AN EVALUATION OF TECHNICAL EFFICIENCY OF RICE FARMS AMONG THE BENEFICIARIES AND NON-BENEFICIARIES OF STATE INTERVENTION PROGRAMMES IN NIGERIA

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ABSTRACT

The crown is the centre of physiological activity, crucial for assessing the tree's vigour. Accurately predicting the crown diameter is crucial in forest management, as it influences tree growth and yield. Diameter at breast height (Dbh) has a strong positive correlation with crown diameter (CD) and forest productivity. This study aimed to develop CD models using linear and nonlinear regression methods for the Department of Forestry and Wildlife, specifically for the Teak and Gmelina plantations at PAAU, Anyigba, Kogi State. Seventeen (17) Temporary Sample Plots of 0.625 ha were randomly laid across two strata identified (Tectona grandis and Gmelina arborea) using simple random sampling techniques at 10% sampling intensity. All tree-related variables were measured using standard procedures. The overall best linear crown prediction equation for the two species is a Multiple Linear-Polynomial model, with standard error of estimate (SEE) and root mean square error (RMSE) values of 1.2049 and 1.1962 for Tectona grandis and Gmelina arborea, respectively. The SEE and RMSE values for these models are 0.433 and 0.4303, respectively. The overall best prediction nonlinear crown prediction equation for Tectona grandis is the Power model, with SEE and RMSE values of 1.2467 and 1.2422, respectively. For Gmelina arborea, the Monomolecular model is the best, with SEE and RMSE values of 0.4385 and 0.4360, respectively. It can be concluded that all the developed models are biologically logical and can be applied to predict the current and future crown diameters of the stand for effective sustainable management, silvicultural treatment, and efficient timber production.

Keywords: technical efficiency, rice production, stochastic frontier analysis, government intervention, agricultural policy, Nigeria

INTRODUCTION

Agriculture remains central to Nigeria's economy, supporting livelihoods for a majority of the population and contributing significantly to food security and rural development. Although the country was once a major exporter of agricultural commodities, the discovery of petroleum shifted national focus toward the extractive sector, leading to a relative neglect of agriculture (Ayanwale et al., 2021). Nonetheless, crop production—particularly rice cultivation—continues to play a pivotal role, accounting for over 90% of Nigeria's agricultural output (FAO, 2020).

Rice has become a staple food consumed across all socio-economic groups in Nigeria, with per capita consumption estimated at 32 kg annually. Yet, domestic production has consistently fallen short of demand, making Nigeria one of the world's largest importers of rice (Abdullahi et al., 2021). This shortfall persists despite the country's substantial agro-ecological potential and repeated policy efforts aimed at increasing local production.

The significance of rice cultivation in Nigeria extends beyond consumption. It plays a vital role in employment generation, poverty alleviation, and income distribution. According to Diao et al. (2021), enhancing agricultural productivity, particularly among smallholder farmers, is a crucial pathway for inclusive growth and poverty reduction in Africa. In this regard, rice farming presents an opportunity to strengthen rural economies and reduce food import dependency. Nevertheless, the performance of rice farmers has remained suboptimal, constrained by a variety of structural and institutional factors (Federal Ministry of Agriculture and Rural Development [FMARD], 2024).

Among the challenges affecting rice production are limited access to quality inputs such as fertilisers and improved seeds, poor mechanisation, inadequate extension services, climate variability, and pest infestations (Adekunle et al., 2020). Moreover, infrastructural deficits, especially in irrigation and transportation, further restrict farmers' productive potential (Africa Rice Centre, 2022). In response to these challenges, the Nigerian government has implemented a series of policy interventions aimed at revitalising the rice sector. Notable among these is the Anchor Borrowers' Programme (ABP) initiated by the Central Bank of Nigeria (CBN), which provides subsidised credit and agricultural inputs to smallholder farmers (CBN, 2020).

These interventions have been complemented by broader policy frameworks such as the Agricultural Transformation Agenda (ATA) and the National Rice Development Strategy, which aim to stimulate local production, enhance value chain integration, and reduce rice imports. State-level initiatives have also been launched, providing land concessions, irrigation investments, and access to mechanisation to attract both small and large-scale investments in rice farming (Osabohien et al., 2022).

