Journal of Arid Agriculture

J. Arid Agric. 2025, Vol. 26 (1): 61 - 71

https://jaaunimaid.ng/index.php/home

0189-7551
https://doi.org/10.63659/JAA/Vol.26/Issue1/008

ENHANCING PRODUCTIVITY AND FOOD SECURITY WITH CLIMATE-SMART MAIZE VARIETIES: EVIDENCE FROM KADUNA STATE, NIGERIA

L. Obute[1], Y.U. Oladimeji[1]*, B.D. Magaji[1], I. Tijani[1], A.S. Hussaini[1], M.A. Owolabi[1] and T. Abdoulaye[2]

[1]Institute for Agricultural Research / Faculty of Agriculture, Department of Agricultural Economics, Ahmadu Bello University, Nigeria.

[2]International Institute for Tropical Agriculture, Mali

*Corresponding Author's email: yusuf.dimeji@yahoo.com

ABSTRACT: A continued decline in food production and productivity could render the goals of achieving food security and eliminating hunger far from reach-objectives at the core of the first of the United Nations' Seventeen Sustainable Development Goals. Hence, efforts have been made to develop adaptation strategies against drought stress, one of which is climate-smart maize varieties (CSMVs). The study aims to analyse the effects of CSMVs on farmers' productivity and food security in Kaduna State Nigeria. A total of 260 maize farmers from a sample frame of 1,053, across three agricultural zones in the state were randomly selected and interviewed in 2022/2023 cropping season. Descriptive statistics, ordinary least squares regression and ordered logit regression were used to analyze the data. The descriptive statistics show that female participation is generally low, although relatively higher among adopters (19%) than non-adopters (16.67%). Only 10% of non-adopters have access to extension services compared to 53% of adopters. While 83.33% of non-adopters have no formal education, only 20% of adopters fall into this category. The OLS results shows that adoption of CSMVs significantly increases output, and adopters have a slightly higher average output of 2,467 kg per ha compared to 2,220 kg per ha for non-adopters. The coefficients of age, farm size and access to credit were positive and statistically significant while gender was also significant but negative. Adoption of CSMVs and extension contact were significant and positive predictors of improved food security while level of education and social organisation have a negative relationship with food security. The study concludes that adoption of the CSMVs among the farmers could be attributed to the availability of information through extension services, access to credit, and the influence of education in the study area. Agricultural institutions and non-governmental organizations (NGOs) should focus on promoting adoption of improved maize varieties, ensuring women and older farmers are adequately supported, and provide access to credit and land to boost agricultural efficiency in order to improve productivity.

Keywords: Adopters, non-Adopters, climate-smart maize varieties (CSMVs), Food Consumption Score (FCS)

INTRODUCTION

Nigerian crop sub-sector of agriculture accounted for 88.1% of agricultural gross domestic product in 2022 (National Bureau of Statistics, NBS, 2023). However, the sub-sector has become highly susceptible to climate variability, reflected in increased frequency of droughts, especially mid-season dry spells, increased temperatures, and altered patterns of precipitation (FAO, 2018; Usman *et al.*, 2022). These result to increased production risks and decline in crop and livestock yields (Oderinde *et al.,* 2022). The resulting impact of this decline could render the goals of achieving food security and eliminating hunger far from reach, which is the first of the United Nations' Seventeen Sustainable Development Goals (SDG Report, 2022).

How to cite this Article: L. Obute, Y.U. Oladimeji, B.D. Magaji, I. Tijani, A.S. Hussaini, M.A. Owolabi and T. Abdoulaye (2025). Enhancing Productivity and Food Security with Climate-Smart Maize Varieties: Evidence from Kaduna State, Nigeria.. *Journal of Arid Agriculture*, *26*(1), 61–71. https://doi.org/10.63659/JAA/Vol.26/Issue1/008 Retrieved from https://jaaunimaid.ng/index.php/home/article/view/67

Maize is cultivated in almost all countries and the most widely cultivated and consumed staple crop in Nigeria (Usman *et al.*, 2022). In nutritional terms, it has a carbohydrate-rich composition, mainly in the form of starch, and also has proteins, lipids, vitamins and minerals (Langner *et al.,* 2019). Maize does not only serve as a source of food for man and livestock but also a source of income, especially for farmers in Nigeria (Kamara *et al.*, 2023). Nigeria is the second largest maize producer in Africa after South Africa, with an estimated production output of about 12.7 million metric tons, cultivated on an estimated land area of 6 million hectares in year 2021 farming season (Usman et *al.*, 2022). This represents about 13.18% of the total continent's output and 47% of the West African region's output (FAOSTAT, 2022).

