Sampling Techniques

In order to assess the efficiency of rice farming in Delta State using Data Envelopment Analysis (DEA), a multistage sampling method was implemented. This approach is appropriate for capturing the diversity of agricultural operations across different local government areas (LGAs) while ensuring representation and reducing sampling bias. The first stage employed a purposive sampling of rice producing LGAs of Delta State such as Aniocha North, Ughelli South, Ndokwa East, Isoko South and Oshimili North. Based on Delta State Agricultural Development Programme (DTADP) data and other relevant sources, the selection was made. As part of the second stage, 45 rice farmers were randomly selected from each of the 5 selected Local LGAs, bringing the total to 225. The data collected was analyzed using Data Envelopment Analysis, Ordinary least squares regression and Modelling Tobit regression.

Model Specifications

$$\sum_i^k u_i x_i \leq \theta \sum_i^k u_i x_i^0$$

$$\sum_j^n v_j y_j \leq 1$$

where

θ denotes the efficiency score of the DMU being assessed.

u_i represents the weight of the i th input.

x_i denotes the values of the i th input utilized by the DMU being assessed.

x_i^0 represents the value of the i th input employed by the most effective DMU.

v_j denotes the weight of the j th output.

y_j represents the value of the j th output obtained from the DMU being assessed.

k denotes the number of inputs.

n represents the number of outputs

The first constraint guarantees that the DMU being assessed utilizes its inputs effectively compared to the most effective DMU, while the second constraint ensures that the DMU produces its outputs effectively in comparison with the other DMUs.

Slack Variables

Slack variables are introduced to account for input excesses and output shortfalls, providing a more accurate measure of efficiency.

Mathematical Formulation:

For input-oriented DEA, slack variables s_i^- and s_r^+ are added to the constraints:

$$\sum_j \lambda_j x_{ij} + s_i^- = \theta x_{ik} \quad \forall i = 1, 2, \dots, m, j = 1, 2, \dots, n$$

$$\sum_j \lambda_j y_{rj} - s_r^+ = y_{rk} \quad \forall r = 1, 2, \dots, s, j = 1, 2, \dots, n$$

Where:

si-si-: Input slack (excess input usage).

sr+sr+: Output slack (shortfall in output production).

Results and Discussion

A measure of technical efficiency (TE) scores presented in Table 1 revealed significant disparities in the productivity levels of rice farmers across Delta State. Using an input-oriented Data Envelopment Analysis (DEA) under the Constant Returns to Scale (CRS) assumption, the study assessed how efficiently farmers utilize inputs to produce rice output.

Table 1 Technical Efficiency Scores of Rice Farmers in Delta State (n=225)

Efficiency Range	Frequency	Percentage (%)	Mean TE Score	Implication
0.81–1.00 (High)	68	30.2	0.92	Fully or near-fully efficient
0.61–0.80 (Moderate)	97	43.1	0.73	Moderate inefficiency (19–39% input waste)
≤0.60 (Low)	60	26.7	0.48	Severe inefficiency (>40% input waste)
Overall	225	100.0	0.71	Weighted average

Source: Field Data 2025

The results show that only **30.2%** of the farmers fall within the high-efficiency range ($TE \geq 0.81$), with an average TE score of **0.92**, indicating they are operating at or near full efficiency. These farmers likely adopt improved practices such as timely irrigation, use of quality seeds, and cooperative input sourcing.

A larger proportion, **43.1%**, fall in the moderate-efficiency range ($TE = 0.61–0.80$), with an average TE of **0.73**. This group shows moderate inefficiency, wasting between 19% and 39% of their inputs. Meanwhile, **26.7%** of the farmers are classified as severely inefficient ($TE \leq 0.60$), with a mean TE of **0.48**, indicating that they waste over 40% of inputs and have substantial room for productivity improvement. Similarly, Ogundari (2016) carried out a national-level DEA study on rice farmers across multiple agro-ecological zones in Nigeria. The mean TE score reported was 0.68, which is slightly below the 0.71 observed in the current study. Ogundari identified key drivers of efficiency as farm size, access to credit, and use of mechanized tools, all of which are consistent with the inefficiency factors found in this study. Shehu and Mshelia (2007) also utilized DEA to assess the technical efficiency of small-scale farmers in Borno State. They discovered that there was a significant range in efficiency levels because of differences in education, access to farm inputs, and extension. Their findings corroborate those of Delta State, especially the stark inefficiency of farmers without irrigation and machinery. These studies confirm that while DEA is a

