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Original Research Article
ISSN: 3041-5322
Journal homepage: agriculture.researchfloor.org

Assessing Technical, Economic, and Allocative Efficiencies of Maize-Rice-Based Farmers Across Scale Economies in Southwest Nigeria

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ABSTRACT

Efficiency plays a vital role in boosting agricultural productivity and ensuring sustainable food security. This study examines the technical, economic, and allocative efficiencies of maize-rice farmers in Southwest Nigeria, with a focus on differences across small, medium, and large-scale farming operations. The research utilized stochastic frontier analysis to assess efficiency levels and identify factors influencing productivity. Primary data were collected through structured questionnaires and focus group discussions (FGDs), involving 100 farmers selected via a multistage sampling technique. The findings revealed notable disparities in efficiency based on farm scale. Small-scale farmers exhibited the lowest technical and allocative efficiencies, primarily due to constraints such as limited access to inputs, credit, and extension services. Medium-scale farmers displayed moderate efficiency, while large-scale farmers achieved the highest efficiency levels, benefiting from economies of scale and access to advanced resources. Significant determinants of efficiency included farm size, education level, farming experience, and credit availability. The study underscores the importance of targeted strategies to improve efficiency across all scales. Key recommendations include enhancing access to credit and extension services, fostering cooperative formations, and encouraging the adoption of modern agricultural technologies. Implementing these measures can address efficiency gaps, boost productivity, and support sustainable agricultural development and food security in Nigeria.

Keywords: *Efficiencies, maize farming, productivity, scale economies, stochastic frontier, Nigeria*

1. Introduction

Agriculture continues to be a cornerstone of Nigeria's economy, playing a vital role in its gross domestic product (GDP) and serving as the primary source of employment for the majority of the population [15] [29] [3]. In Southwest Nigeria, maize-rice cropping systems hold particular importance, as both maize and rice are not only staple foods but also key economic crops [23]. The interplay between these crops within a single farming framework offers numerous advantages, including efficient land use, diversified income streams, and enhanced food security. However, the agricultural sector, especially at the level of small to medium-scale farmers, faces critical challenges, including inefficiencies in production and resource allocation [7] [18] [36]. Efficiency analysis in agriculture evaluates how well farmers use available resources to maximize output and minimize costs.

Citation: Tolulope Seun Olubunmi-Ajayi, Olumide Oyewole Akinrinola, AjololaTaibat Ibrahim, Ife Oluwasina Adeyemi (2025). Assessing Technical, Economic, and Allocative Efficiencies of Maize-Rice-Based Farmers Across Scale Economies in Southwest Nigeria.
Agriculture Archives: an International Journal.
DOI: https://doi.org/10.51470/AGRI.2025.4.1.01

Received on: November 28, 2024
Revised on: December 20, 2024
Accepted on: January 02, 2025

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Three critical dimensions of efficiency (technical, allocative, and economic) play distinct but interconnected roles in achieving sustainable agricultural development. Technical efficiency measures a farmer's ability to obtain maximum output from a given set of inputs, while allocative efficiency assesses the cost-effectiveness of input utilization given prevailing prices [5] [25]. Economic efficiency combines these aspects, reflecting a farmer's ability to produce at the least possible cost while maximizing output. These metrics are crucial for understanding the operational dynamics of smallholder and large-scale farms in Southwest Nigeria.

Studies have highlighted that inefficiencies in these areas can stem from various factors, including limited access to inputs, suboptimal resource allocation, and inadequate technical know-how [4] [10] [14]. Addressing these inefficiencies through targeted policies and capacity-building initiatives can enhance farm productivity, increase income levels, and improve food security outcomes. Farmers in Southwest Nigeria face a range of challenges that affect the productivity of maize-rice-based systems [11]. Land fragmentation, limited access to credit, poor infrastructure, and fluctuating input prices are among the critical barriers to efficient production. Additionally, the effects of climate change, including erratic rainfall and rising temperatures, exacerbate these challenges, particularly for smallholder farmers who rely heavily on natural conditions for cultivation [26] [28].

The inefficiencies associated with resource use are further compounded by socio-economic factors such as education, farm size, and extension services [5]. Farmers with limited educational attainment may lack the technical knowledge to optimize resource use, while those operating on smaller plots often struggle to achieve economies of scale.

DOI: https://doi.org/10.51470/AGRI.2025.4.1.01

These challenges underscore the need for a detailed investigation into the factors influencing technical, economic, and allocative efficiencies within maize-rice-based systems [25]. The concept of scale economies is pivotal in understanding the varying levels of efficiency among small, medium, and large-scale farmers [23] [24]. Scale economies refer to the cost advantages gained as the size of production increases. Larger farms, for example, can benefit from bulk purchasing of inputs, better access to credit, and more advanced technology, which can improve both productivity and cost efficiency [1]. In contrast, smallholder farmers often struggle with resource limitations, which can hinder their ability to achieve similar levels of efficiency.

