



# International Journal of Multidisciplinary Research and Growth Evaluation.

## Analysis of the effect of climate-smart agricultural practices (CSAPs) on food security of maize production in Southeast, Nigeria

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### Article Info

**ISSN (online):** 2582-7138

**Impact Factor:** 5.307 (SJIF)

**Volume:** 05

**Issue:** 02

**March-April 2024**

**Received:** 01-02-2024;

**Accepted:** 04-03-2024

**Page No:** 429-440

### Abstract

This study examines the effect of Climate-Smart Agricultural Practices (CSAPs) on the food security dimensions of availability, accessibility, affordability, stability, and usability of maize production in Southeast Nigeria. A multi-stage random sampling method was adopted to select 375 farmers. Censored and OLS regression analyses were conducted using R software to analyze the data. Results indicate that certain CSAPs significantly influence the availability and accessibility dimensions of food security. Water management, residue management, mulching, crop rotation, adopting early planting, and obtaining credit were associated with higher levels of availability and accessibility, while practices like minimum tillage and improving access to information were associated with lower levels. Practices such as water management, minimum tillage, and adopting early planting positively influence affordability and stability. Furthermore, the study explores the influence of constraints on the practice of CSA in Southeast Nigeria. Farmers' illiteracy (50.6)\*\*\*, high production costs (4.00)\*\*\*, lack of equipment and inputs, limited awareness of CSA practices (5.24)\*\*\*, and resistance to change (13.70)\*\*\* were identified as key constraints. However, the study recommends that promoting awareness and incentivizing sustainable agricultural practices can encourage farmers to overcome resistance to change and embrace CSA initiatives, thus enhancing food security and economic development in Southeast Nigeria.

**DOI:** <https://doi.org/10.54660/IJMRGE.2024.5.2.429-440>

**Keywords:** climate-smart, agriculture, food security, maize production, Southeast Nigeria

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### Introduction

Climate change poses significant challenges to agricultural productivity and food security (Willett *et al.*, 2019; Okoronkwo *et al.*, 2024; Raza *et al.*, 2024) <sup>[54, 40, 43]</sup>, particularly in Southeast Nigeria, where agriculture serves as a cornerstone of livelihoods and sustenance. In response to these challenges, Climate-Smart Agricultural Practices (CSAPs) have emerged as a promising approach to enhancing agricultural resilience (Adegbeye *et al.*, 2020) <sup>[2]</sup>, mitigating climate risks, and improving food security outcomes (Mach, *et al.*, 2019) <sup>[29]</sup>. However, despite growing recognition of the potential benefits of CSAPs, there remains a critical gap in understanding their effectiveness in addressing food security dimensions among maize farmers in Southeast Nigeria.

Food security encompasses multiple dimensions, including availability, accessibility, affordability, stability, and usability (Bilali *et al.*, 2018; Barthel *et al.*, 2019) <sup>[12, 11]</sup>, each of which is intricately linked to agricultural production and resource management. Maize, as a staple crop in Nigeria (Adiaha, 2024) <sup>[5]</sup>, plays a pivotal role in ensuring food security for millions of households across all nations (Rizwanullah *et al.*, 2023) <sup>[44]</sup>. Therefore, assessing the impact of CSAPs on various dimensions of food

security within the maize production system is essential for devising effective strategies to enhance resilience and sustainability in the face of climate change. Despite the importance of this issue, empirical studies examining the effect of CSAPs on food security dimensions among maize farmers in Southeast Nigeria are limited. Furthermore, existing research (Ani *et al.*, 2021; Akinyemi *et al.*, 2021; Adebisi *et al.*, 2022; Oyetunde-Uzman and Shee, 2023; and Kalu, & Mbanasor, 2023) [7, 6, 1, 42, 25] often overlooks the regressive influence of constraints and challenges on the adoption and implementation of CSAPs in Nigeria in general and Southeast in particular. Consequently, there is a pressing need for comprehensive empirical analysis that not only assesses the impact of CSAPs on food security but also identifies and addresses the barriers hindering their adoption and effectiveness.

This study aims to bridge this gap by conducting a rigorous analysis of the effect of CSAPs on food security dimensions among maize farmers in Southeast Nigeria. Specifically, the research focuses on assessing the impact of CSAPs on the availability, accessibility, affordability, stability, and usability of maize production, thereby providing a holistic understanding of their contribution to food security outcomes. Moreover, the study examines the regressive influence of constraints on the practice of Climate-Smart Agriculture (CSA) in the study area, shedding light on the factors hindering the adoption and implementation of CSAPs. An innovative aspect of this study lies in its methodological approach, which utilizes censored regression to understand the individual effects of CSAPs on food security dimensions, a methodology that has not been extensively applied in previous studies in the study area. Additionally, the study employs ordinary least square regression to elucidate the relationship between challenges faced by farmers and their impact on the application of CSAPs in Southeast Nigeria. By employing these analytical techniques, the research aims to provide nuanced insights into the complex dynamics shaping food security outcomes and the adoption of CSAPs in the study area.

The findings of this study are expected to contribute significantly to the existing body of knowledge on climate-smart agriculture and food security in Nigeria and West Africa. Moreover, the insights derived from the analysis will inform evidence-based policy interventions aimed at promoting sustainable agricultural development, enhancing food security, and building resilience to climate change in the study area and beyond. Thus, this research holds substantial implications for policymakers, researchers, and practitioners seeking to address the intersecting challenges of climate change, agriculture, and food security in Nigeria and the broader West African region.