powerful tool for evaluating efficiency, regional differences in resource access, education, and institutional support play a significant role in determining farmer performance. The current study contributes to this growing body of evidence by focusing specifically on rice farmers in Delta State and providing region-specific policy recommendations. Slack analysis revealed widespread input overuse, particularly fertilizer (23%), labor (18%), and seeds (15%), alongside a 14% yield shortfall due to suboptimal practices. Comparatively, Delta's average TE of **0.71** is slightly better than the national benchmark of **0.68** but lower than Ebonyi State's **0.78**, which benefits from stronger extension services.

Table 2: OLS Regression Results of Factors Influencing Rice Farming Efficiency in Delta State (n=225)

Variable	Coefficient	Standard Error	t-value	p-value
Constant	0.412***	0.078	5.28	<0.001
Farm size ha)	0.062**	0.025	2.48	0.014
Education (years)	0.018***	0.005	3.60	<0.001
Access to credit (1=Yes)	0.087*	0.042	2.07	0.040
Extension contract visit yr	0.033***	0.009	3.67	<0.001
Irrigation use (yes=1)	0.154***	0.036	4.28	<0.001
Fertilizer Application Rate (kg/ha	-0.002*	0.001	-2.01	0.046
Cooperative Membership (1=Yes)	0.059*	0.031	1.90	0.059
Model Summary Statistics	R² 0.572	Adjusted R 0.553	F Statistics • 29.84*** p<0.001)	

Source: Field Data, 2024

A thorough grasp of the variables affecting rice farming efficiency in Delta State, Nigeria, can be gained from the Ordinary Least Squares (OLS) regression results shown in Table 2. Numerous socioeconomic and farm-related factors that have a major impact on farming efficiency are identified by the model, which is based on a sample of 225 respondents. The model has a comparatively high explanatory power, explaining roughly 57.2% of the variance in rice farming efficiency with an R² of 0.572. The adjusted R² of 0.553 accounts for the number of predictors, reaffirming the model's robustness. The F-statistic of 29.84

($p < 0.001$) confirms the overall significance of the model, suggesting that the included variables collectively explain a substantial portion of the variation in efficiency levels among rice farmers.

Farm Size (Coefficient = 0.062, $p = 0.014$):

Farm size has a statistically significant positive influence on rice farming efficiency. A one-hectare increase in farm size increases efficiency by 0.062 units. This aligns with economic theory and empirical evidence, which posit that larger farm sizes often benefit from economies of scale, allowing for more efficient resource utilization. A similar finding was reported by Ogundari (2008), who observed that farm size was positively correlated with technical efficiency among Nigerian smallholder crop farmers.

Education (Coefficient = 0.018, $p < 0.001$):

Education significantly enhances rice farming efficiency. Each additional year of formal education improves efficiency by 0.018 units. Education facilitates better decision-making, adoption of new technologies, and improved farm management practices. This finding is in line with the study by Amazaet al. (2006), who found that educated farmers in northern Nigeria demonstrated higher efficiency in maize production due to enhanced access to information and innovative farming techniques.

Coefficient = 0.087, $p = 0.040$, Access to Credit:

Farmers who have access to financing are far more productive than those who do not. Access to credit increases liquidity, making it possible to buy labor and inputs on time. This outcome supports the findings of Oladebo and Fajuyigbe (2007), who found that by reducing capital limitations that impede productivity, loan availability increased the efficiency of rice farmers in Osun State, Nigeria.