By examining efficiency levels across different scales, policymakers can identify targeted interventions to support farmers at each scale. For instance, while large-scale farmers might benefit from technology upgrades, smallholders may require capacity-building programs to enhance their technical skills and access to affordable inputs.

Southwest Nigeria is a critical agricultural zone, characterized by fertile soils and favorable climatic conditions that support the cultivation of a wide variety of crops [2] [31]. Maize and rice are among the most important crops in the region, both in terms of dietary significance and economic value. The integration of these crops into a single system offers potential synergies, including efficient resource use and reduced production risks [24]. However, the region also faces unique challenges, such as land scarcity and high population density, which can impact farming practices and efficiency levels. Understanding the determinants of efficiency in this context is essential for promoting sustainable agricultural development. Factors such as land tenure systems, input markets, and access to extension services play a critical role in shaping efficiency outcomes. This study focuses on identifying the key drivers of technical, allocative, and economic efficiencies among maize-rice-based farmers in the region, with a particular emphasis on scale economies. While numerous studies have explored agricultural efficiencies in Nigeria, there is a lack of comprehensive analysis specific to maize-rice-based systems in Southwest Nigeria. Existing research often generalizes findings across diverse cropping systems, overlooking the unique dynamics of maize-rice integration. Furthermore, limited attention has been given to the role of scale economies in shaping efficiency outcomes within these systems. This study aims to bridge these gaps by examining the technical, allocative, and economic efficiencies of maize-rice-based farmers across small, medium, and large-scale operations. By employing robust econometric techniques, including stochastic frontier analysis, the research seeks to:

- Assess the current levels of efficiency across different scales of farming operations.
- Identify the socio-economic, farm-level, and institutional factors influencing efficiency.
- Provide actionable recommendations for improving efficiency levels and promoting sustainable agricultural practices in Southwest Nigeria.

Addressing inefficiencies in agriculture is imperative for achieving food security, reducing poverty, and fostering rural development in a rapidly growing economy like Nigeria. By focusing on the maize-rice-based farming systems in Southwest Nigeria, this study contributes to a deeper understanding of the challenges and opportunities within this critical sector. The insights gained from this research will inform policy decisions and practical interventions to enhance the productivity and sustainability of farming operations across different scales.

2. Methodology

The research was carried out in Southwest Nigeria, a region known for its agricultural economy and its vital role in ensuring the nation's food security [20] [30]. The area is distinguished by diverse farming systems, with maize and rice serving as primary crops that support the livelihoods of farmers across various scales. The region benefits from fertile soils and favorable climatic conditions, enabling consistent agricultural productivity throughout the year. Data for this study were gathered using a structured survey that included questionnaires, personal interviews, and focus group discussions (FGDs). These tools were designed to capture detailed information on the socio-economic profiles of farmers, farm inputs and outputs, as well as factors influencing technical, economic, and allocative efficiencies in maize-rice-based farming systems.

A multistage sampling strategy was employed to obtain a representative sample from the farming population within the region. In the first stage, three states were deliberately chosen based on their significant contributions to maize and rice cultivation in the Southwest. The second stage involved the random selection of two local government areas (LGAs) from each of these states. In the final stage, farming households within the selected LGAs were randomly chosen. A total of 100 respondents were included, distributed as 70 small-scale farmers, 20 medium-scale farmers, and 10 large-scale farmers. This sampling framework facilitated the collection of data reflecting variations in farming practices, resource utilization, and efficiency levels, ensuring a robust and comprehensive dataset.

Descriptive statistics and stochastic frontier production functions were employed for data analysis. The stochastic frontier approach, in particular, was selected for its ability to incorporate the variability typical of small-scale agricultural production in developing countries. Unlike classical methods, this approach accounts for deviations arising from random errors—such as measurement inaccuracies and statistical noise—as well as inefficiencies specific to individual farms [25]. The stochastic frontier model decomposes the error term into two components: a symmetric random error capturing the influence of external factors, and an inefficiency term reflecting farm-specific challenges. This approach was applied to estimate and contrast the levels of technical, economic, and allocative efficiencies across small, medium, and large-scale maize-rice farmers, offering insights into variations in production practices and efficiency among these groups. This methodology is mathematically expressed as follows:

$InQTY_i = b_0 + b_1 LnFET_1 + b_2 LnHER_2 + b_3 LnLAB_3 + b_4 LnFAM_4 + b_5 LnSEE_5 + (V_{i-} U_i)$ ....(1)

Where:

QTY_i = Quantity of maize-rice-based product produced in kg (after conversion into grain equivalent)

FET_1 = fertilizer (kg)

HER_2 = herbicides (Litres)

LAB_3 = Labour (man days)

FAM_4 = Farm size (ha).