## 1.2. Statement of the Problem

Food security is a fundamental concern in Nigeria, particularly in Southeast Nigeria, where agricultural productivity is crucial for ensuring the availability, accessibility, and affordability of food for millions of households. However, the agricultural sector in Nigeria and Southeast in particular faces increasing challenges posed by climate change, which threatens the stability and usability of food production systems (Willett *et al.*, 2019) [54]. In response to these challenges, Climate-Smart Agricultural Practices (CSAPs) have been promoted as a means to enhance agricultural resilience, mitigate climate risks, and improve

food security outcomes (Chukwu *et al.*, 2023) [14]. Despite the growing emphasis on CSAPs, there remains a critical gap in understanding their effectiveness in addressing food security dimensions among maize farmers in Southeast Nigeria, and Africa in general. The study closest in focus to this was conducted by Tabe-Ojong *et al.* (2023), who explored the relationship between Climate-smart agriculture and food security in West Africa. Their study aimed to investigate the impact of Climate-smart agricultural practices (CSAPs) specifically on food consumption. However, this analysis provided only a partial understanding of the broader concept of food security. A more comprehensive examination of the overall impact of CSAPs on food security is necessary, which requires a detailed empirical survey encompassing various dimensions of food security. In a related study, Martey *et al.* (2020) [30] concentrated on the availability and accessibility aspects of food security. They primarily examined the increased yield effect resulting from the implementation of CSAPs.

Existing studies (Wekesa *et al.*, 2018; Adesina, and Loboguerrero, 2021; Adebisi *et al.*, 2022; Opeyemi *et al.*, 2022) [53, 1, 4, 41] examining the relationship between CSAPs and food security in Nigeria have often focused on broad assessments of agricultural practices without adequately disaggregating their effects on specific food security dimensions. Moreover, methodological limitations have constrained the ability to accurately estimate the impact of CSAPs on food security outcomes, particularly at the individual practice level. As a result, there is a pressing need for empirical research that employs robust analytical techniques to assess the effectiveness of CSAPs in addressing food security dimensions among maize farmers in Southeast Nigeria.

The effectiveness of CSAPs in enhancing food security outcomes is contingent upon their impact on key dimensions of food security, including availability, accessibility, affordability, stability, and usability. However, empirical evidence on the specific effects of CSAPs on these dimensions, particularly in the context of maize production in Southeast Nigeria, is limited. Furthermore, the regressive influence of constraints on the adoption and implementation of CSAPs remains poorly understood, hindering efforts to promote their widespread adoption and effectiveness. The studies by Ekpa *et al.* (2021) [16], Salisu (2022) [45], Kalu, and Mbanasor (2023) [25], and Wakweya (2023) [23] were rather descriptive in their approach. They consistently focused solely on uncovering farmers' decisions to practice climate-smart agriculture (CSA), without utilizing regression analysis to understand the disruptive effect size of the constraints on CSA implementation.

This study seeks to address these gaps by conducting a comprehensive analysis of the effect of CSAPs on food security dimensions among maize farmers in Southeast Nigeria. Specifically, the research aims to determine the impact of CSAPs on the availability, accessibility, affordability, stability, and usability of maize production, thereby spotlighting their contribution to food security outcomes in Southeast, Nigeria and Africa in general. Additionally, the study examines the regressive influence of constraints on the practice of Climate-Smart Agriculture (CSA), shedding light on the factors hindering the adoption and implementation of CSAPs. However, the constraints to the implementation of CSA commonly filtered from the study by Obianefo *et al.* (2019) [39]; Kaptmyer *et al.* (2019) [26];

Salisu (2022) [45]; Fawole, and Aderinoye-Abdulwahab (2021) [17]; Chukwu *et al.* (2023) [14] include the high cost of improved varieties of yam, the high cost of farm labour, and lack of financial resources, poor access to information sources relevant to adaptation, lack of relevant information on adaptation measures, lack of access to weather forecasts and interpretation, lack of irrigation facilities, absence/weak implementation of government policies, scarcity and high cost of farm inputs, lack of drainage facilities, inadequate extension services, insecure land tenure system, and low management skills due to low literacy.

An innovative aspect of this study lies in its methodological approach, which utilizes censored regression to understand the individual effects of CSAPs on food security dimensions, a methodology that has not been extensively applied in previous studies in Southeast Nigeria. Furthermore, the study employs ordinary least square regression to elucidate the relationship between challenges faced by farmers and their impact on the application of CSA practices. By employing these analytical techniques, the research aims to provide nuanced insights into the complex dynamics shaping food security outcomes and the adoption of CSAPs in the study area. Thus, this research holds substantial implications for policymakers, researchers, and practitioners seeking to address the intersecting challenges of climate change, agriculture, and food security in Nigeria and the broader West African region.

### 1.3. Objectives of the study

The main objective of this study is to perform an analysis of the effect of Climate-Smart Agricultural Practices (CSAPs) on the food security of maize production in Southeast, Nigeria. The study is specifically designed to:

1. Determine the effect of CSAPs on food security dimensions among maize farmers; and
2. Examine the regressive influence of constraints on the practice of CSA in Southeast, Nigeria

## 2. Analytical Framework

### 2.1. Tobit regression model

Tobit regression is a regression technique used to estimate models of censored dependent variables (Foster, and Kalenkoski, 2013) [19]. It is also known as a censored regression analysis. It is a type of regression technique that is used when the dependent variable is censored at one or more values (Cholo *et al.*, 2023) [13]. The Tobit model is an extension of the linear regression model and is used to estimate the effects of explanatory variables on a censored response variable (Jiménez-Martín *et al.*, 2023) [23]. In an ideal situation, the ordinary least square (OLS) regression model should be used to identify the climate-smart agricultural practices (CSAPs) that influence food security dimensions if all farmers have equal implementation decisions. In reality, however, not all farmers will have the same food security status due to varying levels of climate-smart agriculture adoption. If the OLS regression model is used in this case, it will be exposed to sample selectivity bias. To address this issue, a two-stage procedure proposed by Tobin in 1958 can be employed. This procedure has been explored extensively by Kim, and Maddala (1992) [28]; Gujarati (1980) [20].