Extension Contact ($p < 0.001$, coefficient = 0.033):

Frequent extension visits positively and significantly impact efficiency. Each additional contact per year increases efficiency by 0.033 units. This supports the idea that extension services are a critical conduit for disseminating modern farming knowledge. According to a study by Shima (2010), rice farmers in southwest Nigeria were much more technically efficient as a result of extension services.

(Coefficient = 0.154, $p < 0.001$)

Irrigation Use:

The use of irrigation contributes significantly to higher efficiency, improving it by 0.154 units. Irrigation reduces dependence on erratic rainfall and allows for better control over water application, leading to improved yields and efficiency. This outcome supports the conclusions of Ogundele and Okoruwa (2006), who

found that the use of irrigation greatly increased Nigeria's rice yield and efficiency.

Fertilizer Application Rate (Coefficient = -0.002, p = 0.046):

Interestingly, the fertilizer application rate has a negative and significant effect on efficiency. This could suggest overuse or misuse of fertilizer, leading to diminishing returns. Such inefficiencies may stem from a lack of soil testing or inappropriate fertilizer combinations. A similar result was observed by Udoh and Etim (2006), who noted that excessive fertilizer use did not necessarily translate to higher efficiency among cassava farmers in Akwa Ibom State.

Cooperative Membership (Coefficient = 0.059, p = 0.059): Although marginally significant ($p \approx 0.05$), cooperative membership is positively associated with efficiency. Cooperatives can provide members with access to shared resources, market information, and collective bargaining power. This supports the study by Yusuf et al. (2015), which indicated that cooperative membership contributed to increased farm efficiency due to improved access to inputs and services.

Table 3. Technical efficiency is influenced by institutional and socioeconomic factors.

Explanatory Variable	Coefficient	Standard Error	t-value	P-value
Age of Farmer (in Years)	-0.012	0.006	-2.00	0.046
Educational Level (Years)	0.023	0.008	2.88	0.004
Farming Experience (Years)	0.015	0.005	3.00	0.003
Household size (number)	-0.008	0.007	-1.14	0.255
Farm Size (Hectares)	0.031	0.011	2.82	0.005
Access to credit (1=yes 0=No)	0.064	0.019	3.37	0.001
Extension Contact (1 =yes, 0=no)	0.071	0.021	3.38	0.001
Membership of Co-op (1=yes, 0=No)	0.057	0.018	3.17	0.002
Market Distance	-0.010	0.004	-2.50	0.013

(km)				
Constant	0.621	0.076	8.18	0.000

Model Statistics

Number of Observation 225

Log-likelihood: -78.45

LR Chi² (9): 42.37

Prob > Chi²: 0.0000

Pseudo R²: 0.212

Table 3 presents the results of the study on the institutional and socioeconomic elements affecting Delta State rice farmers' technical efficiency. Data Envelopment Analysis (DEA), which is especially well-suited for evaluating the performance of decision-making units under various input-output scenarios, was used to calculate the technical efficiency ratings. The dependent variable made the topic model suitable. TE has a range of 0 to 1. The results showed that a number of institutional and socioeconomic factors had a major impact on rice producers' efficiency level.

Age of Farmers: Farmers become less efficient as they age, according to the statistically significant negative coefficient for age. This may be because older farmers are less physically fit and reluctant to use modern methods.

This finding is consistent with Chukwuji et al (2006) found that younger farmers more adaptable to innovations and new technologies, leading to improved efficiency in cassava farming.

Education level: Education significantly and favorably impacted TE. Farmers with higher levels of education are probably more knowledgeable about market data, agronomic techniques, and financial management, all of which increase productivity. This aligns with the work of Enwa, Ogisi and Ewuzie(2024), who found that education significantly increased efficiency levels among food crop farmers in Nigeria. Similarly, Enwa, Ogisi and Achoja(2025) confirmed that higher educational attainment positively influenced technical in Nigeria.

Farming experience: experience has demonstrated a favorable and noteworthy effect on productivity. Farmers with greater experience are probably going to handle risks better and make better production decisions. Battese and Coelli (1995) in their study on rice farmers in Pakistan found that farming experience significantly boosted technical efficiency, corroborating the result in this result in this current study. Farmers with access to credit were significantly more efficient. credit facilities provide the necessary funds for timely acquisition of inputs and adoption of improved technologies. The result resonates with the finding of Enwa and Achoja (2023), who observed that access to credit significantly enhanced technical efficiency in fish production in Rivers State.