SEE_5 = seeds (kg)

Vi = The two-sided normally distributed random error that cannot be influenced by the farmers e.g. weather disaster

U_i = One-sided technical inefficiency component with a -half-normal distribution.

The inefficiency model was defined to estimate the influence of some farmer's socioeconomic variables on the technical efficiency of the farmers.

The model will be specified by;

$U_i = \ddot{a}_0 + \ddot{a}_1 FEP_1 + \ddot{a}_2 AGE_2 + \ddot{a}_3 SEX_3 + \ddot{a}_4 MST_4 + \ddot{a}_5 EDU_5 + \ddot{a}_6 ACT_6 + \ddot{a}_7 HSZ_7 + \ddot{a}_8 MFC_8 + \ddot{a}_9 LOW_9$ .... (2)

Where:

FEP_1 = Farming experience (in years)
AGE_2 = Age of the farmer (in years)
SEX_3 = Sex (male = 1, female = 0)
MST_4 = Marital status (married =1, otherwise =0)
EDU_5 = Educational level (years of formal education)
ACT_6 = Access to credit (Yes = 1; No = 0)
HSZ_7 = Household size (number)
MFC_8 == Membership of farmers' cooperative (yes = 1; No = 0)
LOW_{10} = Land ownership (Inherited =1, Lease = 0)

This was included in the model to indicate their possible contributions to and influence on the farmers' technical inefficiencies. $\ddot{a}_s$ are scalar parameters to be estimated.

Stochastic Frontier Cost Function Model

The stochastic production function typically utilizes two main functional forms: the Cobb-Douglas and the translog. Among these, the Cobb-Douglas form is renowned for its simplicity and self-dual properties, which make it a preferred choice for modeling agricultural production technologies in various developing regions [9] [10]. Consequently, this study adopted the Cobb-Douglas function as the cost frontier to analyze the allocative efficiency within maize-based cropping systems in the study area. In line with the methodology described by [8], the model integrated a deterministic element into the cost frontier function while accounting for the inefficiency component. All parameters were estimated using a single-step maximum likelihood estimation approach, as outlined in [19]. The Cobb-Douglas function is implicitly written as: $Y_i = f(\beta o X_i^{bi} e_i)$

In the case of the cost frontier, the model is re-written as:

$InC = f(P_i, Y_i; b). (V_i + U_i)$ .... (3)

Where *C* is the total production cost incurred by the ith maize-rice-based farmer. *Y* is the output level; *P* is a vector of input prices; b is a vector of parameters to be estimated; *f (Pi, Yi;* b*)* is the minimum cost frontier; *V* represents random effects and *U* represents the cost inefficiency.

The Cobb-Douglas cost function for the maize-based farmers was explicitly expressed as:

$InTC_i = b_0 + b_1 InFET_1 + b_2 InHER_2 + b_3 InLAB_3 + b_4 InFAM_4 + b_5 InSEE_5 + b_6 QTY_6 + (V_i + U_i)$ ....(4)

Where:

In = the natural logarithm (logarithm to base e)
TC_i = total production cost of the i-th maize-rice-based farmers in Naira,
FET_1 = cost of fertilizer (Naira)
HER_2 = cost of herbicides Naira)
LAB_3 = cost of Labour (Naira)
FAM_4 = cost of land (Naira).
SEE_5 = cost of seeds (Naira)
QTY = Quantity of maize-rice-based crops produced in kg (after conversion into grain equivalent)
$b_0 – b_5$ = estimated parameters

Again, V_i = random variables which are assumed to be iid. $N(0,{}_V^2)$, and independent of the $U_{it} = (U_i exp(-(t-T)$,

U_i = non-negative random variables which are assumed to account for cost inefficiency in production and are assumed to be iid. as truncations at zero of the $N({}_{,U}^2)$ distribution;

= parameter to be estimated. Therefore, we utilize the parameterization of [1] who replaces${}_V^2$ and ${}_U^2$ with ${}^2 = {}_V^2 + {}_U^2$ and = ${}_U^2/({}_V^2 + {}_U^2)$.

This was performed to calculate the maximum likelihood estimates. The parameter, γ, needs to fall within the range of 0 to 1, and as such, this range can be explored to determine a suitable initial value for use in an iterative maximization process like the Davidon-Fletcher-Powell (DFP) algorithm.

Allocative Efficiency

Technical efficiency (TE) refers to a farm or firm's ability to maximize output from a given set of resource inputs. On the other hand, allocative efficiency (AE) focuses on the ability to utilize inputs in the most optimal proportions, considering their respective prices and the current production technology. While TE assesses the capacity of a farmer to operate on the production frontier, AE evaluates the efficiency of producing a specific level of output using input combinations that minimize costs. Economic efficiency (EE) combines these concepts, reflecting the farmer's ability to achieve a target level of output at the lowest possible cost, given the technological constraints [14].