The Tobit model uses a maximum likelihood estimation procedure to estimate the model parameters and can be used to extend the linear regression model to censored variables

(Smithson, and Verkuilen, 2006; Audu *et al.*, 2023) [46, 9]. According to McDonald (2009) [32], the Tobit model can also be used to estimate the effect of explanatory variables on truncated dependent variables. Tobit regression is an effective and reliable method of managing selection bias. Maximum likelihood estimation (MLE) and marginal effects (MEs) are the outcomes of this approach. MEs demonstrate the effect of the CSAPs on the food security outcomes of maize farmers. MEs may be compared to OLS coefficients even though the latter can be misleading (Adejebi *et al.*, 2006; Nekui, 2023) [3, 37].

The Tobit model is a hybrid of a Logit or Probit regression and an ordinary least squares (OLS) regression (Khonje *et al.*, 2015; Assefa, 2023) [27, 8]. It is used to answer two questions: (1) what are the CSAPs that influence the probability of being food secure (which is answered by a Logit or Probit model), and (2) what factors determine the level or magnitude of the food security (which is answered by an OLS model). This type of econometric model can be used to investigate the CSAPs determinants of food security dimension among maize farmers while controlling for selection bias.

$$Y^* = \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \dots + \beta_n Z_n + \mu_i \quad (1)$$

$$Y = 0 \text{ if } y \leq 0, \quad (2)$$

$$y = Y^* \text{ if } y > 0. \quad (3)$$

$Y^*$  = index of food security dimensions

$\beta$  = estimated parameter or coefficient

$Z_i$  = the explanatory variables (determinants)

$\mu_i$  = error term and is normally distributed with zero mean and constant variance.

The dependent variable  $y$  equals 0 if the latent variable  $Y^*$  is below the mean threshold of 5-points Likert scale for food security variables. If the values of the latent variable are positive, the dependent variable is equal to the latent variable.

$$y^* = \frac{\beta_0 + x\beta + \mu_i}{z \text{ Normal}(0, \sigma^2)} \quad (4)$$

$$y^* = \max. (0, y^*) \quad (5)$$

The latent variable  $y^*$  satisfies the classical linear model assumptions; in particular, it has a normal, homoscedastic distribution with a linear conditional mean.

Equation (5) implies that the observed variable  $y$ , equals  $y^*$  when  $y^* \geq 0$ , but  $y = 0$  when  $y^* < 0$ . Because  $y^*$  is normally distributed,  $y$  has a continuous distribution over a strictly positive value. In particular, the density of  $y$  given  $z$  is the same as the density of  $y^*$  given  $z$  for positive values. Furthermore;

$$P\left(y = \frac{0}{z}\right) = P\left(y^* < \frac{0}{z}\right) = P(\mu < -z\beta) \quad (6)$$

$$= P\left(\frac{\mu}{\sigma} < -\frac{z\beta}{\sigma}\right) = \Phi\left(-\frac{z\beta}{\sigma}\right) = 1 - \Phi\left(\frac{z\beta}{\sigma}\right) \quad (7)$$

Because  $\mu/\sigma$  has a standard normal distribution and is independent of  $z$ ; then absorb the intercept into  $z$  for notational simplicity. Therefore, if  $z_i$  and  $y_i$  are randomly drawn from the population, the density of  $y_i$  given  $z_i$  is:

$$\frac{(2\pi\sigma^2)^{-1/2} \exp[-(y-z_i\beta)^2]}{(2\sigma^2)} = \frac{\left(\frac{1}{\sigma}\right)\Phi[(y-z_i\beta)]}{\sigma}, y > 0 \quad (8)$$



$$P\left(y_i = \frac{0}{z_i}\right) = 1 - \Phi\left(\frac{z_i\beta}{\sigma}\right) \tag{9}$$

Where  $\Phi$  is the standard normal density function. From (8) and (9), the log-likelihood function for each *ith* observation is then obtained;

$$l_i(\beta, \sigma) = 1(y_i = 0) \log[1 - \Phi\left(\frac{z_i\beta}{\sigma}\right)] + 1(y_i > 0) \log\left\{\frac{1}{\sigma}\Phi\left[y_i - \frac{z_i\beta}{\sigma}\right]\right\} \tag{10}$$

The log-likelihood for a random sample size *n* is obtained by summation of equation (10) across all *ith*. The maximum likelihood estimates of  $\beta$  and  $\sigma$  is obtained by maximizing the log-likelihood which is easily executed in R-software.

### 3. Materials and Methods

#### 3.1. Study Area

The study took place in Nigeria's Southeast geopolitical zone, encompassing five states: Anambra, Imo, Enugu, Abia, and Ebonyi. These states are subdivided into 101 local government areas, further divided into 346 communities. The Southeast zone covers approximately 41,440 square

