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A Stochastic Frontier Analysis of Maize Production Efficiency and Its Climate-Smart Agricultural Practice Determinants in Southeast, Nigeria

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Abstract
Efficient maize production and resource allocation are crucial for agricultural sustainability, particularly in climate-vulnerable areas like Southeast Nigeria. This study employs stochastic frontier analysis (SFA) to investigate the efficiency of maize production and the determinants of allocative efficiency under climate-smart agricultural practices (CSAPs). The study includes 375 maize farmers selected randomly for the research sample. The analysis begins with estimating the efficiency parameter of maize production, revealing a relatively low Sigma-square value (0.029) and a moderate Gamma value (0.786). The study found a positive association between various inputs such as landholding, seed quality, and organic manure application. The mean TE and AE are 0.894 and 0.747 respectively. Allocative efficiency analysis reveals that while water management practices significantly affect technical efficiency positively, they unexpectedly lead to lower AE. Access to information and adoption of early planting positively influence allocative efficiency. Further examination of socioeconomic determinants indicates the role of extension services (3.07)*** in enhancing AE, while cooperative membership negatively impacts it, possibly due to information asymmetry. These findings emphasize the need for tailored interventions to optimize resource allocation strategies and enhance agricultural productivity and sustainability in Southeast Nigeria, particularly amidst the challenges posed by climate change. Comprehending the complex dynamics of resource allocation and efficiency in agriculture is crucial for crafting efficient policies and interventions aimed at improving productivity and resilience amidst changing climate conditions.

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Keywords: Climate-smart, agriculture, efficiency, Southeast, maize production

1. Introduction

Maize (*Zea mays L.*) is a crucial staple crop in Nigeria, serving as a primary source of food, feed, and income for millions of households across the nation (Obianefo *et al.*, 2022) [54]. As the demand for maize continues to rise in response to population growth and changing consumption patterns, ensuring the efficiency and sustainability of its production becomes imperative (Boakye, 2023) [20]. Given the challenges posed by climate change variabilities, embracing climate-smart agricultural practices (CSAPs) has emerged as a promising strategy to enhance agricultural productivity while mitigating environmental impacts (Assefa, 2023 & Asante *et al.*, 2024) [17, 16]. In Southeast Nigeria, where maize cultivation is prevalent, understanding the efficiency of maize production under the influence of CSAPs and socioeconomic determinants is essential for devising effective policies aimed at promoting sustainable agriculture and food security.

According to Obianefo *et al.* (2021) [55]; Obianefo *et al.* (2023) [53] and Keghter *et al.* (2023) [35], Stochastic Frontier Analysis (SFA) has been widely employed to assess the efficiency of agricultural production systems by separating observed output from the maximum achievable output given the same inputs and technology. By estimating the efficiency parameter of maize production, researchers gain insights into the performance of maize farmers relative to the production frontier (Ng'ombe, and Kalinda, 2015; Ng'ombe, 2017; Yakubu *et al.*, 2022) [49, 48, 68], thereby identifying areas for improvement and optimization. However, previous studies by Biam *et al.* (2016) [19]; EbukiBa *et al.* (2020); and Kehinde *et al.* (2024) [36] on maize production efficiency in Nigeria and Africa in general have often overlooked the specific influence of CSAPs and socioeconomic factors on efficiency levels, thus restricting the comprehension of the fundamental mechanisms propelling productivity within the context of shifting climatic conditions.

This study fills this void by conducting an exhaustive analysis of maize production. efficiency in Southeast Nigeria, with a particular focus on the role of CSAPs and socioeconomic determinants. By employing SFA, the efficiency levels among maize farmers are estimated, allowing for the identification of factors contributing to variations in productivity (Ng'ombe, 2017; Obianefo *et al.*, 2020; Tsiboe *et al.*, 2022) [48, 52, 65]. Moreover, the study examines the adoption and impact of CSAPs on maize output, considering their interaction with socioeconomic characteristics. By integrating CSAPs variables with socioeconomic determinants, this research aims to provide policymakers with actionable insights into designing interventions that promote sustainable maize production to meet the growing food demand in Nigeria and beyond.

The significance of this study lies in its potential to inform evidence-based policies and interventions aimed at enhancing the resilience and productivity of maize farming systems in Southeast Nigeria. By understanding the determinants of efficiency and the role of CSAPs, policymakers can formulate targeted strategies to support farmers in adopting practices that improve productivity, conserve natural resources, and mitigate the adverse effects of climate change (Oyetunde-Usman, and Shee, 2023) [60]. Furthermore, by focusing on Southeast Nigeria, where maize production is a vital component of the agricultural landscape, this research contributes to the broader discourse on sustainable agricultural development in Nigeria and Africa as a whole.

1.2 Statement of the Problem

Maize production in Southeast Nigeria faces multifaceted challenges stemming from both internal and external factors, including climate variability, resource constraints, and socio-economic dynamics (Obianefo *et al.*, 2022; Orgu *et al.*, 2024) [54, 58]. Despite the significance of maize as a staple crop and a vital livelihood source for millions of farmers in Africa (Martey *et al.*, 2020) [44] and Nigeria in particular, there remains a critical knowledge gap regarding the efficiency of maize production and the determinants shaping productivity under the ambit of climate-smart agricultural practices (CSAPs) (Anuga *et al.*, 2019) [14]. Understanding the efficiency of maize production and the factors influencing it is essential for devising targeted interventions that promote sustainable agricultural development (Hassan *et al.*, 2014) [30] and ensure food security in Nigeria and Africa at large.