However, maize productivity in Nigeria is currently low, about 2 tons per hectare, despite attainable yields of over 5 tons per hectare (Kamara *et al*., 2023). This could further be threatened by climate shocks such as drought and flood (Tofa *et al.*, 2021). According to Oyinbo *et al.* (2019), maize yields in Nigeria have consistently lagged behind those in the rest of the world with the yield in Nigeria being only one-fourth of the average global yield in 2016 and are currently even lagging behind on the average yield in Africa. In Nigeria, climate-smart maize varieties (CSMVs) have been developed over the years by the collaborative efforts of national research institutes, particularly the Institute for Agricultural Research (IAR) and International Institute for Tropical Agriculture (IITA). In particular, efforts have been made to develop adaptation strategies against drought stress. Notable among these was the Drought Tolerant Maize for Africa (DTMA) project which was initiated with the aim of developing and deploying drought-tolerant maize varieties (DTMVs) which are also known as CSMVs (Kamara *et al*., 2023; Wossen *et al*., 2023). As the project targeted production zones where the rainfall patterns and climatic conditions varied considerably within and among seasons, the varieties that were developed were selected for high yield potential under both drought stress and favourable growing conditions (Wossen *et al.*, 2017) to enhance improve livelihood of rural households and nation's food security.

Food insecurity is a major challenge in Nigeria, especially among agrarian households (Villacis *et al*., 2022; Wudil *et al*., 2023). The impact of changing climate on different ecological zones in Nigeria negatively affects its potential to feed its teeming population (Ani *et al*., 2022). To meet the food needs of the rapidly expanding population, it continually depends on food importation to bridge the food demand-supply gap (Adesina and Loboguerrero, 2021). According to Wossen *et al*. (2023), the impacts of climate change with the attendant negative effects on crop productivity and food security of farmers underscores the need to identify measures that can improve their climate resilience and food security. To this effect it becomes significant to analyze the effects of CSMVs on productivity and food security among maize farmers in Kaduna State, Nigeria. The broad objective of the study was to analyze the effect of climate-smart maize varieties on productivity, and food security among maize farmers in Kaduna State, Nigeria.

RESEARCH METHODOLOGY

Description of the Study Area

The study area is Kaduna State, Nigeria. The state occupies about 46,016 Km^2 which represent about 5% of the Nigerian land mass of 923,768 square kilometers in the central region of Nigeria. The physical properties of the soil which include loamy and clay soil are moderately good and allow continuous cropping of a wide variety of crops such as maize, sorghum, cassava, cowpea, soya beans, ginger, and cotton (Kaduna State Bureau of Statistics, KSBS, 2015).

Sampling Procedure, Sample Size and Data Collection

Data were collected from primary source with the aid of structured questionnaire using Computer-Assisted Personal Interviewing (CAPI). The data used in this study was derived from farm household survey for the 2022/2023 farming season. A multi-stage sampling procedure was used to collect the data which involved a purposive selection of three agricultural zones: Samaru, Maigana and Lere with less security challenges and as well suitable for maize production in Kaduna State. The second stage involved the proportionate random sampling of Local Government Areas (LGAs) that are within the three agricultural zones where CSMVs have been, and are still being promoted by agricultural research institutes like the Institute for Agricultural Research (IAR), National Agricultural Extension Research and Liaison Services (NAERLS), and Kaduna Agricultural Development Project (KADP). This resulted in the random selection of a total of seven (7) LGAs. In the third stage, three (3) communities were randomly selected from each of the LGAs to give a total of twenty-one (21) communities. In the final stage, maize farmers were randomly selected from the sample frame in each of the 21 communities. Therefore, a total of 260 maize farmers across three agricultural zones in Kaduna State were randomly selected for this study from a population of 1,053 maize farmers. The 260 maize farmers randomly collected were sieved to 200 adopters and 60 non-adopters.