Relative to AE, [19] following [25] explained that *AE* index can be obtained from *EE* values, given that EE = TE x AE. Therefore,

$$\text{Allocative Efficiency (AE)} = \frac{Technical\ Efficiency\ (TE)}{Economic\ Efficiency\ (EE)} \quad \ldots\ldots\ldots\ldots (5)$$

3. Results and Discussion

3.1 Estimation of the Stochastic Frontier Production Function

Table 1 provides an overview of the estimated stochastic production function for the maize-rice cropping system. The sigma-squared (σ^2) value confirms a strong model fit and validates the assumed distribution of the composite error term. The gamma (Υ) values were estimated at 0.999 for small- and medium-scale farms and 0.950 for large-scale farms, indicating that systematic influences not captured by the production function account for most of the variability in the error term. For small-scale farms, the coefficients for the quantity of fertilizer (kg) and labor costs were positively associated with maize and rice output. Conversely, variables such as herbicides, farm size, and seed quantity showed negative relationships with output. These findings suggest that farmers could increase production and profitability by expanding their cultivated land. Optimizing farm size appears to be key to achieving higher productivity and profitability, allowing farmers to cover production costs and break even. This result diverges from findings by [21], which noted a significant positive effect of farm size on maize output.

In medium-scale farms, the coefficient for fertilizer use was negative and insignificant, indicating inefficiencies or possible diminishing returns from fertilizer application. This could stem from suboptimal nutrient management, soil fertility issues, or fluctuating fertilizer prices. Improved practices such as soil testing, precision fertilization, and crop rotation could address these inefficiencies and enhance fertilizer efficiency. Herbicide usage was positively correlated with maize and rice output, with a significant 15.9% increase at the 10% significance level, underscoring the importance of effective weed control. Additionally, farm size exhibited a significant positive relationship with output at the 1% level, where a unit increase in farm size resulted in a 39.6% output increase. This highlights the role of economies of scale, as larger farms generally have better access to resources like machinery and capital, enabling higher productivity. However, seed use showed a negative but significant association with output, while fertilizer and labor also had negative coefficients.

For large-scale farms, farm size demonstrated a positive and significant relationship with maize-rice output at the 10% level, where a unit increase in farm size led to a 17.2% increase in output. However, seed use, labor costs, and herbicide application were negatively associated with output, with the scale of operations significantly affecting productivity.

In the combined analysis of all farm scales, the sigma-squared (δ^2) value of 0.872 indicated a strong model fit, supporting the assumed distribution of composite error terms. The gamma (γ) value of 0.633 for combined scales showed that technical inefficiency accounted for 63.3% of the variability in maize output. This underscores the need to enhance technical efficiency within maize-rice cropping systems. When examining specific factors, fertilizer use negatively impacted maize output, with statistical significance at the 1% level. A 1% increase in fertilizer application resulted in a 45% reduction in maize output, suggesting diminishing returns from over-application. Conversely, farm size had a positive and significant impact, with a 29.4% increase in output per percentage increase in farm size. This finding highlights the advantages of larger farms, including economies of scale and better resource allocation.

These results align with studies by [17] and [37], which similarly observed the influence of fertilizer use and farm size on maize productivity in maize-rice cropping systems. However, the negative relationship between fertilizer use and output challenges conventional expectations that associate higher fertilizer application with increased yields. It underscores the potential adverse effects of excessive fertilizer use, such as inefficient nutrient absorption and soil health degradation.

Table 1: Maximum Likelihood Estimates of Stochastic Production Function for Maize-Rice Farmers

Variables	parameters				Cropping Pattern								
		Small Scale			Medium Scale			Large Scale			Pooled		
		coefficients	Std. error	t value	Coefficients	Std. error	t value	Coefficients	Std. error	t value	coefficients	Std. error	t value
Constant	β_0	15.669***	0.976	16.041	18.963***	0.999	18.981	7.899***	0.2804	28.210	1.347	1.019	1.32
Fertilizer	β_1	0.0962	0.167	0.575	-0.461	0.889	-0.518	0.0143	0.036	0.397	-0.450***	0.072	-6.25
Herbicides	β_2	-0.385	0.586	-0.656	1.592*	0.898	1.773	-0.232***	0.057	-4.070	-0.124	0.137	-0.91
Labour	β_3	0.277	0.238	1.116	-0.158	0.935	-0.169	-0.397***	0.064	-6.203	-0.020	0.126	-0.16
Farm size	β_4	-0.729	0.826	-0.883	3.963***	0.999	3.964	1.726***	0.089	19.393	-0.294**	0.140	-2.10
Seeds	β_5	-0.087	0.465	-0.316	-1.485*	0.845	-1.758	-0.770***	0.161	-4.782	0.074	0.227	0.33
Sigma-squared	σ^2	10.043***	0.998	10.045	283.836***	1.000	283.625	0.3705***	0.034	10.793	0.872***	0.140	6.25
Gamma	Γ	0.999***	0.000	420288.26	0.999	2.371	42.175	0.950***	0.013	73.076	0.633***	0.134	4.73
LR Test			-26.829			-15.249			192.777			46.027*	