The existing literature by Adedeji *et al.* (2011) [4]*; Aye*, and Mungatana (2012) [18]; Chan *et al.* (2017) [23]; Fasakin, & Akinbode (2020) [29]; and Oluwole *et al.* (2021) [57] on maize production efficiency in Nigeria and Africa provides valuable insights into the technical, allocative, and economic efficiency of farming systems. However, the majority of these studies have focused on conventional production practices without adequately considering the influence of climate-smart agricultural practices (CSAPs) and their interaction with socioeconomic factors. As climate change continues to exert pressure on agricultural systems, there is an immediate requirement to evaluate the effectiveness of CSAPs in improving productivity, resilience, and sustainability in maize farming, as highlighted by Sadiq *et al.* (2019) [63].

Furthermore, while previous research such as Zakaria *et al.* (2020) [69]; Acevedo *et al.* (2020) [2]; Oyetunde-Usman & Shee (2023) [60]; and Ankrah *et al.* (2023) [13] have examined the adoption and impact of CSAPs in various agricultural contexts, including Southeast Nigeria, there remains limited empirical evidence on their specific effects on maize production efficiency. Furthermore, the existing literature lacks a thorough analysis that combines CSAP variables with socioeconomic determinants to clarify the actual impact of these practices on maize output in Anambra State. Such an analysis is crucial for policymakers seeking to design evidence-based interventions aimed at promoting sustainable maize production and meeting the increasing food demand in Nigeria and Africa as a whole.

Several studies have shed light on the factors that influence the practice of Climate-Smart Agriculture (CSA) and their impact on food productivity. The study by Mashi *et al.* (2022) [45] identified a range of CSAPs such as mulching, controlled irrigation, crop rotation, and residue management, alongside climate knowledge and experience, as key influencers of food productivity. Socioeconomic determinants also played a significant role, with variables including farm size, cooperative membership, contact to extension services, age, household size, and education level being identified as crucial factors in the application of CSAPs. Afolami and Faleye (2020) [6] as well as Kalu and Mbanasor (2023) [32] delved into the adoption dynamics of CSAPs, revealing that farm size, age, access to credit, education level, and ownership of means of transport are influential factors. Ebukiba *et al.* (2020) [26] conducted a study focusing on maize productivity, finding a mean technical efficiency (TE) value of 0.950, indicating a high level of efficiency in their sample. Abubakar and Onwujioba (2023) explored various efficiency metrics, reporting mean efficiencies of 97.5% for TE, 46.5% for allocative efficiency (AE), and 45.0% for economic efficiency (EE). In contrast, Umaru and Maurice identified a lower mean TE value of 62% in their study. These findings collectively underscore the multifaceted nature of CSAP adoption and its implications for agricultural productivity and efficiency.

Therefore, this study seeks to address the following key research questions:

1. Can the study estimate the efficiency parameter of maize farmers in Southeast, Nigeria?
2. What is the level of efficiency in maize production among farmers in Southeast Nigeria?
3. What are the determinants of maize production efficiency, including the influence of climate-smart agricultural practices (CSAPs) and socioeconomic factors?

By exploring these research questions through the lens of SFA and a comprehensive assessment of CSAPs and socioeconomic determinants, This study seeks to add to the current body of knowledge regarding efficiency in maize production and inform evidence-based policies and interventions for sustainable agricultural development in Southeast Nigeria.

1.3 Objectives of the study

The main aim of this study is to stochastically investigate maize production efficiency and its Climate-Smart Agricultural Practices determinants in Southeast, Nigeria. The study is specifically designed to:

1. Estimate the efficiency parameter of maize production in Southeast, Nigeria;
2. Ascertain the level of efficiencies among maize farmers under the CSAPs in Southeast, Nigeria; and
3. Describe the CSAPs determinants of Maize farmers' efficiency.

2.1 Analytical Framework

Efficiency is a common term in production economics used to describe the extent to which time, effort, or scarce resources are well managed for production purposes (Ehirim *et al*., 2016; Chukwujekwu *et al*., 2021) [28, 24]. Technical and allocative efficiencies are both vital components in agricultural production systems, particularly in Southeast Nigeria where farming is a significant economic activity, being that efficiency is used to refer to the success of producing the highest amount of output possible at a given level of input (*Ajayi et al., 2018)* [8]. A Stochastic Frontier Analysis (SFA) of maize production efficiency of this nature provides a clue into how efficiently resources are being utilized and allocated within the agricultural sector, particularly in the maize subsector. However, investigating the factors influencing efficiency in the adoption of climate-smart agriculture highlights strategies for improving productivity while mitigating climate risks.

Technical efficiency refers to the ability of producers to obtain the maximum output from a given set of inputs, considering the current state of technology (Adeoye, 2021) [5]. In the case of maize production in Southeast Nigeria, technical efficiency measures how effectively farmers utilize resources such as land, labour, capital, and inputs like fertilizers and pesticides to maximize maize yields. A high level of technical efficiency implies that farmers are utilizing resources optimally and effectively managing production processes to achieve higher yields. A corroborative assertion by Brown *et al*. (2015) [21] and Chukwujekwu *et al*. (2021) [24] noted that the practical application of TE leads to a better crop yield, food security, and improved standard of living.