Despite the proliferation of these interventions, empirical assessments of their impact on productivity and efficiency remain limited. Technical efficiency, defined as the ability of a farm to produce the maximum possible output from a given set of inputs, is a key metric for evaluating the effectiveness of agricultural interventions (Kassie et al., 2020). A technically efficient farmer maximizes output without wasting inputs, thereby achieving higher profitability and competitiveness.

Evaluating the technical efficiency of rice farmers in Nigeria, especially in the context of government intervention, is therefore essential for evidence-based policy formulation. It provides insights into whether beneficiaries of state programmes are more productive compared to non-beneficiaries and identifies specific areas of inefficiency that require attention.

Several studies have investigated efficiency levels in Nigerian agriculture using frontier models, yet few have explicitly compared beneficiaries and non-beneficiaries of intervention schemes (Ogunniyi et al., 2021; Ogundari & Ojo, 2020).

Despite various government interventions aimed at revitalising the rice sub-sector in Nigeria such as the Anchor Borrowers' Programme and the Agricultural Transformation Agenda, domestic rice production continues to lag behind national demand. While these initiatives were designed to enhance access to inputs, improve productivity, and reduce import dependency, evidence on their actual impact, particularly in terms of technical efficiency among smallholder farmers, remains limited and fragmented.

The persistent productivity gap between local production and consumption, coupled with continued reliance on rice imports, raises critical questions about the effectiveness and equitability of these state-led programmes. Moreover, while some farmers benefit from subsidised inputs, access to credit, and land support, others operate independently, often with fewer resources and institutional backing.

It is unclear whether government-supported rice farmers achieve significantly higher technical efficiency than their non-beneficiary counterparts, or whether inefficiencies persist regardless of intervention. Without a rigorous empirical comparison, policy decisions may be misdirected, potentially reinforcing inefficiencies or excluding deserving farmers from support. Therefore, there is a need to assess and compare the technical efficiency of rice farms among beneficiaries and non-beneficiaries of state intervention programmes in Nigeria, and to identify the socio-economic and institutional factors influencing efficiency levels.

This study seeks to fill this gap by conducting a comparative analysis of the technical efficiency of rice farmers who have benefitted from government intervention programmes and those who have not. It addresses three key research questions: (1) What is the level of technical efficiency among rice farmers in Nigeria? (2) Are there significant differences in efficiency between beneficiaries and non-beneficiaries of state intervention programmes? (3) What socio-economic and institutional factors influence technical efficiency? To answer these questions, the study aims to: (i) estimate the technical efficiency of rice farmers in Nigeria; (ii) compare efficiency levels between programme beneficiaries and non-beneficiaries; and (iii) identify the socio-economic and institutional determinants of technical efficiency.

MATERIALS AND METHODS

Study Area

This study was conducted in six major rice-producing states across Nigeria's geopolitical zones: Kebbi (North West), Taraba (North East), Kwara (North Central), Ekiti (South West), Ebonyi (South East), and Akwa Ibom (South South). These states were purposively selected due to their prominence in national rice production and participation in government-led agricultural interventions such as the Anchor Borrowers' Programme (ABP). Their inclusion captures diverse agro-ecological conditions and production systems, ranging from irrigated lowlands to upland rain-fed fields.

Kebbi State, located in the north-western region, is a key beneficiary of the Federal Government's rice production drive. It has a semi-arid climate and benefits from irrigation facilities, particularly the Rima River Basin, which supports large-scale rice cultivation under both rain-fed and irrigated systems. The state is widely recognised for its involvement in the Anchor Borrowers' Programme and has become a leading contributor to national rice output (CBN, 2020; Osabohien et al., 2022).

Taraba State, situated in the north-eastern region, possesses vast arable land and favourable climatic conditions for rice farming. The state's topography, which includes lowland and upland areas, supports different rice ecologies. Despite infrastructural challenges, Taraba has experienced increased rice production due to government and donor-supported interventions (FMARD, 2024; Africa Rice Centre, 2022).