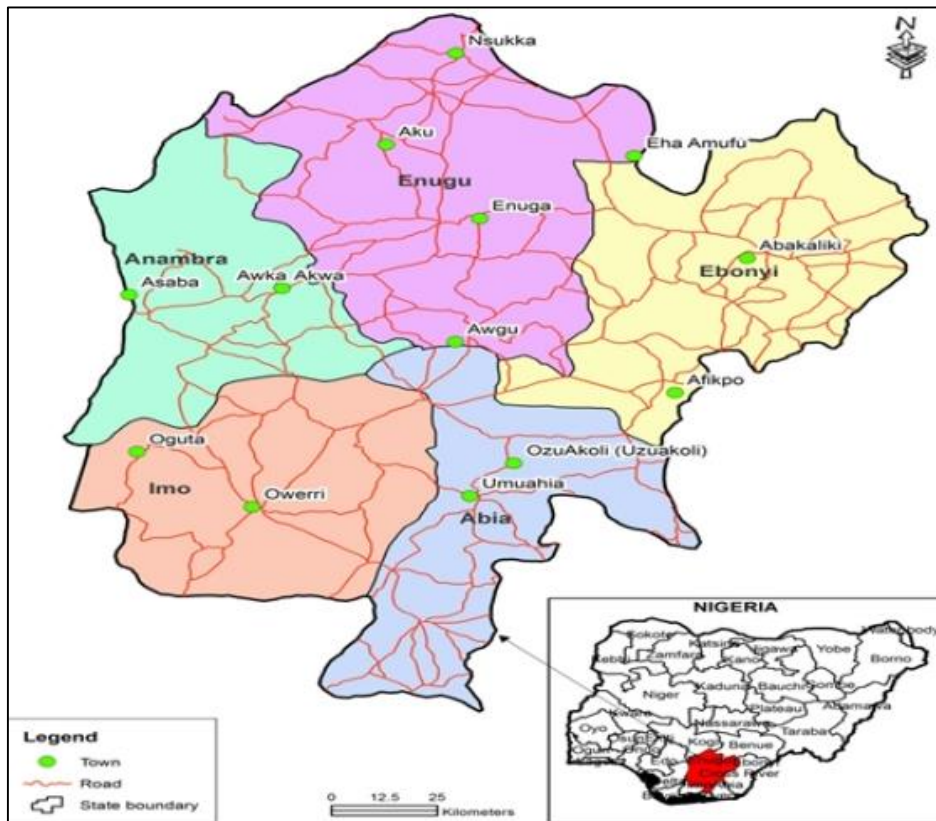
kilometers and shares borders with Akwa Ibom and Cross River States to the east, Benue and Kogi States to the north, Edo and Delta States to the west, and Rivers and Bayelsa States to the south (Merem *et al.*, 2019) [33].

**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) documented an approximate population of 22,012,828 individuals residing in the five states of Southeast, Nigeria, as detailed in Table 1. As per Mba *et al.* (2021), the Southeast zone is situated between latitudinal coordinates of 04°47' and 07°07' North and longitudinal coordinates 6°35' and 8°27' East.



Source: Merem *et al.* (2019) [33]

**Fig 1:** Map of Nigeria showing Southeast region

#### 3.2. Sample Size and Sampling Techniques

The study utilized an infinite sample size determination technique adapted from Chukwujekwu *et al.* (2022) [15] to calculate the sample size, considering that the exact population of smallholder 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:

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

In this study, a multi-stage sampling technique was applied, encompassing both purposive and random selection methods. In the first stage, three states (Anambra, Ebonyi, and Enugu) were purposively selected due to their significant history with maize farming and the presence of numerous studies on climate change mitigation strategies available for reference. During the second stage, 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 the third stage, from each community, four villages were randomly selected, accumulating to a total of 96 villages for the study. Lastly, in the final stage, four smallholder maize farmers practicing CSAT will be randomly sampled from each village, leading to 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**

The researcher(s) enlisted and trained eight research assistants to aid in data collection. These assistants were instructed on the questionnaire's contents, and the fieldwork spanned five weeks, from October 26th to December 6th, 2023. To improve the accuracy and efficiency of data collection, an Android data collection toolkit named "Kobocollect" was utilized.

**Data Analysis**

The study utilized econometric techniques such as censored regression (Tobit), and ordinary least-square (OLS) regression analysis. Objective one was achieved using the Tobit regression model, and the OLS model was used to achieve objective two. All the analysis was done in recent R-software updated January 2024.

**3.4. Model Specification**

The Tobit model for objective one is defined as:

$$y^* = \beta_0 + \beta_i z_i + \mu; y_i = y^*_i \text{ if } \begin{cases} y^*_i \geq 0 \\ y_i = 0 \end{cases}$$

Where:  $z_i$  and  $\beta_i$  are the vectors of the selected explanatory 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, and obtaining credit) and their coefficients, respectively, whereas  $y_i$  and  $y^*_i$  are the observed food security score and the vector of a latent variable. The explicit definition of the OLS regression model used to achieve objective two is stated as:

$$CSAPs_i = \beta_0 + \beta_1 Z_1 + \beta_2 Z_2 + \dots + \beta_n Z_n + \epsilon_i$$

Where:  $CSAPs_i$  is the constructive value of  $i^{th}$  climate-smart agriculture practiced.  $Z_i$  is the covariates of all the constraints (farmer illiteracy, insufficient financial, inadequate storage facilities, lack of equipment and inputs, poor extension services, high production cost, labour shortages, limited awareness of CSA practices, resistance to change, and bad road network) encountered.

**4. Results and Discussion**

**4.1.1. Effect of CSAPs on food security dimensions of availability and accessibility**

The result of the effect of Climate-Smart Agricultural practices (CSAPs) on the food security dimension of availability and accessibility is presented in Table 3. The climate-smart agriculture (CSA) practiced by the farmers was ranked and the top ten (10) practices were selected for the censored regression. The estimates are presented with their standard errors and t-values. Additionally, the table includes the Log-Sigma values, which represent the standard deviation of the error term in the log-transformed scale.