Allocative efficiency, conversely, concentrates on allocating resources in the most economically efficient way. *Mahesh & Mahima (2018)* [39] *observed that* it ensures that resources are allocated among different inputs in a way that maximizes output and minimizes production costs. Concerning maize production, allocative efficiency entails farmers allocating resources such as labour, land, and capital in a manner that maximizes profitability considering input prices and output prices (Ohajianya *et al*., 2013) [56].

A Stochastic Frontier Analysis provides a statistical framework for assessing both technical and allocative efficiency by distinguishing between the observed level of production and the maximum achievable level of production given the existing technology and resource constraints. This analysis helps identify the gap between actual and potential output, thereby offering insights into inefficiencies in resource utilization and allocation (Aigner *et al., 1977;* Malinga *et al., 2015)* [7, 43].

Mathematically, the stochastic production function as adapted from Chukwujekwu *et al*. (2021) [24] is defined as:

$$Y_i = f(X_i, \beta) + \exp(V_i - U_i), i = 1, 2, \dots n \qquad (1)$$

Where: Y_i is the maximum observed output from the *ith* maize farmers, X_i is the vector of inputs used by the *ith* farmers, β is the estimated parameter, V_i is the random error term, assumed to be normally distributed with mean zero and standard deviation of σ. (Ehirim *et al*. 2016*;* Obianefo *et al*.*, 2020,* U_i is the technical inefficiency component [28] (a non-negative random variable representing inefficiency or deviations from the frontier due to factors beyond the control of the firm (Osawe *et al*.*, 2018)* [59].

According to Ng'ombe (2017) [48] and Chukwujekwu *et al*. (2021) [24], the adoption of the maximum likelihood estimation procedure produces an SFA estimator, such as Sigma (σ) and Gamma (γ), which they mathematically define as:

$$\sigma^2 = \sigma^2{}_v + \sigma^2{}_u \qquad (2)$$

$$\gamma = {\sigma^2{}_u}/{\sigma^2} \qquad (3)$$

Gamma (γ) represents the parameters associated with the inefficiency term in the stochastic frontier model, indicating how the explanatory variables affect the level of inefficiency observed in the data with a value between zero to one ($0 \leq \gamma \leq 1$).

The farm-specific technical efficiency adapted from Akinbode (2011) is defined in terms of the ratio of observed output (Y_i) to the corresponding frontier output (Y_i*) using the available technology:

$$TE = \frac{Y_i}{Y_i^*} = \frac{f(X_i,\beta) + \exp(V_i - U_i)}{f(X_i,\beta) + \exp(V_i)} = \exp(-U_i) \qquad (4)$$

Again, the stochastic frontier cost functions model from where the level of farmers' allocative efficiency was estimated adapted from Akinbode (2011) [9] and Chukwujekwu *et al*. (2021) [24] is specified as:

$$C_i = g(Y_i, P_i; \propto) + exp(V_i + U_i), i = 1, 2, \dots n \qquad (5)$$

Where C_i represents the total production cost, Y_i remains as previously explained, P_i represents the prices of inputs, $\propto$ represents the parameters of the cost function, and $\exp(V_i + U_i)$ remained as previously defined.

The cost efficiency proxied for farm level allocative efficiency (AE) is defined as:

$$AE = \frac{C_i}{C_i^*} = \frac{E(C_i | U_i = 0, Y_i, P_i)}{E(Y_i, | U_i, Y_i, P_i)} = \mathrm{E}[exp(+U_i | \varepsilon) \qquad (6)$$

Here AE takes values of 0 to 1. Moreover, examining the determinants of efficiency in maize production within the framework of climate-smart agriculture is particularly pertinent. Climate change poses significant challenges to agricultural productivity, with unpredictable weather patterns, increased occurrence of extreme events, and changing pest and disease dynamics (Ali *et al*., 2017). Adopting climate-smart agricultural practices such as conservation agriculture, crop diversification, and efficient water management techniques can enhance resilience to climate change while improving productivity and sustainability (Malhi *et al.*, 2021) [41]. In this study, the factors influencing efficiency comprise access to information about climate and advisory services, the uptake of resilient crop varieties against climate stress, the presence of irrigation infrastructure, the adoption of conservation tillage practices to diminish soil erosion and moisture loss, and access to credit for investing in climate-smart technologies. Analyzing the relationship between these determinants and efficiency provides a valuable insight into strategies for enhancing productivity and resilience in maize production systems in Southeast Nigeria.

The determinants of inefficiency among maize farmers operating under the climate-smart agricultural practices is defined as:

$$U_i = \delta_0 + \delta_1 Z_1 + \delta_1 Z_1 + \delta_1 Z_1 + \cdots \delta_{10} Z_{10} + \delta_{11} W_{11} + \cdots \delta_{11} W_{11} \qquad (7)$$

Where: $Z_{1\text{-}10}$ represent the CSAPs variables (water management, minimum tillage, residue management, use of irrigation pump for dry season planting, mulching, crop rotation, improving access to information, adopting early planting, obtaining credit, and use of organic fertilizer to improve soil texture and structure); and $W_{11\text{-}20}$ represents: W_{11} = sex (dummy; male = 1, female = 0), W_{12} = age (year), $W1_3$ = marital status (dummy; married = 1, otherwise = 0), W_{14} = years of formal learning (year), W_{15} = farming experience (year) and W_{16} = household size (No), W_{17} = cooperative membership (dummy: yes = 1, no = 0), W_{18} = access to credit (dummy: yes = 1, no = 0), W19 = number of extension advisory contact, and W_{20} = ever trained on CSAPs (dummy: yes = 1, no = 0).