Cooperative Membership: membership in cooperatives significantly improved efficiency. cooperatives serve as platforms for sharing information, accessing credit, and collectively purchasing inputs at lower costs. Ogebe et al. (2022).

Confirmed that cooperative membership improved farmers access to productive resources and enhanced efficiency.

Market Distance: Market distance had a negative and significant relationship with efficiency. Longer distances to market increase transportation costs, reduce profit margins and can delay the sales of perishable produce.

The model's log-likelihood of -78.45 and a highly significant likelihood ratio chi square (LR $\chi^2 = 42.37$, $p < 0.001$) suggest that the model has good explanatory power. The Pseudo R² of 0.212 indicates that about 21.2% of the variation in efficiency is explained by the included variables in an acceptable fit cross-sectional data model.

Table 4 limitations that farmers encounter

Constraints	Frequency	Percentage (%)
High cost of inputs	65	28.9
Limited access to credit	50	22.2
Poor irrigation infrastructure	40	17.8
Pest and disease infestation	30	13
Lack of modern farming equipment	25	11
Poor market access	15	6
Total	225	100

Source: Field Data, 2025

The information in Table 4 sheds light on the main obstacles that rice growers in Delta State, Nigeria, must overcome. The most frequently cited challenge was the high cost of inputs, reported by 65 farmers, representing 28.9% of the respondents. This suggests that a significant proportion of rice farmers struggle to afford essential agricultural inputs such as fertilizers, improved seeds, herbicides, and pesticides. The rising cost of inputs may be attributed to inflation, subsidy removal, and poor access to government support programs. This challenge not only reduces the scale of production but also affects overall productivity and profit margins.

The second major limitation, as indicated by 50 respondents (22.2%), is limited access to credit. Many smallholder rice farmers in Delta State lack access to formal credit facilities due to collateral requirements, high-interest rates, and bureaucratic bottlenecks. This finding aligns with studies such as Ogunlade et al. (2020) and Omonona and Awoyemi (2017), which observed that limited access to agricultural credit significantly hampers investment in improved technologies and inputs among small-scale farmers in Nigeria.

Poor irrigation infrastructure was also identified as a key issue by 40 respondents (17.8%). Inadequate water supply, especially during the dry season, restricts multiple cropping and year-round cultivation. This finding is consistent with the work of Adeoye et al. (2016), who highlighted that unreliable or poorly maintained irrigation systems are a persistent issue for rice farmers in South-South Nigeria, particularly in flood-prone and water-logged areas.

Another constraint, mentioned by 30 respondents (13%), was pest and disease infestation. Farmers often experience significant losses due to attacks from pests like stem borers and birds, as well as diseases like rice blast. The lack of proper training in integrated pest management and limited access to effective pesticides may exacerbate this problem. Similar challenges were reported by Ekeleme et al. (2019), who emphasized the need for training and extension services to manage biotic stresses in rice production.

Lack of modern farming equipment was cited by 25 respondents (11%). The reliance on manual labor and outdated tools reduces efficiency and increases the drudgery of rice farming. Mechanization is limited due to cost, unavailability, or lack of technical knowledge, as echoed in the findings of Ike and Inoni (2015). Lastly, poor market access, though the least reported constraint (15 respondents or 6%), is still relevant. Challenges such as poor road networks, middlemen exploitation, and lack of storage facilities discourage farmers from expanding production.

Conclusion and Recommendation

In order to determine the main determinants influencing production, the study used data envelopment analysis (DEA) to analyze the effectiveness of rice farming in Delta State. The findings showed notable differences in efficiency between farms, suggesting room for improvement through more effective use of inputs. Important elements that have been identified as major drivers of efficiency include mechanization, fertilizer use, extension services, and credit availability. Closing these gaps can result in significant improvements in the region's rice output and food security.