Kwara State, in the north-central region, represents a transition zone between the savannah and forest belt. It has a strong tradition of rice farming and has benefitted from both public and private agricultural initiatives. The state's location and moderate rainfall patterns make it suitable for both upland and lowland rice cultivation (Abdullahi et al., 2021).

Ekiti State, in the south-western zone, contributes significantly to rice production in the region, albeit on a smaller scale compared to northern states. The area is characterised by forest ecology and a bimodal rainfall pattern, allowing for two cropping seasons annually. Smallholder rice farmers in Ekiti have received various forms of state-level support, including access to inputs and mechanisation services (Osabohien et al., 2022).

Ebonyi State, located in the south-east, is one of the most prominent rice-producing states in southern Nigeria. It boasts expansive lowland rice fields, particularly in areas like Ikwo, Izzi, and Abakaliki. The state government has made substantial investments in rice milling and processing infrastructure, aiming to promote value addition and reduce post-harvest losses (Africa Rice Centre, 2022; FMARD, 2024).

Akwa Ibom State, in the south-south region, is emerging as a notable rice producer, aided by recent government efforts to diversify the economy from oil dependence.

The state has initiated various support programmes for rice farmers, including land development, distribution of improved seed varieties, and training in modern agronomic practices (World Bank, 2022; UN Women, 2023).

Data Collection and Sampling Techniques

The target population for this study comprised all registered rice farmers across six selected states in Nigeria, representing each of the six geo-political zones. These states are Kebbi, Taraba, Kwara, Ekiti, Ebonyi, and Akwa Ibom. They were purposively selected due to their prominence in rice production and their participation in various government agricultural intervention programmes, particularly the Anchor Borrowers' Programme and related initiatives at both federal and state levels.

The sampling frame was drawn from official registers maintained by the Rice Farmers Association of Nigeria (RIFAN) and state agricultural development programmes (ADPs), ensuring that only duly registered and actively cultivating rice farmers were considered. This approach allowed for a systematic identification of both beneficiaries and non-beneficiaries of state support programmes, facilitating an objective comparative analysis.
A total of 1,568 farmers were surveyed, comprising 928 small-scale, 289 medium-scale, and 131 large-scale farmers. The sample was proportionally distributed across states to reflect their share of the rice farming population. (see Table 1).

Table 1: Breakdown of the sample allocation by state and scale of operation.

State	Small-Scale	Medium-Scale	Large-Scale	Total
Kebbi	160	52	24	236
Taraba	154	48	20	222
Kwara	152	47	21	220
Ekiti	150	45	20	215
Ebonyi	160	50	24	234
Akwa Ibom	152	47	22	221
Total	**928**	**289**	**131**	**1,568**

This sampling structure ensured that all scales of production were adequately represented, allowing for robust analysis of technical efficiency across different categories of rice farmers. Moreover, by including both beneficiaries and non-beneficiaries of government programmes in each category, the study design facilitates a direct comparison of efficiency outcomes attributable to policy interventions.

Data Collection

Primary data were collected using structured questionnaires administered by trained enumerators. The questionnaire captured information on rice output, input use (e.g., seed, labour, fertilizer, herbicides, pesticides, irrigation cost), and farmer characteristics (e.g., age, gender, education, household size, farming experience). It also included questions on programme participation and access to extension services and credit.

Analytical Techniques

This study employed a combination of descriptive and econometric techniques to achieve its objectives. Specifically, descriptive statistics, the stochastic frontier production model, and the inefficiency effects model were applied to evaluate and compare the technical efficiency of rice farmers who are beneficiaries and non-beneficiaries of state intervention programmes across Nigeria.

Descriptive Statistics

Descriptive statistics were used to summarise the socio-economic characteristics of the rice farmers in the sample. These included variables such as age, gender, years of farming experience, educational level, household size, access to extension services, and farm size. Frequency distributions, means, and percentages were calculated and presented in Table 1 to provide insight into the respondents' demographic and institutional profiles. These statistics served as a foundation for interpreting efficiency outcomes and identifying possible relationships between farmer characteristics and technical efficiency.