**For the food security dimension of availability**

The estimated coefficient of water management is positive (0.010), and statistically significant at conventional levels (significant at 10%). This suggests that water management practices have a slightly positive effect on availability. This suggests that farmers who practice water management experience more maize availability by 1.0%. This result is in agreement with Kadapa *et al.* (2024) [24] who noted that water management has a positive effect on millet availability and yield. The coefficient of residue management is positive (0.019) and statistically significant (significant at 1%), indicating that residue management practices have a positive effect on availability. Farmers who engage in residue management may experience higher levels of maize availability by 1.9%. This result corroborates Vasileiou *et al.* (2024) [51] who suggested that residue management is a transformational agricultural sustainability practice. The coefficient of mulching is positive (0.020) and statistically significant (significant at 1%), indicating that mulching practices have a positive effect on maize availability. Farmers who use mulching may experience higher levels of maize availability by 2.0%. The coefficient of crop rotation is positive (0.020) and statistically significant (significant at 1%), indicating that crop rotation practices have a positive effect on availability. This result aligns with the assertion by

Feigenwinter *et al.* (2023) [18] who argued that farmers who practice crop rotation experience higher levels of maize availability.

The coefficient of adopting early planting is positive (0.070) and highly statistically significant (significant at 1%), indicating that adopting early planting practices has a significant positive effect on availability. Farmers who adopt early planting may experience higher levels of maize availability by 7.0%. The coefficient of obtaining credit is positive (0.072) and highly statistically significant (significant at 1%), indicating that obtaining credit has a significant positive effect on availability. Farmers who have access to credit may experience higher levels of maize availability by 7.2%. The coefficient of the use of organic fertilizer to improve soil texture and structure is positive (0.015), and statistically significant at conventional levels (significant at 10%). This suggests that using organic fertilizer may have a slightly positive effect on availability by 1.5%.

The coefficient of minimum tillage is negative (-0.063) and highly statistically significant (significant at 1%). This

indicates that minimum tillage practices have a significant negative effect on availability, suggesting that farmers who adopt minimum tillage may experience lower levels of maize availability. The coefficient of improving access to information is negative (-0.037) and highly statistically significant (significant at 1%), indicating that improving access to information has a significant negative effect on availability. This implies that farmers who request access to information are not seeking those tailored to promote CSAPs. However, practices such as residue management, mulching, crop rotation, early planting, and obtaining credit are associated with higher levels of availability, while minimum tillage and improving access to information are associated with lower levels of availability. The practices associated with higher levels of maize availability economically translate to increased supply in the market, potentially leading to lower prices for maize products. Additionally, higher availability can enhance food security by ensuring a consistent and sufficient food supply, reducing the risk of food shortages and price volatility.

**Table 3:** Effect of CSAPs on food security dimensions of availability and accessibility

Climate-smart agricultural practices (CSAPs)	Availability			Accessibility		
	Estimate	Std. Error	t value	Estimate	Std. Error	t value
(Intercept)	3.089	0.033	93.19	2.935	0.023	129.60
Water management	0.010	0.006	1.68*	0.132	0.004	29.80***
Minimum tillage	-0.063	0.007	-9.24***	-0.010	0.005	-2.11**
Residue management	0.019	0.006	3.00***	-0.018	0.004	-4.24***
Use of irrigation pump for dry season planting	0.003	0.006	0.52	-0.012	0.004	-3.27***
Mulching	0.020	0.007	2.91***	0.021	0.004	4.61***
Crop rotation	0.020	0.006	3.16***	-0.044	0.004	-10.35***
Improving access to information	-0.037	0.006	-6.49***	-0.064	0.004	-15.44***
Adopting early planting	0.070	0.006	11.27***	0.200	0.004	46.99***
Obtaining credit	0.072	0.008	9.02***	-0.018	0.005	-3.28***
Use of organic fertilizer to improve soil texture and structure	0.015	0.008	1.90*	-0.036	0.005	-6.67***
Log-Sigma	-2.071	0.037	-56.42	-2.487	0.038	-64.91
Log-likelihood	237.354			344.351		

**Source:** Field Survey, 2023: \*, \*\*, and \*\*\*); Significant @ 10%, 5%, and 1% level of significance

#### For the food security dimension of accessibility

The coefficient of water management is positive (0.132) and highly statistically significant (significant at 1%), indicating that water management practices have a significant positive effect on accessibility. Farmers who practice water management may experience better access to maize by 13.2%. This assertion corroborates Ng'ombe *et al.* (2023) [38] argument on building a resilient and sustainable sorghum value chain in Tanzania's lake zone region. The coefficient of mulching is positive (0.021) and statistically significant (significant at 1%), indicating that mulching practices have a significant positive effect on accessibility. Farmers who use mulching may experience better access to maize by 2.1%. The coefficient of adopting early planting is positive (0.200) and highly statistically significant (significant at 1%), indicating that adopting early planting practices has a significant positive effect on accessibility. Farmers who adopt early planting may experience better access to maize by 20.0%.

The coefficient of minimum tillage is negative (-0.010) and statistically significant (significant at 5%), indicating that minimum tillage practices have a significant negative effect on accessibility. Farmers who adopt minimum tillage may experience lower levels of accessibility to maize by 1.0%.

The coefficient of residue management is negative (-0.018) and highly statistically significant (significant at 1%), indicating that residue management practices have a significant negative effect on accessibility. Farmers who engage in residue management may experience lower levels of accessibility to maize by 1.8%. The coefficient of use of irrigation pump for dry season planting is negative (-0.012) and statistically significant (significant at 1%), indicating that using irrigation pumps for dry season planting has a significant negative effect on accessibility. This suggests that farmers who wrongly use irrigation pumps for dry season planting may experience lower levels of accessibility to maize by 1.2%. Policymakers need to be careful with this findings considering that Barbosa *et al.* (2015) confirmed that access to irrigation enables year-round farming, fostering sustainable agricultural practices for food production.