The findings suggested that

- i. Government should provide subsidies or support programs to ensure rice farmers can access quality seeds, credit and modern farming tools

- ii. Government should increase the availability of agricultural extension agents to train farmers on best practices and efficiency resource use
- iii. There is the need for formation of cooperatives to improve resource sharing, knowledge transfer and collective bargaining power
- iv. Rice farmers should encourage to adopt farm machinery through cooperatives ownership models or government supported leasing schemes

References

1. Aigner, D., K. Lovell, and P. Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6 (1): 21–37.
2. Abate T.M, Dessie A.B. and Mekie M.T (2019). Technical efficiency of smallholder farmers in red pepper production in North Gondar Amhara regional State, Ethiopia, *Journal of Economic structures*, 8(1).
3. Asante, M.K. and Kuwornu, J.K. A (2014) comparative Analysis of the profitability of pineapple-mango blend and pineapple fruit juice processing in Ghana. *Appl. Stud. Agribus. Commer.* 8, 33–42.
4. Ajiboye, A.O. (2018). Technical efficiency of small holder cocoafarmers in Nigeria : Evidence from Ondo state, Springer
5. Amaza P. Bila, Y and Iheanacho A. (2006). Identification of factors that influence technical efficiency of food crop production in West Africa, *International Journal of Tropical Agriculture*, 18 (3)
6. Adams, A.; Balana, B. and Lefore, N. (2020). Efficiency of small-scale irrigation farmers in Northern Ghana: A data envelopment analysis approach. *Margin J. Appl. Econ. Res*, 14, 332–352
7. Ajiboye, A. (2018). Efficiency of rice farmers in Kwara State, Nigeria: A DEA approach. *Journal of Agricultural Economics*, 69(2), 257-272.
8. Adeoye I. A., Oladeji, J.O. and Adepoju (2016). Nigerian poultry egg production's technical efficiency. *The International Journal of Poultry Science*, A stochastic frontier approach 15(3), 123-130.
9. Ali, M., Khan, M. A., & Khan, M. (2018). Factors influencing the efficiency of rice farmers in Pakistan: A DEA analysis. *Journal of Agricultural Science and Technology*, 18(3), 537-548.
10. Bravo-Ureta, B. E., Solís, D., & López, V. H. (2007). Technical efficiency of small-scale farmers in developing countries: A review of the evidence. *Journal of Agricultural Economics*, 58(2), 257-275.
11. Boakye K., Lee F.W., Anoor F.F., Dadzie S. F.N and Salisu I. (2024). Data Envelopment Analysis (DEA) to Estimate Technical and Scale Efficiencies of Smallholder Pineapple Farmers in Ghana, *Agricultural Economics, Policies and Rural Management*, 14(7)
12. Coelli, T. J., Rao, D. S. P., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer.
13. Delta State Ministry of Agriculture. (2020). *Delta State agricultural development strategy*.
14. Chirwa, E.W. (2007). Sources of technical efficiency among smallholder maize farmers in Southern Malawi (No. RP_172 Keywords: smallholder maize farmers, technical efficiency, southern Malawi). Nairobi: African Economic Research Consortiu.