Analytical Tools and Model Specification

Descriptive statistics such as frequency mean, standard deviation etc. and inferential statistics such as t-statistic, ordinary least regression and ordered logit regression were used to achieve the study.

Ordinary Least Squares Regression (OLS)

OLS was used to estimate the factors influencing total maize output among the farmers.

$Y_1 = \beta_0 + B_1X_1 + B_2X_2 + B_3X_3 + B_4X_4 + B_5X_5 + B_6X_6 + B_7X_7 + B_8X_8 + B_9X_9 + B_{10}X_{10} + \beta_{11}X_{11} + \varepsilon_1$…..(1)

Where; Y_1 = Normalized output (kg), X_1= Adoption of CSMVs (number of CSMVs adopted), X_2= Gender (male =1, female =0), X_3=Age (years), X_4=Household size (persons), X_5= farm size (ha), X_6 = Education (years), X_7=Farming experience (years), X_8= Distance from CSMVs source (km), X_9=Cooperative (yes or no), X_{10}= Extension contact (yes or no), X_{11}=Credit (yes or no), ε=error term, $\beta_0 = constant\ \beta_{1-}\beta_{11}$(Regression coefficients for the respective variables in the model).

Ordered Regression Model

Ordered regression model was used to estimate the effect of climatic-smart maize varieties on farmers' food security status. The ordinal variable Y is a function of another variable Y_1^* that's is continuous and not measured and has various thresholds points. The value of the observed variable depends on whether or not it crossed a particular thresholds value. The effect of climatic-smart maize varieties on maize farmers' food security status were determined using ordered logit regression analysis.

For an index model for a single latent variable y^* which is unobservable, we only know when it crosses threshold as it's in the formula below

$$Y_1^* = X_1\beta + \mu_1 \quad (1)$$

The continuous latent variables Y^* is equal to;

Where: Y*: Continuous latent variable, X: Vector of independent variables, β: Coefficient vector and μ: Random disturbance term, which is normally distributed.

The observed ordinal variable Y is determined by applying thresholds to the latent variable Y*. The relationship is represented as follows:

$$Y_1 = \begin{cases} 1\ if\ Y_1^* \le \alpha_1 \\ j if \alpha_{j-1} < Y_1^* \le \alpha_j (j = 2,3,\cdots,J-1) \\ J\ if\ Y_1^* \le \alpha_{J-1} \end{cases} \quad (2)$$

$$P(Y_1 = j) = F(\alpha_j - X_1\beta) - F(\alpha_{j-1} - X_1\beta)\backslash n - (F) \quad (3)$$

The error term reflects the fact that the variable may not be perfectly measured and some relevant variables may not be introduced in the equation, the vector of β parameters is estimated by the Maximum Likelihood method.

Three ordered levels were used. The empirical model is stated thus:

$LOG\ Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \beta_7X_7 + \beta_8X_8 + \beta_9X_9 + \beta_{10}X_{10} + \beta_{11}X_{11} + U \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$

Where Y-classes of food security status FCS < 21 → Poor food consumption; 21.5 ≤ FCS ≤ 35 → Borderline food consumption and FCS > 35 → Acceptable food consumption score (World Food Programme, 2008).

X_1= Adoption of CSMV, X_2= Gender, X_3=Age, X_4=Household size, X_5= farm size, X_6 = Education, X_7=Farming experience, X_8= Distance from source, X_9=Cooperative, X_{10}= Extension Contact, X_{11}=Credit, U=Error term, $\beta_0 = constant\ \beta_{1-}\beta_{11}$(Regression coefficients for the respective variables in the model).

Food Consumption Score (FCS)

The FCS was first created in Southern Africa in 1996, and This indicator is a composite score based on households' dietary diversity, food consumption frequency, and relative nutritional value of different food groups (WFP, 2008). The FCS is calculated by asking how often households consume food items from the 8 different food groups (plus condiments) during a 7-day reference period. In addition to this, the FCS module collects data on sources of the consumed foods acquired by households.