The coefficient of crop rotation is negative (-0.044) and highly statistically significant (significant at 1%), indicating that crop rotation practices have a significant negative effect on accessibility. Farmers who practice crop rotation may experience lower levels of accessibility to maize by 4.4%. The coefficient of improving access to information is negative (-0.064) and highly statistically significant (significant at 1%), indicating that improving access to

information has a significant negative effect on accessibility. This suggests that farmers who have better access to information may experience lower levels of accessibility to maize by 6.4%.

The coefficient of obtaining credit is negative (-0.018) and statistically significant (significant at 1%), indicating that obtaining credit has a significant negative effect on accessibility. Farmers who have access to credit may experience lower levels of accessibility to maize by 1.8%. The coefficient of use of organic fertilizer to improve soil texture and structure is negative (-0.036) and highly statistically significant (significant at 1%), indicating that using organic fertilizer has a significant negative effect on accessibility. This suggests that farmers who use organic fertilizer may experience lower levels of accessibility to maize by 3.6%.

Thus, practices such as water management, mulching, and adopting early planting are associated with better access to maize, while minimum tillage, residue management, crop rotation, improving access to information, obtaining credit, and using organic fertilizer are associated with lower levels of accessibility. Again, the practices associated with better access to maize economically enhanced market participation and trade opportunities for farmers, leading to increased income generation and economic growth.

#### 4.1.2. Effect of CSAPs on food security dimensions of affordability and stability

The result of the effect of Climate-Smart Agricultural practices (CSAPs) on the food security dimension of affordability and stability is presented in Table 4. The estimates are accompanied by their standard errors and t-

values, providing insights into the significance and magnitude of the relationships.

#### For the food security dimension of affordability

Water management ( $\beta = 0.105$ ), minimum tillage ( $\beta = 0.134$ ), use of irrigation pump for dry season planting ( $\beta = 0.031$ ), adopting early planting ( $\beta = 0.158$ ), use of organic fertilizer ( $\beta = 0.067$ ) are the practices associated with positive coefficients, indicating that they have a positive effect on affordability by varying magnitude of the coefficient. Farmers who adopt these practices may experience lower production costs, increased yields, or improved access to inputs, contributing to enhanced affordability of maize production. Specifically, practices such as water management, minimum tillage, and adopting early planting exhibit strong positive effects on affordability, as evidenced by their high t-values and statistical significance levels (significant at 1%).

Residue management ( $\beta = -0.053$ ), mulching ( $\beta = -0.034$ ), crop rotation ( $\beta = -0.066$ ), improving access to information ( $\beta = -0.137$ ), obtaining credit ( $\beta = -0.014$ ) conversely are the practices associated with negative coefficients, indicating that they negatively affected maize affordability. Farmers who engage in these practices may incur higher costs, face resource constraints, or experience difficulties accessing necessary inputs or information, leading to reduced affordability of maize production. Notably, improving access to information exhibits a strong negative effect on affordability, as indicated by its high t-value and statistical significance level (significant at 1%). These results is an indication of wrong application of the practices.

**Table 4:** Effect of CSAPs on food security dimensions (affordability and stability)

Climate-smart agricultural practices (CSAPs)	Affordability			Stability		
	Estimate	Std. Error	t value	Estimate	Std. Error	t value
(Intercept)	2.863	0.030	95.70	3.475	0.044	78.26
Water management	0.105	0.006	18.50***	0.016	0.008	1.95*
Minimum tillage	0.134	0.006	22.46***	0.035	0.009	3.86***
Residue management	-0.053	0.006	-9.36***	-0.018	0.009	-2.06**
Use of irrigation pump for dry season planting	0.031	0.005	6.39***	-0.003	0.007	-0.44
Mulching	-0.034	0.006	-5.71***	-0.015	0.009	-1.69*
Crop rotation	-0.066	0.006	-11.85***	-0.099	0.008	-11.75***
Improving access to information	-0.137	0.005	-25.43***	-0.011	0.008	-1.42
Adopting early planting	0.158	0.006	28.47***	0.097	0.008	11.73***
Obtaining credit	-0.014	0.007	-2.06**	0.017	0.011	1.57
Use of organic fertilizer to improve soil texture and structure	0.067	0.007	9.49***	0.001	0.011	0.13
Log-Sigma	-2.218	0.039	-57.14	-1.780	0.037	-47.49
Log-likelihood	238.729			113.466		

Source: Field Survey, 2023: \*, \*\*, and \*\*\*); Significant @ 10%, 5%, and 1% level of significance

#### For the food security dimension of stability

Water management ( $\beta = 0.016$ ), minimum tillage ( $\beta = 0.035$ ), and adopting early planting ( $\beta = 0.097$ ) are the practices associated with positive coefficients, indicating that they have a positive effect on stability. Farmers who adopt these practices may experience increased resilience to environmental stressors, improved yield consistency, or enhanced risk management, contributing to greater stability in maize production. Notably, minimum tillage, and adopting early planting exhibit strong positive effects on stability, as evidenced by their high t-values and statistical significance levels (significant at 1%).

Residue management ( $\beta = -0.018$ ), mulching ( $\beta = -0.015$ ), and crop rotation ( $\beta = -0.099$ ) are the practices associated with negative coefficients, indicating that they have a negative effect on stability. Farmers who engage in these practices may face challenges related to soil health, pest management, or market uncertainties, leading to reduced stability in maize production. Notably, crop rotation exhibits a strong negative effect on stability, as indicated by its high t-value and statistical significance level (significant at 1%). Farmers need serious training on the right application of these practices.