Note: and *** mean significant at 10% and 1% respectively*
Source: Computed from field Survey, 2023

3.2 Estimation of Stochastic Cost Function for Maize-Rice Cropping Pattern

Table 2 provides the estimated stochastic cost function for the maize-rice cropping pattern. The sigma-squared (δ^2) value serves as an indicator of the model's fit and validates the assumed distribution of the composite error terms. The gamma (γ) values were 0.712, 0.899, and 0.050 for small-scale, medium-scale, and large-scale farms, respectively. These values indicate that 71.2%, 89.9%, and 5% of the variations in total production costs for the respective farm scales were attributable to cost inefficiencies.

For small-scale farms, the cost of fertilizer was statistically significant at the 5% level, showing a positive relationship with total production costs. Specifically, a unit increase in fertilizer usage led to a 28.1% rise in farm operation costs. Similarly, labor costs were positively correlated with production costs, although this relationship was not statistically significant. The under-utilization of these inputs by farmers suggests inefficiencies in resource allocation within this scale of operation. In contrast, the coefficients for herbicides, farm size, and seeds showed a negative relationship with production costs, implying that an increase in these variables would reduce total costs. This suggests over-utilization of these inputs, with farmers operating in Stage II of the production function, characterized by decreasing returns to scale.

For medium-scale farms, the coefficients of herbicides, labor, fertilizer, and farm size all showed positive relationships with production costs. Fertilizer and farm size were statistically significant at the 5% and 1% levels, respectively. A 4.4% increase in production costs was observed for each unit increase in fertilizer usage, while an increase in farm size resulted in over a 100% rise in farm operation costs. Similar to small-scale farms, the coefficient for seed usage was negative, suggesting over-utilization of this input. Farmers in this category were in Stage I of the production scale, indicating increasing marginal returns to scale.

For large-scale farms, the coefficient of farm size had a positive and statistically significant relationship with production costs, reflecting the substantial impact of scale on operational expenses. Conversely, the coefficients of herbicides, labor, and seeds had negative relationships with production costs, indicating cost reductions with increased use of these inputs. Farmers operating at this scale were in Stage II of the production function, experiencing decreasing returns to scale.

The pooled analysis of the maize-rice cropping system further explored cost efficiency across all farm sizes. The sigma-squared (δ^2) value of 0.531 highlighted considerable variability in cost efficiency, indicating significant differences in how resources were utilized by different farmers. The gamma (γ) value of 0.766 revealed that approximately 76.6% of the variation in cost efficiency among maize producers was due to inefficiencies in resource utilization, underscoring the critical role of addressing inefficiency to improve production outcomes. The fertilizer coefficient, representing the impact of fertilizer usage on total production costs, was negative and statistically significant at the 1% level. This finding suggests that excessive fertilizer use reduces cost efficiency and may increase production costs, highlighting the importance of optimal fertilizer management. The positive coefficient for farm size indicates that larger farms are more cost-efficient, likely benefiting from economies of scale. This relationship was highly significant at the 1% level, reinforcing the idea that scale advantages contribute to improved efficiency. Additionally, the positive coefficient for seed usage revealed a significant relationship at the 1% level, showing that higher seed quantities increase total production costs. However, this result also implies that appropriate investment in seeds can lead to more effective maize-rice production.

Table 2: Maximum Likelihood Estimates of Stochastic Cost Function for Maize-Rice Farmers

Variables	parameters				Scale of Production								
		Small Scale			Medium Scale			Large Scale			Pooled		
		coefficients	Std. error	t value	coefficients	Std. error	t value	coefficients	Std. error	t value	coefficients	Std. error	t value
Constant	β_0	13.066	8.923	1.464	-4.502***	0.999	-4.503	27.899***	0.6804	41.003	10.909***	1.567	6.96
Fertilizer	β_1	0.281*	0.150	1.869	0.044	0.963	0.464	0.0525	0.036	1.458	-0.240***	0.09	-2.67
Herbicides	β_2	-0.458	0.406	-1.126	2.038**	0.960	2.121	-0.232***	0.057	-4.070	-0.023	0.049	-0.46
Labour	β_3	0.361	0.151	0.237	0.242	0.888	0.272	-0.397***	0.064	-6.20	0.081	0.128	0.64
Farm size	β_4	-0.843	1.046	-0.804	4.001***	0.999	4.004	1.726***	0.189	9.132	0.261***	0.075	3.47
Seeds	β_5	-0.164	0.729	-0.225	-0.944	0.997	-0.946	-0.770***	0.161	-4.782	0.325***	0.089	3.65
Sigma-squared	σ^2	4.145***	1.504	2.756	53.39***	1.000	5.339	0.785***	0.034	23.088	0.531***	0.124	4.28
Gamma	Γ	0.712***	0.143	4.981	0.899***	0.020	44.323	0.050	1.666	0.050	0.766***	0.095	8.08
LR Test			-31.949			-17.521			189.425		-7.511***		