15. Charnes A. Cooper W.W. and Rhodes E. (1978)., Measuring the efficiency of decision making units. *European, Journal of operational Research*, 2(6), 429-444.
16. Enwa S., Ogisi O.D. and Ewuzie P. O. (2024). Gender role and effects on climate change adaptation practices among vegetable farmers in Delta Central Zone, Nigeria, *World Journal of Environmental Biosciences* 13, (1), 22-29.
17. Enwa S. Ogisi O.D. and Achoja F.O. (2024). Analyzing the financial viability and technical efficiency of aquaculture farming in Delta State: Lessons from cluster operations, *GSC Advanced Research and Reviews*, 18 (3), 308-316
18. Enwa S. and Achoja F.O. (2023), Impact of flooding disaster on economic returns of fish farmers in Rivers State Nigeria, *World Journal of Environmental Biosciences*, 12 (4), 20-26
19. Farwell, M.J. (1957). The measurement of productive efficiency, *Journal of the Royal Statistical society : A series (General)*, 120 (3). 253-290
20. Greene, W.H. (2008). The econometric approach to efficiency analysis. *The Measurement of Productive Efficiency and Productivity Growth* 1: 92–250.
21. Getachew M, and Bamlak A (2014). Analysis of technical efficiency of small holder maize growing farmers of Horo Guduru Wollega zone, Ethiopia: a stochastic frontier approach. *Sci Technol Arts Res J* 3(3):204–212
22. Food and Agriculture Organization. (2019). The future of livestock in Kenya. Opportunities and challenges in the face of uncertainty. Rome Farrell M.J. (1957). The measurement of productive efficiency *journal of the royal statistical society. A series (general)*, 120,(3), 253-290
23. FAOSTAT (2016) Crop production in Africa. Retrieved 2018, August 18. Countries—select all; regions—Africa+(Total); elements—area and production quantity; items—red pepper; Years-2010-2016. www.fao.org.
24. Laha, A. (2014). Technical efficiency in agricultural production and access to credit in west Bengal, India: A stochastic frontier approach. *International Journal of Food and Agricultural Economics* 1 (2): 53–64.
25. Latrobe, L. 2010. Competitiveness, productivity and efficiency in agricultural and agri-food sectors. OECD Food, Agriculture and Fisheries Papers, No. 30, OECD Publishing.
26. Kumbhakar, S.C., and L. Hjalmarsson. 1991. Estimation of technical efficiency and technical progress free from farm-specified effects:

- an application to Swedish dairy farms. Memorandum-Department of Economics, Gothenburg University, School of Economics and Legal Science (Sweden).
27. Mester, Loretta J. 2003. Applying efficiency measurement techniques to central banks, Working Paper No. 03-13, Federal Reserve Bank of Philadelphia.
 28. National Bureau of Statistics (2021). Nigerian Gross Domestic Product Report Q4 and Full Year 2020. Abuja: NBS.
 29. Nigerian Meteorological Agency (NiMet) (2020). 2020 Seasonal Rainfall Prediction and Socio-Economic Implications for Nigeria. Abuja: NiMet.
 30. Onoja, A. O., & Achike, A. I. (2020). Climate Variability and Agricultural Productivity in Nigeria: Implications for Food Security. *Journal of Agricultural Extension*, 24(2), 33–45.
 31. Omonona B.T. and Awoyemi T.T. (2017). Determinants of Technical Efficiency Differentials among Maize Farmers in Nigeria: A Gender Perspective. *African Journal of Agricultural and Resource Economics*, 12. (1) 1-13.
 32. Ogunlade I. Oladipo J.A. and Olawuyi S.O. (2020). Technical Efficiency of Cassava farmers in Oyo State, Nigeria: A stochastic Frontier Analysis. *Nigerian Journal of Agricultural Economics*, 10 (1) 45-53.
 33. Ogundari K. (2008). Resource-productivity, allocative efficiency and determinants of technical efficiency of rainfed rice farmers: A guide for food security policy in Nigeria. *Agric.-Economic Czech*, 54 (5), 224-233.
 34. Ogebe O.F, Daniel A. and Oladapo O.I (2022), Access to credit and rice production efficiency of ruralhouseholds in Benue State, Nigeria. *Nigerian Journal of Agriculture and Agricultural Technology*, 2 (1).
 35. Ray S.C (1985). Measurement and test of efficiency offarms in a developing economy: the case of West Bengal, India. *Oxford Bulletin of Economics and statistics*, 47(3), 257-271
 36. Kolawole, O. 2006. Determinants of efficiency among small scale rice farmers in Nigeria: A profit function approach. *Research Journal of Applied Sciences* 1 (1): 116–122.
 37. Russell, N.P., and T. Young. (1993). Frontier production functions and the measurement of technical efficiency. *Journal of Agricultural Economics* 34: 139–150.
 38. Wang, H.J., and P. Schmidt. 2002. One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis* 18 (2): 129–144.