Stochastic Frontier Production Function

To estimate the technical efficiency of rice farms, the study adopted the Stochastic Frontier Analysis (SFA) framework developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). The Cobb-Douglas functional form was specified for the production frontier due to its simplicity and interpretability, and its suitability given the nature of agricultural production with multiple input factors. The stochastic frontier model is expressed as:

$$Y_i = f(X_i; \beta). e^{(v_i - u_i)}$$

Where:

Y_i is the output of the i^{th} farmer (rice output in kg),

X_i is a vector of input variables (e.g., land size, seed, fertiliser, labour, and agrochemicals),

β is a vector of parameters to be estimated,

v_i is the two-sided random error term capturing statistical noise, assumed to be independently and identically distributed $N(0, \sigma_v^2)$,

u_i is the non-negative inefficiency term, assumed to follow a truncated normal distribution.

Maximum Likelihood Estimation (MLE) was employed to estimate the parameters of the stochastic production function. The results of this estimation are presented in Table 2, which shows the estimated coefficients of production inputs and their level of significance.

Inefficiency Effects Model

To further identify the socio-economic and institutional factors that influence technical inefficiency, the inefficiency effects model proposed by Battese and Coelli (1995) was incorporated into the stochastic frontier model. This allows for simultaneous estimation of the production frontier and the inefficiency effects. The inefficiency model is specified as:

$$u_i = \delta_0 + \sum_{j=1}^{n} \delta_j Z_{ij} + w_i$$

Where:
u_i is the technical inefficiency effect for the i^{th} farmer,
Z_{ij} is a vector of explanatory variables influencing inefficiency (e.g., age, education, extension contact, programme participation, access to credit),
δ_j are parameters to be estimated,
w_i is a random error term.

RESULTS AND DISCUSSION

Distribution of respondents based on gender and participation in state intervention programmes

The Table 2 presented offers a clear comparison between beneficiaries and non-beneficiaries, as well as male and female farmers, providing valuable insights into the role of government interventions and other determinants in shaping productivity among rice farmers in Nigeria.

It summarizes the demographic and program participation characteristics of the rice farmers surveyed in the study. The sample is broken down by gender, participation in state intervention programmes, and overall representation.

Out of the 1,568 respondents, 1,052 (67.09%) were male and 516 (32.91%) were female. This gender disparity is reflective of the general structure of agricultural labour in Nigeria, where male farmers dominate land ownership and field-level decision-making, especially in commercial crop cultivation like rice. This observation is consistent with the findings of UN Women (2023), which highlight persistent gender gaps in agricultural labour division, largely due to socio-cultural constraints and limited resource access for women.

Among the respondents, 864 (55.10%) were beneficiaries of government intervention programs while 704 (44.90%) were non-beneficiaries. This almost even distribution allows for a robust comparative analysis of the technical efficiency levels between the two groups, which is essential for assessing the impact of state support on productivity. Government programs like the Anchor Borrowers' Programme (ABP) have targeted increased rice output, but their effectiveness varies across demographic segments and geographic locations (Central Bank of Nigeria, 2023).

For both male and female farmers, the split between beneficiaries and non-beneficiaries is nearly even, suggesting gender-neutral targeting by intervention programs on the surface. However, as past studies have shown, gender equity in enrolment does not necessarily translate to equality in resource utilization or benefits derived (Osabohien et al., 2022).

Table 2: Distribution of respondents based on gender and participation in state intervention programmes

Respondent	Frequency	Percentage	Frequency	Percentage
	Male		**Female**	
Rice farmers	1,052	67.09%	516	32.91
Beneficiaries	580	55.13	284	55.04
Non-beneficiaries	472	44.87	232	44.96
Total	1,052	100.00	516	100.00
	Beneficiaries		**Non-beneficiaries**	
Government intervention	864	55.10	704	44.90

Source: Authors' Computation

Technical efficiency of rice farmers in the study area

The Table 3 presents the results of the Stochastic Frontier Production Function (SFA) model, which was used to estimate the technical efficiency of rice farmers in the study area.