3 Materials and Methods

3.1 Study Area

This study was conducted in the Southeast geopolitical zone of Nigeria, which consists of five States (Anambra, Imo, Enugu, Abia, and Ebonyi). These states are divided into 101 local government areas, which are further divided into 346 communities. Southeast, Nigeria has a landmass of 41440 Square-km, and is bordered by Akwa Ibom and Cross River States to the east, Benue and Kogi States to the north, Edo and Delta States to the west, and Rivers and Bayelsa States to the south (Merem *et al.*, 2019) [46].

Table 1: The Distribution of Population in the South East

State	Population
Abia	3,841,943
Anambra	5,599,910
Ebonyi	3,007,155
Enugu	4,396,098
Imo	5,167,722
Total	**22,012,828**

Source: NPC (2020) and NBS (2020)

The National Population Commission (NPC, 2020) and National Bureau of Statistics (NBS, 2020) reported an estimated population of 22,012,828 people for the five States in Southeast, Nigeria as shown in Table 1. According to Mba, *et al.* (2021), the Southeast zone lies within the latitudinal coordinates of 04°47' and 07°07' North and longitudinal coordinates 6°35' and 8°27' East.

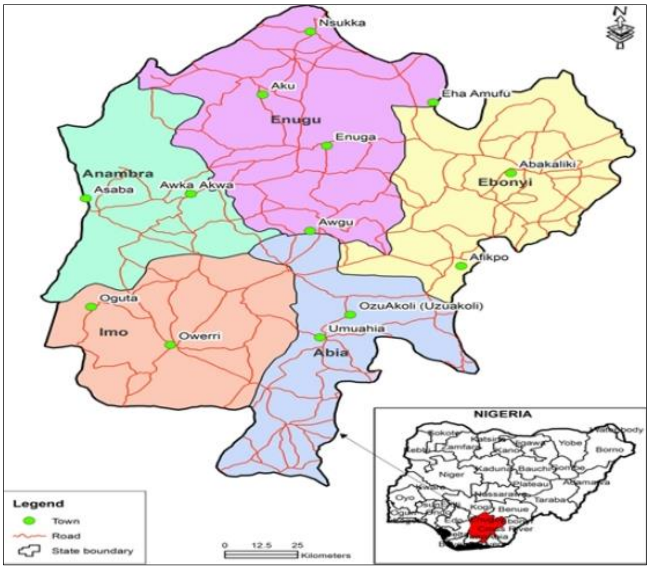

Fig 1: Map of Nigeria showing Southeast region. Source: Merem *et al*. (2019) [46]

3.2 Sample Size and Sampling Techniques

The study utilized an infinite sample size determination technique adapted from Obianefo *et al.* (2021) to calculate the sample size, considering that the exact population of smallscale maize farmers in Southeast Nigeria is unknown, suggesting an infinite population of maize farmers practicing climate-smart agriculture.

$$n = \frac{Z * P(1-P)}{e^2}$$

Where:

n = sample size

Z = Z-score at 95% confidence interval

P = probability of success

1 – P = failure

e = error term at 0.05 level of probability.

However, the sample is calculated as:

$$n_i = \frac{1.96^2 * 0.50(1-0.50)}{0.05^2} = 384$$

A multistage sampling technique was utilized, incorporating both purposive and random selection methods for the study.

In stage I, three states (Ebonyi, Enugu, and Anambra) were purposively chosen because of the prevalence of maize farming in these areas and the availability of numerous studies on climate change mitigation strategies for reference.

In stage II, four Local Government Areas (LGAs) were randomly chosen from each state, amounting to a total of 12 LGAs. From these, two communities were randomly selected from each LGA, resulting in a total of 24 communities.

In stage III, from each community, four villages were randomly selected, accumulating to a total of 96 villages for

the study.
Finally, in the last stage, four smallholder maize farmers who practice CSA will be selected randomly from each village, resulting in a sample size of 384 respondents.

Table 2: Selected study location

States	Local Government Areas	Communities
Anambra	Ogbaru,	Umunankwo, and Ossomala
	Orumba North	Ufuma, and Ndikelionwu
	Awka North	Achalla, and Amanuke
	Ayamelum	Omor, and Anaku
Ebonyi	Ikwo	Ekpelu, and Alike
	Izzi	Agbaja Mgbo, and Agbaja Offia Onwe
	Ishielu	Ntezi, and Agba
	Ohaozara	Ugwulangwu, and Okposi
Enugu	Udi	Oghu, and Abor
	Nsukka	Nsukka, and Opi-Agu,
	Awgu	Isu-Awa, and Ogbaku
	Ezeagu	Umuana-ndiagu, and Mgbabu-owa

3.3 Data Collection
Eight research assistants were recruited and trained by the researcher(s) to help with the data collection. They were taught about the contents of the questionnaire, and the fieldwork lasted for a period of five weeks (26th October to 6th December 2023). An Android data collection toolkit called "Kobocollect" was used to enhance the quality and precision of data collection.

Data Analysis
The study used a combination of analytical tools including descriptive statistics, stochastic frontier analysis (SFA), and beta regression analysis. Objective one was achieved using the SFA, descriptive statistics was used to achieve objective two, and a beta regression model was used to achieve objective three.