Note:,**and *** mean significant at 10% , 5% and 1% respectively*
Source: Computed from field Survey, 2023

3.3 Efficiencies Distribution of the Maize-Rice Farmers

Table 3 outlines the distribution of technical, economic, and allocative efficiencies among farmers operating within the maize-rice cropping system, expressed as percentages. The results indicate that the average technical efficiency for farmers was 0.356 for small-scale farms, 0.576 for medium-scale farms, and 0.996 for large-scale farms. These figures suggest that on average, small-scale farmers achieved 35.6% of their potential maximum output, medium-scale farmers achieved 57.6%, and large-scale farmers achieved 99.6% efficiency.

For small-scale farms, 53.33% of the farmers exhibited technical efficiency scores of 0.3 or less, with a minimum score of 0.0008 and a maximum score of 0.9994. On medium-scale farms, 60% of farmers scored between 0.61 and 0.90, with a range from 0.028 to 0.874. Meanwhile, all large-scale farmers had technical efficiency scores between 0.995 and 1.00, indicating near-perfect efficiency. These findings highlight that small-scale farms face significant constraints, likely related to resource availability and management challenges. Medium-scale farms represent an intermediate stage, with moderate efficiency levels and room for improvement, while large-scale farms demonstrate highly efficient operations, suggesting effective resource utilization and management practices.

The average economic efficiency across farm scales was 0.993 for small-scale farms, 0.573 for medium-scale farms, and 0.998 for large-scale farms. Small-scale farmers demonstrated nearly perfect economic efficiency, effectively utilizing 99.3% of their inputs. However, medium-scale farms lagged behind, utilizing only 57.3% of their inputs efficiently. Large-scale farms, similar to their technical efficiency, exhibited nearly perfect economic efficiency at 99.8%. In small-scale operations, all farmers had economic efficiency scores exceeding 0.9, ranging from 0.993 to 0.994. On medium-scale farms, most farmers fell into the 0.3 efficiency range, with scores between 0.009 and 0.988. For large-scale farms, all farmers scored above 0.9, with values ranging from 0.995 to 1.00. These findings suggest that medium-scale farmers face greater challenges in input utilization compared to both small- and large-scale farmers, possibly due to limited economies of scale or management inefficiencies.

Allocative efficiency also varied significantly among farm scales. Small-scale farms had the lowest average efficiency at 0.375, followed by medium-scale farms at 0.826, and large-scale farms at 0.996.

These results indicate that small-scale farmers utilized only 37.5% of their inputs optimally, compared to 82.6% for medium-scale farmers and 99.6% for large-scale farmers. On small-scale farms, 53.33% of farmers operated with allocative efficiency scores around 0.3, with scores ranging from 0.0008 to 1.006. For medium-scale farms, 40% of farmers scored between 0.61 and 0.90, with scores spanning from 0.0283 to 895.17. All large-scale farmers had allocative efficiency scores exceeding 0.9, with a range from 0.992 to 1.00. These disparities underline significant challenges in resource allocation among small-scale farmers, while medium-scale farmers exhibit moderate efficiency and variability. Large-scale farms, however, consistently demonstrate near-perfect allocative efficiency, reflecting effective resource management.

When comparing these efficiencies, small-scale farmers excel economically but lag technically and allocatively. Medium-scale farms show moderate technical and allocative efficiencies but face challenges in economic efficiency. In contrast, large-scale farms achieve high levels of technical, economic, and allocative efficiencies. These findings align with those of [22], who explored efficiency differences in honeybee enterprises and reported technical efficiencies of 0.84 and 0.59 for modern and traditional systems, respectively, similar to values observed here. Similarly, [34] applied a data envelopment analysis approach to assess rice farms and found that many operated with low technical efficiency, supporting the conclusions of this study.

From the pooled data, none of the farmers had technical efficiency scores below 0.3, although 3.70% had economic efficiency scores below this range, and 29.63% had allocative efficiency scores in this range. Approximately 7.41% of farmers demonstrated technical, economic, or allocative efficiencies between 0.31 and 0.6, reflecting moderate efficiency in resource utilization and allocation. Within the 0.61–0.9 range, 22.22% of farmers had high technical efficiency, though none exhibited high economic efficiency, while 33.33% displayed high allocative efficiency. Notably, 70.37% of farmers achieved technical efficiency scores between 0.9 and 1.00, 88.89% demonstrated high economic efficiency, and 18.52% exhibited allocative efficiency at this level.