Overall, the results suggest that certain CSAPs have significant implications for the affordability and stability of



maize production in Southeast Nigeria. Practices such as water management, minimum tillage, adopting early planting, and using organic fertilizer emerge as key drivers of affordability and stability, offering potential pathways for enhancing agricultural resilience, productivity, and economic viability. Conversely, practices such as improving access to information and obtaining credit may pose challenges to affordability and stability, highlighting the importance of addressing barriers and constraints in agricultural development initiatives.

#### 4.1.3. Effect of CSAPs on food security dimensions of usability

The result of the effect of Climate-Smart Agricultural practices (CSAPs) on the food security dimension of usability is presented in Table 5. The estimates are accompanied by their standard errors and t-values, providing insights into the significance and magnitude of the relationships. Water management ( $\beta = -0.029$ ), minimum tillage ( $\beta = -0.041$ ), crop rotation ( $\beta = -0.054$ ), and adopting early planting ( $\beta = 0.010$ ) are the practices associated with negative coefficients, indicating that they have a negative effect on usability. Farmers who engage in these practices may face challenges related to crop quality, post-harvest losses, or marketability, leading to reduced usability of maize products. Notably, minimum tillage, crop rotation, and adopting early planting exhibit strong negative effects on usability, as indicated by their high t-values and statistical significance levels (significant at 1%). Farmers who engage in practices that diminish usability may face lower incomes, increased food

waste, and reduced market opportunities. Therefore, promoting CSAPs that enhance usability can benefit farmers' households by increasing their economic resilience and well-being.

Residue management ( $\beta = 0.014$ ), use of irrigation pump for dry season planting ( $\beta = 0.018$ ), mulching ( $\beta = 0.013$ ), and obtaining credit ( $\beta = 0.041$ ) are the CSAPs practices associated with positive coefficients, indicating that they have a positive effect on usability. Farmers who adopt these practices may experience improvements in crop quality, reduced post-harvest losses, or enhanced marketability, leading to increased usability of maize products. Notably, obtaining credit exhibits a strong positive effect on usability, as indicated by its high t-value and statistical significance level (significant at 1%). Practices that enhance usability, such as residue management, use of irrigation pumps for dry season planting, mulching, and obtaining credit can contribute to improved marketability and value of maize products. This can stimulate economic activities within the agricultural sector, including increased trade, value addition, and profitability. The findings presented here stand out distinctly from those of Martey *et al.* (2020) [30], Tilahun *et al.* (2023) [48], and Tabe-Ojong *et al.* (2023). While their studies focused on the impact of CSAPs on household food security, highlighting practices such as efficient water management, irrigation, soil conservation, early planting, and mulching as factors enhancing food security among adopters, our research reveals unique insights by categorizing the effect to reflect availability, accessibility, affordability, stability, and usability.

**Table 5:** Effect of CSAPs on food security dimensions of usability

Climate-smart agricultural practices (CSAPs)	Usability		
	Estimate	Std. Error	t value
(Intercept)	3.734	0.025	147.05
Water management	-0.029	0.005	-5.99***
Minimum tillage	-0.041	0.005	-7.74***
Residue management	0.014	0.005	2.93***
Use of irrigation pump for dry season planting	0.018	0.004	4.32***
Mulching	0.013	0.005	2.51**
Crop rotation	-0.054	0.005	-11.27***
Improving access to information	-0.006	0.004	-1.33
Adopting early planting	-0.010	0.005	-2.00**
Obtaining credit	0.041	0.006	6.73***
Use of organic fertilizer to improve soil texture and structure	0.001	0.006	0.24
Log-Sigma	-2.337	0.037	-63.86
Log-likelihood	341.749		

**Source:** Field Survey, 2023; \*, \*\*, and \*\*\*); Significant @ 10%, 5%, and 1% level of significance

#### 4.2. The regressive influence of constraints on the practice of climate-smart agriculture CSA in Southeast, Nigeria

Table 4 presents the regressive influence of various constraints on the practice of Climate-Smart Agriculture (CSA) in Southeast Nigeria. These constraints reflect challenges that farmers may encounter in adopting and implementing CSAPs. This result considered their economic implications for the agricultural sector and farmers' household food security. The mean score of the individual CSA variables was the regressand for the top ten (10) constraints faced by maize farmers in implementing CSA. F-statistics value of 32.31\*\*\* was significant at a probability level of 0.01, this is an indication that at least; one of the regressor (constraints) influenced the practice of CSA in

Southeast Nigeria. Due to the large number of independent variables included in the model, the Adjusted R-square value of 0.470 implies that 47.0% of the variability in CSAPs was determined by the listed constraints, and the remaining 53.0% is linked to the farmer's managerial prowess. This Adjusted R-square value is in line with the 0.25 – 0.49 effect size considered moderately okay by Hair *et al.*, 2011; Hair *et al.*, 2013; Moore *et al.*, 2013; and Uchemba *et al.*, 2021) [22, 21, 34, 50].

Farmer illiteracy ( $\beta = 0.204$ ), and high production costs ( $\beta = 0.144$ ) are the constraints associated with positive coefficients, indicating a regressive influence on the practice of CSA. Farmer's illiteracy and high production costs significantly hinder the adoption and implementation of



CSAPs. These constraints may lead to suboptimal utilization of resources, reduced productivity, and limited access to market opportunities.

Insufficient financial ( $\beta = -0.199$ ), lack of equipment and inputs ( $\beta = -0.112$ ), limited awareness of CSA practices ( $\beta = -0.178$ ), and resistance to change ( $\beta = -0.491$ ). The constraints associated with negative coefficients indicate a regressive influence on the practice of CSA. Insufficient financial resources, lack of equipment and inputs, Limited awareness of CSA practices, and resistance to change significantly impede the adoption and implementation of CSAPs. These

constraints may limit farmers' ability to invest in sustainable agricultural practices, access modern farming technologies, and adapt to changing environmental conditions.