3.4 Model Specification
A). Cobb Douglass (Double-log) Functional Form
A more restrictive Cobb Douglass (Double-log) stochastic frontier analysis (SFA) technique under the MLE was used to evaluate the production and cost function. The analysis was estimated with current (2024) R software. The model is explicitly defined as:

$$LnY = \beta_0 + \beta_1 LnX_1 + \beta_2 LnX_2 + \beta_3 LnX_3 + \beta_4 LnX_4 + exp\ (V_i - U_i)$$

Where: X_1 = landholding (ha), X_2 = seed (kg), X_3 = organic manure (kg), X_4 = labour (man-day). We anticipate that all the explanatory variables will exhibit positive significance. Therefore, $\beta_0 > 0; \beta_1 > 0; \beta_2 > 0; \beta_3 > 0;$ and $\beta_4 > 0$. V_i and U_i remained as earlier defined. U_i is assumed to follow an exponential function under two-stage maximum likelihood estimation procedure. Therefore, the farm specific efficiency is given as 1 – TE values (Coelli and Battese, 1996).
Again, the cost function is defined as:

$$LnC = \beta_0 + \beta_1 LnP_1 + \beta_2 LnP_2 + \beta_3 LnP_3 + \beta_4 LnP_4 + \beta_5 Y_i + exp(V_i + U_i)$$

Where: C = total cost of production, P_1 = normalized cost of landholding (N), P_2 = normalized cost of seed (N), P_3 = normalized cost of organic manure (N), P_4 = normalized cost of labour (N), and Y_i = total output of maize (kg). Summation of exp $(V_i + U_i)$ is because the farm manager is expected to produce at a minimal cost.

B). Beta regression analysis
The explicit form of the beta regression model for multiple covariates to estimate the determinants of efficiencies are defined as:

$$logit(\mu_i) = \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \cdots \beta_n Z_n + \beta_{11} W_{11} + \cdots \beta_n W_n$$

Where: μ_i is the value of efficiencies with a beta distribution for observation *i*. Z_i and W_i is the covariate as previously explained. β_0 is the intercept. B_i is the coefficient associated with the covariate *Z and W*. These parameters (β_0 and β_i) are estimated using maximum likelihood methods.

4 Result and Discussion
4.1.1 Estimation of the efficiency parameter of maize production in Southeast, Nigeria
The stochastic frontier analysis (SFA) of maize farmers' production function is reflected in Table 3. The model adopted the maximum likelihood estimation approach to arrive at the best model fit index. The study revealed that maize farmers' stochastic production function had a Sigma-square value of 0.029, significant at a 1% level of probability. The study by Obianefo *et al.* (2022) argues that the Sigma-square represents the variance in the production frontier associated with the stochastic random noise. A lower Sigma-square value suggests that many of the observed variations in maize production is explained by the specified inputs and model, indicating relatively efficient production practices among maize farmers under CSAPs in Southeast Nigeria. This implies that only 2.9% of deviation from frontier maize output is associated with external factors not accounted for by the farmers' managerial decision to practice climate-smart agriculture (CSA) as added in the model. Equally, the Gamma value of 0.786 is significant at a 1% level of significance. Obianefo *et al.* (2022) and Obianefo *et al.* (2023) equally noted that Gamma represents a parameter linked to the extent of technical inefficiency effects within the stochastic frontier model of maize production. A higher Gamma value indicates a low technical inefficiency index. However, the value of 0.786 suggests that there is still 21.4% room for improvement in productivity by adopting more efficient agricultural practices or technologies.
The coefficient of intercept (β = 2.267) is positive and significant at a 1% (36.76)*** level of probability. This intercept reflects the baseline level of maize production not explained by the other variables in the model. This implies that maize output is expected to increase by 2.267 units when there are no landholding, seed, organic manure, or labour inputs.
The coefficient of landholding (β = 0.370) is positive and significant at 1% (16.60)*** level of significance. This suggests that increasing landholding leads to higher maize production, holding other factors constant. Larger landholdings contribute positively to maize productivity under CSAPs by 0.370 units.

The coefficient of seed (β = 0.184) is positive and significant at a 1% (8.25)*** level of probability. This is an indication that increasing the logarithm of seed input results in higher maize production by 0.184 units, assuming other factors remain constant. This underscores the importance of seed quality or quantity in enhancing maize yields under CSAPs (Kansiime, and Mastenbroek, 2016) [34]. This result revealed that seed as an important input in maize production.
The coefficient of organic manure (β = 0.035) is significant at a 5% (2.67)** level of probability. This suggests that increasing the logarithm of organic manure application leads to higher maize production by 0.035 units, all else being equal. This highlights the beneficial effect of organic manure in improving soil fertility and crop yields as argued by Alengebawy *et al.* (2021) [10].
The coefficient of labour (β = 0.149) is positive and significant at a 1% (6.96)*** level of probability. This is an indication that increasing labour supply (logged) results in higher maize production by 0.149 units, holding other factors constant. This underscores the importance of labour in agricultural production processes, possibly through activities such as planting, weeding, and harvesting. This result reveals that CSAPs are labour-intensive as suggested by Kangogo *et al.* (2021) [33] in their study of adoption of climate-smart agriculture among smallholder farmers.