The mean technical efficiency for all farmers was 0.901, indicating an average input utilization of 90.1%, with a standard deviation of 0.126 and scores ranging from 0.491 to 1.000. Mean economic efficiency was 0.508, with a standard deviation of 0.285 and scores ranging from 0.051 to 0.930. Allocative efficiency averaged 0.575, with a standard deviation of 0.316 and scores between 0.051 and 0.935. Overall, pooled data suggest high levels of technical, economic, and allocative efficiencies across the board.

Table 3: Technical, Economic and Allocative Efficiencies of Maize-Rice Farmers

Efficiency Range	Small scale			Medium Scale			Large Scale			Pooled		
	TE	EE	AE	TE	EE	AE	TE	EE	AE	TE	EE	AE
	%	%	%	%	%	%	%	%	%	%	%	%
< 0.3	53.33	0	53.33	20	80	20	0	0	0	0.00	3.70	29.63
0.31-0.6	26.67	0	26.67	20	20	20	0	0	0	7.41	7.41	18.52
0.61-0.9	6.67	0	6.67	60	0	40	0	0	0	22.22	0	33.33
> 0.9	13.33	100	13.33	0	20	20	100	100	100	70.37	88.89	18.52
Total	100	100	100	100	100	100	100	100	100	100	100	100
Mean	0.356	0.993	0.375	0.576	0.573	0.826	0.995	0.998	0.996	0.901	0.508	0.575
SD	0.3209	0.0014	0.3230	0.327	0.403	398.52	0.276	0.485	0.392	0.126	0.285	0.316
Minimum	0.0080	0.993	0.0081	0.028	0.009	0.0285	0.996	0.995	0.992	0.491	0.051	0.051
Maximum	0.9994	0.994	1.000	0.874	0.988	895.17	1.000	1.000	1.000	1.000	0.930	0.935

Source: Computed from field survey, 2023

3.4 Determinants of Allocative Efficiency of Maize–Rice Farmers

Table 4 presents the analysis of the factors influencing allocative efficiency among maize-rice farmers in the study area. The diagnostic tests indicate that the Ordinary Least Squares (OLS) results are reliable. The R-square values were 0.499, 0.607, and 0.695 for small-scale, medium-scale, and large-scale farms, respectively, suggesting that the explanatory variables account for approximately 50%, 60%, and 70% of the variations in allocative efficiency for the respective scales. Additionally, the F-values of 0.780 for small-scale farms and 1.752 and 2.076 for medium- and large-scale farms, respectively, were significant at the 5% level, confirming that the independent variables collectively influence the dependent variable. The analysis revealed that four out of ten variables in the model significantly influenced allocative efficiency in small-scale farms, six variables were significant in medium-scale farms, and five variables were significant in large-scale farms. Furthermore, seven variables positively influenced allocative efficiency in small-scale farms, six in medium-scale farms, and six in large-scale farms. For small-scale farms, household size and education level exhibited positive but non-significant effects on allocative efficiency. However, variables such as gender, access to credit, marital status, farming experience, and source of labor were significant. The coefficient for age was negative and significant at the 5% level, indicating that a one-year increase in age decreases allocative efficiency by 19.9%.

This result aligns with findings in the literature that link reduced efficiency in older farmers to physical limitations and diminished adaptability to modern practices. Conversely, farming experience showed a positive and significant effect at the 10% level, with an additional year of experience increasing allocative efficiency by 0.1%. This suggests that experienced farmers are better equipped to allocate resources effectively. Gender also had a significant positive effect, with male farmers exhibiting a 58.1% higher allocative efficiency than female farmers. Access to credit was positively associated with allocative efficiency, significant at the 10% level, indicating that credit availability enhances efficiency by 72%. Access to both hired and family labor increased allocative efficiency by 8.9%, significant at the 1% level, highlighting the value of diversified labor sources.

In medium-scale farms, household size negatively impacted allocative efficiency, with a significant coefficient at the 1% level. An increase in household size led to a 44.8% decrease in efficiency, likely due to increased consumption and financial burdens. Farming experience had a positive and significant effect at the 10% level, with an additional year of experience improving efficiency by 1.1%. Farm size was significant at the 10% level, contributing to a 48.4% increase in allocative efficiency, suggesting that larger farms benefit from better resource utilization. Labor source was also significant at the 5% level, with farmers using both hired and family labor achieving 14.7% higher efficiency.

For large-scale farms, marital status positively influenced allocative efficiency, with married farmers achieving a 10.2% increase, significant at the 10% level. Age had a positive and significant effect at the 1% level, where each additional year increased allocative efficiency by 3.8%. Surprisingly, education level had a negative effect, significant at the 10% level, with higher education reducing efficiency by 34%. This finding may indicate that more educated farmers are less involved in direct farm operations, relying instead on others to manage their farms. Access to credit also showed a negative and significant effect at the 1% level, decreasing efficiency by 56.6%, potentially due to the misuse of credit for non-farm activities. Land acquisition positively influenced efficiency, significant at the 5% level, with an increase in land size boosting efficiency by 6.7%.