The regressive influence of constraints on the practice of CSA has significant economic implications for the agricultural sector. Constraints such as high production costs, insufficient financial resources, and resistance to change can hamper agricultural productivity, increase production inefficiencies, and hinder sectoral growth. This can lead to reduced competitiveness, lower agricultural output, and decreased contribution to overall economic development.

**Table 6:** Regressive influence of constraints on the practice of CSA in Southeast, Nigeria

Constraints to CSAPs	Coefficients	Standard Error	t Stat
Intercept	3.145	0.099	31.84
Farmer illiteracy	0.204	0.040	5.06***
Insufficient financial	-0.199	0.042	-4.74***
Inadequate storage facilities	0.043	0.038	1.14
Lack of equipment and inputs,	-0.112	0.037	-3.05***
Poor extension services	-0.034	0.036	-0.96
High production costs	0.144	0.036	4.00***
Labour shortages	0.017	0.049	0.36
Limited awareness of CSA practices	-0.178	0.034	-5.24***
Resistance to change	-0.491	0.036	-13.70***
Bad road network	0.097	0.101	0.96
F-stat.	32.31***		
R-Square	0.470		
Adjusted R-Square	0.456		
Observation	375		

Source: Field Survey, 2023. \*, \*\*, and \*\*\*); Significant @ 10%, 5%, and 1% level of significance

Constraints affecting the practice of CSA also have direct implications for farmers' household food security. Farmer illiteracy, inadequate storage facilities, and limited awareness of CSA practices can limit farmers' ability to produce, store, and market their agricultural products effectively, thereby jeopardizing food security at the household level. Additionally, constraints related to insufficient financial resources and resistance to change can exacerbate poverty and food insecurity among farming households by restricting income-generating opportunities and adaptive capacities. These findings are consistent with the issues raised by Kptymer *et al.* (2019) [26], Salisu (2022) [45], Fawole, and Aderinoye-Abdulwahab (2021) [17], and Chukwu *et al.* (2023) [14] as the important constraints to CSAPs.

Furthermore, promoting awareness and incentivizing sustainable agricultural practices can encourage farmers to overcome resistance to change and embrace CSA initiatives.

## 5. Conclusion and Recommendation

The study sheds light on the Analysis of the effect of climate-smart agricultural practices (CSAPS) on food security of maize production in Southeast, Nigeria. Specifically, practices such as water management, residue management, mulching, crop rotation, early planting, and obtaining credit exhibit positive effects on availability, accessibility, affordability, and stability of maize production. These findings underscore the importance of promoting and incentivizing the adoption of CSAPs to improve agricultural productivity, income generation, and food security outcomes in the study area.

Conversely, certain CSAPs, such as minimum tillage and improving access to information, demonstrate negative effects on certain dimensions of food security. This suggests

the need for targeted interventions to address challenges associated with these practices, such as providing technical assistance and extension services to farmers to ensure proper implementation and utilization of CSAPs.

Furthermore, the study highlights the critical role of addressing constraints to the adoption and implementation of CSA. Constraints such as farmer illiteracy, insufficient financial resources, lack of equipment and inputs, limited awareness of CSA practices, and resistance to change significantly hinder the uptake of CSAPs among farmers. Addressing these constraints through targeted policies, capacity-building initiatives, and financial support mechanisms is crucial to promoting the widespread adoption of sustainable agricultural practices and improving food security outcomes in Southeast, Nigeria.

Overall, the findings contribute to a better understanding of the factors influencing the adoption and impact of CSAPs on food security dimensions in Southeast Nigeria. By addressing constraints and promoting CSAPs, policymakers, agricultural stakeholders, and development practitioners can work towards enhancing agricultural sustainability, resilience, and food security for maize farmers and their households in Nigeria and Africa at large.

## 6. Compliance with ethical standards

### Acknowledgments

We would like to express our sincere gratitude to all the maize farmers in Southeast, Nigeria, who participated in this study on the analysis of the effect of climate-smart agricultural practices (CSAPs) on food security of maize production. Your valuable insights and cooperation were essential for the success of this research.

We also extend our thanks to the broader community of

farmers who practice CSAPs in the study area. Your dedication to sustainable agricultural practices is instrumental in shaping the future of food security and environmental sustainability.

Furthermore, we acknowledge that this research received no external funding and was conducted without the involvement or influence of any third party. We are grateful for the independence and autonomy this provided, allowing us to conduct the study with integrity and impartiality.

Once again, we thank all the maize farmers who contributed to this study. Your participation is deeply appreciated, and we hope that the findings of this research will contribute to the advancement of agricultural practices and food security initiatives in Southeast Nigeria and beyond.

*Author Contributions:* Conceptualization, O.A.C. and U.E.E.; Data curation, O.A.C., I.A.C., and O.C.O.; Formal analysis, O.A.C.; Investigation, O.A.C, I.A.C., U.E.E., and O.C.O.; Methodology, O.A.C., and U.E.E.; Project administration, I.A.C., and O.J.N.; Resources, O.A.C., U.E.E., I.A.C. and O.C.O.; Software, O.A.C.; Supervision, U.E.E.; Validation, U.E.E., and I.A.C.; Visualization, O.A.C., and O.C.O.; Original draft, O.A.C. and U.E.E.; Writing—review & editing, O.A.C., I.A.C., and U.E.E. All authors have read and agreed to the published version of the manuscript.

*Funding:* This research received no external funding.

*Disclosure of conflict of interest:* The authors declare no conflict of interest.

*Data Availability Statement:* Data are available upon reasonable request from the corresponding author

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