Table 3: Estimation of the production parameter of maize production in Southeast, Nigeria

Parameters	Estimate	Std. Error	Z value
(Intercept)	2.267	0.062	36.76***
Landholding	0.370	0.022	16.60***
Log (Seed)	0.184	0.022	8.25***
Log (Organic manure)	0.035	0.013	2.67**
Log (Labour)	0.149	0.021	6.96***
Sigma-Square	0.029	0.003	9.61***
Gamma	0.786	0.044	17.87***
Log-likelihood ratio	266.905		
Likelihood ratio test	**41.67***		
Observation	375		

Source: Field Survey, 2023. (**, and ***) Significant @ 5% and 1% respectively.

Furthermore, the study highlights the necessity of addressing technical inefficiencies to further enhance productivity. These insights can inform policy interventions and agricultural extension services geared towards promoting sustainable and efficient maize production practices in Southeast Nigeria, taking into account participation in the African Continental Free Trade Area (AfCFTA).

4.1.2 Estimation of the allocative parameter of maize production in Southeast, Nigeria

Table 4 reflects the results of cost function of maize production under climate-smart agricultural practices (CSAPs) in Southeast Nigeria. The Sigma Square value of 0.274 represents variation in inefficiency term in the cost function. A higher value indicates greater variability in costs that cannot be explained by the specified inputs and model (Pérez-Gómez *et al.*, 2018) [61]. It suggests that 27.4% of inefficiencies in cost management within maize production under CSAPs are associated with stochastic random noise. Equally, the extremely high Gamma value of 0.988 suggests very low levels of allocative inefficiency, implying that the estimated costs are close to the frontier.

The intercept represents the baseline level of costs not explained by the other variables in the model. In this case, the coefficient ((β = 5.996) is positive and significant at a 1% level of significance, it indicates that there are 5.996 units of fixed costs involved in maize production that are not captured by the specified inputs.
The coefficient cost of land rent (β = 0.094) is positively significant at the 5% level of probability, this suggests that a unit increase in the cost of land rent leads to higher total production costs by 0.094 units. It indicates that land rental expenses contribute to the overall cost burden of maize farming (Achmad *et al.*, 2022 and Lelea *et al.*, 2022) [3, 37].
The coefficient of cost of seed (β = 0.318) is positively significant at the 1% level of significance, indicating that a higher expenditure on seeds is associated with increased total production costs by 0.318. This result is in agreement with the study by Japheth *et al.* (2020) who noted that the application of organic manure in the agricultural sector reduces production cost and maximizes profit. It highlights the importance of seed quality or quantity in maize farming and its impact on overall costs (Altieri *et al.*, 2015) [12].
The positive and significant coefficient cost of organic manure (β = 0.069) at the 1% level of significance suggests that higher costs associated with organic manure contribute to increased total production costs by 0.069 units. It underscores the beneficial effect of organic manure in improving soil fertility (Alengebawy *et al.*, 2021) [10] but also implies additional expenses for farmers. This study is in agreement with Ume *et al.* (2023) who found organic manure as a significant determinant of agricultural productivity in Southeast Nigeria.
The coefficient of labour (β = 0.175) positively significant at the 1% level of probability indicates that higher labour costs lead to increased total production costs by 0.175 units. It emphasized the crucial of labour in agricultural production processes (Lencucha *et al.*, 2020) [38], suggesting that labour-intensive practices may contribute significantly to overall costs.
The negative coefficient of maize output (β = 0.157) is significant at a 10% level of probability, this implies that higher maize output is associated with lower total production costs by 0.157 units. This result may seem counterintuitive at first glance, but it suggests economies of scale or efficiency gains as production levels increase.
However, these results revealed the role of factors such as land rent, seed costs, organic manure expenses, labour inputs, and maize output in determining the total production costs of maize farming under CSAPs in Southeast Nigeria.

Table 4: The cost function of maize production in Southeast, Nigeria

Parameter estimate	Estimate	Std. Error	Z value
(Intercept)	5.996	0.305	19.64***
Log (cost of land rent)	0.094	0.037	2.55**
Log (cost of seed)	0.318	0.034	9.42***
Log (cost of organic manure)	0.069	0.019	3.57***
Log (labour)	0.175	0.030	5.86***
Log (maize output)	-0.157	0.080	-1.97*
Sigma-square	0.274	0.022	12.60***
Gamma	0.988	0.004	222.71***
Log-likelihood	-54.454		
Likelihood ratio test	249.12***		
Observation	375		

Source: Field Survey, 2023. (**, and ***) Significant @ 5% and 1% respectively.

4.2 The level of efficiencies among maize farmers under the CSAPs in Southeast, Nigeria

The technical and allocative efficiency index of maize production under the CSAPs production system is presented in Table 5.

Technical Efficiency (TE)

Relative to TE index (TEI), the result categorized farmers into four groups, the TEI ≤ 0.299 represents farmers with very low level of TE. However, none of the farmers fall into this category, indicating that there are no farmers with extremely poor TE. Again, a small percentage (0.8%) of farmers have TEI of 0.300 - 0.599, suggesting that there are a few farms with room for improvement in their TE. It was also observed that 37.1% of farmers have TEI value of 0.600 - 0.899, indicating that a greater proportion of farmers exhibit moderate to high levels of TE. These farmers are operating fairly efficiently but still have some potential for further improvement. Furthermore, the last 62.1% of the farmers have a TEI ranging from 0.900 - 1.000, indicating that farmers under this category are operating very efficiently, with minimal room for further improvement in technical efficiency.