From the pooled data, the R^2 value of 0.326 indicates that approximately 32.6% of the variation in allocative efficiency is explained by the variables in the model. The F-value of 1.241, significant at the 10% level, suggests that the model as a whole is statistically significant. Age, gender, marital status, farm size, and access to credit were identified as significant determinants of allocative efficiency. The coefficient for age (0.287) indicates that a 1% increase in age improves allocative efficiency by 0.287%. Similarly, gender (0.247) demonstrates that male farmers are 24.7% more efficient in resource allocation. Marital status contributes to a 43.9% increase in efficiency, highlighting the benefits of shared responsibilities and labor availability in married households. Farm size positively impacts efficiency (coefficient: 0.015), consistent with studies emphasizing the advantages of larger farms in accessing resources and achieving economies of scale. Access to credit, with a coefficient of 0.032, also enhances allocative efficiency, aligning with research that links credit availability to improved agricultural productivity. These findings align with studies by [16], [12], [35], [1], and [33], which identify age, gender, marital status, education, farm size, and access to credit as critical factors influencing efficiency. The results also echo conclusions by [19], [25], and [38], emphasizing the importance of targeted interventions to improve resource allocation and productivity in maize-rice cropping systems.

Table 4: Determinants of Allocative Efficiency of Maize – Rice Farmers

Variables	Parameters		Cropping Pattern						
		Small Scale		Medium Scale		Large Scale		Pooled	
		coefficients	P-Value	Coefficients	P – Value	coefficients	P - Value	coefficients	P - Value
Constant	Z_0	-2.318	-0.376	-1346.856	2.689	-1.212	0.201	0.744	264
Age	Z_1	-0.032**	1.997	-0.018**	2.002	0.038***	3.006	0.287**	0.018
Gender	Z_2	0.581**	2.252	0.062*	3.229	0.834	0.386	0.427***	0.000
Marital Status	Z_3	0.114	0.335	0.074	0.120	0.102*	1.952	0.439*	0.001
Household size	Z_4	0.277	0.010	-0.448***	3.211	0.148	0.090	0.146	0.206
Educational level	Z_5	0.068	0.321	0.675	0.000	-0.34*	1.932	0.006	0.387
Farming Experience	Z_6	0.001*	1.948	0.011*	1.961	-0.005	0.043	0.009	0.362
Farm size	Z_7	-0.155	0.711	0.484***	3.501	-0.382	0.26	0.015*	0.082
Access to credit	Z_8	0.720*	1.965	-0.275	0.001	-0.566**	2.045	0.032**	0.049
Land acquisition	Z_9	-0.322	0.478	-0.369	0.210	0.067***	5.453	-0.015	0.119
Source of Labour	Z_{10}	0.089***	2.777	0.147**	2.078	0.067	0.049	0.141	0.101
R2		0.499		0.607		0.695		0.326	
F-Value		0.480		1.752**		2.076**		1.241*	

*Note: *,** and *** mean significant at 10%, 5% and 1% respectively.*
Source: Field Survey, 2023

Conclusion

This research investigated the technical, economic, and allocative efficiencies of farmers engaged in maize-rice cropping systems in Southwest Nigeria. The study particularly emphasized the role of economies of scale across small, medium, and large-scale farming operations. The findings revealed significant variations in efficiency levels among these groups, underscoring the critical role of farm size, resource allocation, and institutional support in shaping agricultural productivity. The results demonstrated that small-scale farmers often struggle with technical and allocative inefficiencies due to limited access to inputs, inadequate extension services, and a lack of economies of scale. Medium-scale farmers exhibited moderate efficiency levels, benefiting from improved resource allocation but still constrained by limited managerial capacity and financial resources. Large-scale farmers achieved the highest levels of efficiency, highlighting the advantages of scale in accessing technology, credit, and market opportunities. Key determinants of efficiency included factors such as farm size, education level, access to credit, extension services, and farming experience. The study emphasized the importance of addressing these determinants through targeted interventions to enhance efficiency and ensure the sustainability of maize-rice-based systems in the region. To improve overall efficiency and productivity, the study recommends that the government should develop policies that promote equitable access to credit, land, and inputs for small and medium-scale farmers. Government support for sustainable land-use planning and resource allocation is critical. Strengthen agricultural extension programs to provide technical training and knowledge transfer, particularly for smallholder farmers. Facilitate the adoption of modern farming technologies and practices to enhance productivity and reduce inefficiencies. Encourage the establishment of farmer cooperatives to improve access to inputs, markets, and shared resources. Implement measures to help small and medium-scale farmers achieve scale economies, such as group farming or mechanization initiatives. Conduct campaigns to educate farmers about best practices in resource management, crop rotation, and integrated farming systems. Overall, by addressing the identified inefficiencies and leveraging the strengths of each farming scale, the efforts will not only enhance agricultural productivity but also contribute to broader goals of food security, poverty alleviation, and rural development.

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