Labour has a highly significant and positive coefficient (0.150; $p<0.01$). This finding underlines the labour-intensive nature of rice farming in Nigeria, where mechanization remains limited and manual labour is still a major determinant of productivity. This is corroborated by Ayanlade et al. (2023), who emphasized the critical role of family labour and hired labour in determining the efficiency of smallholder rice farms.

Herbicides, pesticides, and seeds also exhibit positive and statistically significant coefficients. The use of herbicides (0.099), pesticides (0.138), and seeds (0.096) is essential in modern rice farming, not only for yield improvement but also for maintaining plant health and weed control, especially under the constraints of changing climate patterns and soil fertility loss. This trend is supported by Uche et al. (2023), who demonstrated that access to high-quality inputs significantly boosts technical efficiency among rice farmers in Nigeria.

Fertilizer, however, was not statistically significant ($p = 0.234$). This result may reflect inefficiencies in fertilizer application or the use of substandard products, which is a recurring problem in the Nigerian input supply chain (Agbugba et al., 2024). It also hints at possible knowledge gaps in the appropriate use of chemical fertilizers among smallholders.

Sex, age, and education are all statistically significant. The positive coefficients suggest that older, male, and more educated farmers tend to exhibit higher technical efficiency. These outcomes are consistent with global findings on human capital's role in enhancing farm productivity (Ojo et al., 2023).

Interestingly, the coefficient of experience is negative and highly significant (-59.076; $p<0.01$). While experience is often assumed to improve efficiency, in this case, the negative relationship might suggest that seasoned farmers rely on outdated practices, as newer entrants might be more likely to adopt modern technologies (Gbegbelegbe et al., 2022).

The positive and significant coefficient of irrigation costs (3.850; $p<0.05$) underlines the importance of water management in rice production. Proper irrigation remains a critical input, especially under increasingly erratic rainfall patterns driven by climate change (World Bank, 2022).

Surprisingly, for government intervention, the intervention variable carries a negative and significant coefficient (-99.424; $p<0.01$). This suggests that, contrary to expectations, being part of a government program might correlate with lower technical efficiency. This paradoxical finding has been echoed in recent literature, which notes structural inefficiencies and delays in input distribution as common pitfalls in public agricultural schemes (Adeniran et al., 2024).

Sigma u and Sigma v measure the variance components for inefficiency and random error, respectively. Both are statistically significant, confirming the relevance of inefficiency effects in the model. Lambda is the ratio of these variances, indicating that a substantial portion of the output deviation from the frontier is due to inefficiency rather than random shocks, which aligns with expectations for smallholder-dominated systems (Salau & Gbadebo, 2023).

Table 3: Estimation of the technical efficiency of rice farms

lnRice output per ha	**Coefficient**	**Standard Error**	**P>z**
Frontier			
lnFertilizer kg/ha	0.018	0.015	0.234
lnLabor manday/ha	0.150	0.016***	0.000
lnHerbicides lt/ha	0.099	0.019***	0.000
lnPesticide lt/ha	0.138	0.024***	0.000
lnSeed kg/ha	0.096	0.020***	0.000
_cons	7.275	0.085***	0.000
Mu			
Sex (yes = 1)	49.294	21.410**	0.021
lnAge (years)	118.335	46.698**	0.011
lneducation (years)	20.463	9.391**	0.029
lnHousehold size	16.817	10.056*	0.094
lnExperience	-59.076	21.267***	0.005
lnIrrigation cost (₦)	3.850	1.810**	0.033
lnTotal farm size (ha)	-6.026	8.823	0.495
Marital status (married=1)	40.903	26.755	0.126
Government intervention	-99.424	35.889***	0.006
Constant	-601.353	220.596***	0.006
Usigma			
Constant	4.851	0.344***	0.000
Vsigma			
Constant	-1.988	0.068***	0.000
Sigma u	11.310	1.947***	0.000
Sigma v	0.370	0.013***	0.000
Lambda	30.561	1.948***	0.000
Number of observations = 1568			
Wald chi2(5) = 283.23			
Prob > chi2 = 0.0000			
Log likelihood = -1539.9475			

Estimated efficiency scores across various groups

Table 4 provides the descriptive statistics for the estimated efficiency scores across various groups. Male farmers exhibited higher mean technical efficiency (0.6548) than their female counterparts (0.5583). This pattern aligns with widespread research on gender gaps in access to agricultural resources and training, which often leaves female farmers at a disadvantage (UN Women, 2023).