The mean TEI of 0.894 suggests that, on average, maize farmers in Southeast Nigeria are operating at a relatively high level of TE under CSAPs. This indicates that the practice of CSA has generally led to efficient resource utilization and production processes leaving room for a 10.6% improvement. Furthermore, the standard deviation of 0.061 suggests variability in technical efficiency levels among farmers. Some farms may be operating significantly below the average efficiency level, indicating potential areas for improvement. This result on mean TE is in higher than the 0.620 reported in Umaru and Maurice (2019) and little lower than the 0.950 reported in Ebukiba *et al.* (2020) [26].

Allocative efficiency

Approximately 6.9% of farmers have allocative efficiency value of ≤ 0.299, indicating that a small proportion of farmers have significant room for improvement in resource allocation. Around 4.5% of farmers have allocative efficiency index of 0.300 - 0.599, suggesting that we still have some farmers with suboptimal resource allocation practices.

Equally, the majority (73.1%) of farmers have allocative efficiency index value of 0.600 - 0.899, indicating that the majority of farmers exhibit moderate to high levels of allocative efficiency. These farmers are allocating their resources fairly but may still have some room for improvement. The last 15.5% of farmers have an efficiency value of 0.900 - 1.000. These farmers are optimally allocating resources to maximize production outputs.

The mean allocative efficiency index of 0.747 suggests that, on average, farmers in the sample are operating at a moderately high level of allocative efficiency under CSAPs. This indicates that the practice of CSA has generally led to efficient resource allocation within farms. These findings uncover the need to optimize resource allocation strategies to enhance farm profitability and sustainability. This result is higher than the 0.450 reported in Abubakar and Onwujioba (2023). Efficient resource allocation can lead to increased productivity, reduced waste, and improved resilience to external shocks (Campbell *et al*., 2016). This also aligns with Aryal *et al.* (2019) who noted that strategies such as better farm management practices, access to timely information, and technology adoption can help improve allocative efficiency on farms.

Table 5: level of efficiency index

	Technical efficiency		Allocative efficiency	
Efficiency index	**Frequency**	**Percentage**	**Frequency**	**Percentage**
≤ 0.299	0	0	26	6.9
0.300 - 0.599	3	0.8	17	4.5
0.600 - 0.899	139	37.1	274	73.1
0.900 - 1.000	233	62.1	58	15.5
Mean	0.894		0.747	
Std. dev.	0.061		0.186	

Source: Field Survey, 2023.

4.3.1 Determinants of Maize farmers' technical efficiency

Table 6 provides insight into the determinants of maize farmers' technical efficiency under climate-smart agricultural practices (CSAPs) in Southeast Nigeria. The coefficient of water management ($\beta = 0.059$) was positive and significant at a 5% level of probability, this suggests that better water management practices contribute to higher technical efficiency among maize farmers. The result happens to be in agreement with Raihan *et al.* (2023) who noted that efficient water usage, such as through irrigation systems or rainwater harvesting, enhances productivity.

The use of an irrigation pump for dry season planting, mulching, obtaining credit, and use of organic fertilizer to improve soil texture and structure were not significant but had the positive sign expected in *a-priori*. These variables do not show statistically significant effects on technical efficiency, suggesting that their impact may be negligible or context-dependent. This result was in agreement with Mashi *et al.* (2022) [45] who reported irrigation farming as a CSAPs in their study.

Again, age, sex, household size, marital status, and training in the use of CSAPs were not significant but had the positive sign expected in *a-priori*, suggesting that their effect on productivity may be minimal in this context. These significant variables are in agreement those reported by Afolami and Faleye (2020) [6] who noted that age, sex, and household size has a positive effect on the decision to adopt CSAPs.

Further research is needed to understand the interactions between different agricultural practices and socioeconomic factors in determining technical efficiency. This will help tailor interventions to specific contexts and maximize their impact on agricultural productivity and sustainability. While certain climate-smart agricultural practices show promise in enhancing technical efficiency among maize farmers, the overall determinants of efficiency are multifaceted and context-specific. Addressing these factors effectively can help improve productivity and resilience in agricultural systems under climate change.

Table 6: Determinants of maize farmers' technical efficiency.

Technical efficiency	Estimate	Std. Error	Z value
(Intercept)	1.924	0.223	8.61***
CSA Practices Determinants			
Water management	0.059	0.026	2.27**
Minimum tillage	-0.019	0.029	-0.68
Residue management	-0.014	0.027	-0.54
Use of irrigation pump for dry season planting	0.011	0.024	0.48
Mulching	0.007	0.028	0.25
Crop rotation	0.010	0.026	0.38
Improving access to information	-0.028	0.024	-1.13
Adopting early planting	0.021	0.026	0.84
Obtaining credit	-0.010	0.033	-0.31
Use of organic fertilizer to improve soil texture and structure	0.001	0.034	0.03
Socioeconomic determinants			
Age	0.001	0.002	0.66
Education	-0.002	0.004	-0.36
Sex	0.062	0.057	1.10
Marital status	0.031	0.032	0.99
Farming experience	0.000	0.004	-0.05
Household size	0.011	0.009	1.17
Cooperative member	-0.041	0.057	-0.73
Credit access	-0.087	0.156	-0.56
Extension advisory	-0.029	0.022	-1.31
Training on CSAPs	0.060	0.156	0.38
Phi coefficients	34.93	2.564	13.62***
Log-likelihood:	606.2		

Source: Field Survey, 2023. (**, and ***) Significant @ 5% and 1% respectively.