Non-beneficiaries had a surprisingly higher mean technical efficiency (0.7910) compared to beneficiaries (0.4861). This raises important questions about the efficacy of intervention programs. Some literature suggests that while beneficiaries receive inputs, they may lack sufficient technical knowledge to optimize their use, or programs may inadvertently foster a dependency mindset, reducing individual initiative (Adeniran et al., 2024).

Female non-beneficiaries showed higher technical efficiency (0.7510) compared to female beneficiaries (0.3943). Similarly, male non-beneficiaries also outperformed male beneficiaries. This pattern reinforces the earlier point that mere program membership does not automatically translate to improved efficiency and highlights the need for well-targeted training and monitoring within intervention schemes.

Table 4: Summary statistics for the estimated efficiency scores across various groups

Efficiency	Observation	Mean	Standard deviation	Maximum	Minimum
Pooled male	1,052	0.6548	0.9571	0.0854	8.5325
Pooled female	516	0.5583	0.5022	0.0823	3.5646
Beneficiaries	864	0.4861	0.6435	0.0854	7.8851
Non-beneficiaries	704	0.7910	0.9996	0.0823	8.5325
Male beneficiaries	508	0.5311	0.7563	0.0854	7.8851
Male non-beneficiaries	472	0.8067	1.1396	0.0938	8.5325
Female beneficiaries	284	0.3943	0.2820	0.1235	2.3100
Female non-beneficiaries	232	0.7510	0.6256	0.0823	3.5646

Source: Authors' Computation

Conclusion

This study assessed the technical efficiency of rice farmers in Nigeria, comparing beneficiaries and non-beneficiaries of state intervention programmes. The results revealed that key inputs such as labour, herbicides, pesticides, and seeds significantly enhance technical efficiency, while fertilizer use showed no significant effect—likely due to inefficiencies in application or poor product quality. Surprisingly, non-beneficiaries demonstrated higher average efficiency scores than beneficiaries, suggesting that participation in government programmes does not automatically translate into improved productivity.

Several socio-demographic factors influenced efficiency outcomes. Male, older, and more educated farmers tended to be more technically efficient, while greater years of farming experience were negatively associated with efficiency, potentially reflecting resistance to adopting modern practices.

The negative association between government intervention and efficiency suggests that current programmes may be hampered by issues such as poor implementation, limited technical support, and delayed input delivery.

While government agricultural interventions remain essential for achieving food security and rural transformation, their design and execution require significant reform. Interventions must move beyond input distribution and incorporate sustained capacity-building, farmer education, and stronger monitoring and evaluation systems. Moreover, the gender disparities observed highlight the need for inclusive programming that ensures women farmers have equal access to land, finance, and extension services.

Limitations: This study relies on cross-sectional data, which limits its ability to establish causal relationships. Additionally, programme participation was self-reported, and the analysis may be influenced by selection bias or unobservable factors. Future research could explore the long-term impacts of intervention programmes using panel data and mixed-methods approaches.

Recommendations

Based on the findings of this study, to improve technical efficiency among rice farmers, government intervention programmes must move beyond input distribution and focus on strengthening agricultural extension systems. Providing targeted, practical training on input use—particularly fertilizers and pest control—can help farmers maximize productivity and reduce waste. Additionally, programmes should prioritize timely and transparent delivery of support, with robust monitoring mechanisms that track not only input distribution but also on-farm outcomes. Ensuring the quality of inputs, such as fertilizers and seeds, through better regulation and supply chain oversight is also essential.

Furthermore, interventions must be designed with gender equity in mind. Female farmers, who exhibited lower technical efficiency despite programme participation, require targeted support that addresses structural constraints such as limited access to land, credit, and decision-making opportunities. Inclusive programme design should ensure women are not just included numerically but empowered substantively. Finally, retraining older, experienced farmers to adopt modern, climate-smart agricultural practices could help close the efficiency gap and promote a more resilient and productive rice sector overall.

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