4.3.2 Determinants of Maize farmers' allocative efficiency

Table 7 provides an insight into the determinants of maize farmers' allocative efficiency (AE) under climate-smart agricultural practices (CSAPs) in Southeast, Nigeria. The result of the beta regression analysis revealed a significantly negative coefficient of water management ($\beta = -0.096$) at the 5% level of probability suggesting that better water management practices lead to lower allocative efficiency among maize farmers. This unexpected result may indicate that farmers with more sophisticated water management techniques may be over-allocating resources in certain areas, leading to suboptimal resource utilization.

The positive and significant coefficient Improving Access to Information ($\beta = 0.072$) at the 10% level of probability implies that better access to information has a positive effect on allocative efficiency, although the effect is only marginally significant. This suggests that access to information may enable farmers to make more informed decisions about resource allocation.

Table 7: Determinants of allocative efficiency of maize farmers under CSAPs system

Allocative efficiency	Estimate	Std. Error	Z value
(Intercept)	0.739	0.350	2.11**
CSA Practices determinants			
Water management	-0.096	0.041	-2.34**
Minimum tillage	-0.006	0.045	-0.13
Residue management	-0.002	0.042	-0.04
Use of irrigation pump for dry season planting	0.025	0.037	0.66
Mulching	-0.040	0.044	-0.91
Crop rotation	0.036	0.041	0.87
Improving access to information	0.072	0.038	1.87*
Adopting early planting	0.086	0.040	2.14**
Obtaining credit	0.013	0.052	0.26
Use of organic fertilizer to improve soil texture and structure	-0.035	0.053	-0.65
Socioeconomic determinants			
Age	0.000	0.003	0.08
Education	0.001	0.007	0.09
Sex	0.093	0.088	1.06
Marital status	0.045	0.049	0.90
Farming experience	-0.001	0.006	-0.23
Household size	0.000	0.014	0.03
Cooperative member	-0.265	0.090	-2.96***
Credit access	0.120	0.254	0.47
Extension advisory	0.108	0.035	3.07***
Training on CSAPs	0.025	0.255	0.10
Phi coefficients	6.1357	0.4288	14.31***
Log-likelihood:	186.4		

Source: Field Survey, 2023. (**, and ***) Significant @ 5% and 1% respectively.

The coefficient of Adopting Early Planting (β = 0.086) was positive and significant at the 5% level of probability, indicating that adopting early planting practices contributes to higher allocative efficiency among maize farmers. This implies that early planting may lead to better resource allocation decisions, resulting in improved productivity.

Among the minimum tillage, residue management, use of irrigation pump for dry season planting, mulching, crop rotation, and use of organic fertilizer; none of these variables show statistically significant effects on allocative efficiency. This suggests that their impact on resource allocation may be limited or context-dependent.

Based on the socioeconomic determinants, cooperative membership had a negative and significant coefficient (β = 0.265) at the 1% level of significance, suggesting that being a cooperative member is associated with lower levels of allocative efficiency. This is an indication that information asymmetry within cooperatives could lead to misallocation of resources and hinder farmers' ability to make informed decisions regarding resource allocation.

Furthermore, extension advisory services (β = 0.108) had a positive and significant coefficient at the 1% level of probability, suggesting that farmers who receive extension services are better equipped to make informed decisions about resource allocation, leading to improved efficiency in utilizing inputs such as land, labour, seeds, fertilizers, and capital among others. Teklewold *et al*. (2019) and Mahmood *et al*. (2021) noted that farmers who receive extension services are likely to adopt CSAPs better. These practices contribute to efficient resource allocation to ameliorate the negative impact of climate change on agriculture.

Summarily, the results underscore the importance of understanding the complex interplay between different factors influencing allocative efficiency in agriculture. Effective resource allocation is crucial for maximizing productivity and sustainability, and targeted interventions may be needed to address specific challenges identified in this analysis.

5 Conclusion and Recommendation

The results exposed the efficiency and determinants of maize production under climate-smart agricultural practices (CSAPs) in Southeast Nigeria. Through stochastic frontier analysis (SFA), the study revealed insights into both technical and allocative efficiency, along with the factors influencing these efficiencies. Technical efficiency analysis indicated that, on average, maize farmers in Southeast Nigeria are operating at a relatively high level of efficiency under CSAPs. However, there remains room for improvement, particularly in enhancing water management practices and leveraging extension advisory services. Allocative efficiency analysis further emphasized the importance of effective resource allocation strategies, with a notable negative association between cooperative membership and allocative efficiency. This suggests potential challenges related to information asymmetry within cooperatives. However, the following recommendation was proposed:

1. Given the good response of extension advisory services on allocative efficiency, there is a need to strengthen extension programs. This could involve increasing the reach of extension services, improving the quality of information dissemination, and providing tailored support to farmers to enhance their decision-making processes.
2. Policymakers and agricultural stakeholders should address the challenges associated with cooperative membership and resource allocation. Efforts to reduce information asymmetry within cooperatives, improve governance structures, and enhance decision-making processes could contribute to improved allocative efficiency among farmers.
3. Encouraging the practice of climate-smart agriculture such as early planting, efficient water management, and soil conservation techniques can contribute to both technical and allocative efficiency. Providing incentives, training programs, and access to relevant information and technologies can facilitate the adoption of these practices.

By implementing these recommendations, policymakers, and other stakeholders in the sector can contribute to enhancing maize production efficiency and promoting sustainable agricultural development in Southeast Nigeria amidst the challenges posed by climate change and evolving market dynamics.

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