The Food Consumption Score is given as:

$$FCS = \left(C_{staples} \times 2\right) + \left(C_{pulses} \times 3\right) + \left(C_{vegetables} \times 1\right) + \left(C_{fruits} \times 1\right) + (C_{meat} \times 4) + (C_{milk} \times 4) + \left(C_{sugar} \times 0.5\right) + (C_{oil} \times 0.5)$$

According to WFP, (2008), the thresholds for Food Security Classification:

$FCS < 21 \rightarrow$ Poor Food Consumption; $21.5 \leq FCS \leq 35 \rightarrow$ Borderline Food Consumption and
$FCS > 35 \rightarrow$ Acceptable Food Consumption

RESULTS AND DISCUSSION

Socioeconomic Characteristics of the Maize Farmers

The socioeconomic characteristics of both adopters and non-adopters of climate-smart maize varieties show distinct patterns, shedding light on key factors that influence adoption. The gender distribution between adopters and non-adopters shows less disparity, with male dominating both groups (Table 1). Female participation, though lower, is relatively higher among adopters (19%) than non-adopters (16.67%), suggesting a potentially growing interest in climate-smart practices among female farmers. Age appears to be a significant different variable between the adopters and non-adopters with non-adopters older with a mean age of about 48 years, while adopters are considerably younger, averaging about 33 years.

Education plays a crucial role in adoption, as shown by the substantial difference in education levels between the two groups statistically significant at 5% level of probability. A striking 83.33% of non-adopters have no formal education, whereas only 20% of adopters fall into this category. Adopters tend to have higher levels of education, with 41.5% having secondary education compared to just 1.67% of non-adopters. This suggests that education is a key driver for the adoption of climate-smart maize varieties, likely due to better understanding of the benefits and practices involved. Household size shows that non-adopters have significantly larger households, with a mean household size of about 13, while adopters average 8 persons. The average farm size is relatively similar for both groups, though adopters have slightly larger farms 1.987 hectares compared to 1.767 hectares. The average farm size for the pooled data was found to be 1.94. The mean farming experience of non-adopters is about 39 years and is significantly higher than that of adopters with 14 years with P>0.01, indicating that more experienced farmers may be more resistant to change, possibly due to familiarity with traditional practices.

Access to agricultural extension services strongly correlates with adoption. Only 10% of non-adopters have access to extension services, compared to 53% of adopters. These findings suggest that being connected to information networks and support systems is crucial for the adoption of climate-smart maize varieties. Access to credit is another critical factor, with only 1.67% of non-adopters having access to credit, compared to 21% of adopters. This demonstrates that financial resources play a significant role in enabling farmers to invest in climate-smart technologies. The results of socio-economic and institutional characteristics are comparable with with the findings of Alhassan *et al.* (2022), Chete (2021), Opeyemi *et al.* (2021), Babuga *et al* (2021), and Ren *et al*. (2019) reported similar findings.

Journal of Arid Agriculture. 2025, Vol. 26 (1): 61 - 71

Table 1: Socioeconomics characteristics of maize farmers in the study area

	Characteristic	Non-Adopters	Adopters	Pooled
Gender	Male	83.33	81	81.54
	Female	16.67	19	18.46
Age***	Under 30	6.67	39	31.54
	30 – 60	86.66	61.00	66.92
	Over 60	6.67	0	1.54
	Mean±	47.55±11.10	33.2±8.47	36.54±10.95
Formal education**	Nil	83.33	20	34.62
	Primary	15	36	31.15
	Secondary	1.67	41.5	32.31
	Tertiary	0	2.5	1.92
Marital status	Single	0	9.5	7.31
	Married	98.33	90.5	92.31
	Widow	1.67	0	0.39
Household size**	1 - 4	1.67	21	16.54
	5 - 8	30	60.5	53.46
	9 and above	68.33	18.5	30
	Mean ±std dev	12.85±5.414	7.845±3.114	9±4.312
Farm size	Mean ±std dev	1.767±0.812	1.987±2.549	1.936±2.27
Farm experience***	Mean±std dev	38.9±67.61	14.025±7.992	19.765±34.65
Extension	Yes	10	53	43.077
	No	90	47	56.923
Membership of	Yes	13.333	58.5	48.077
Association	No	86.667	41.5	51.923
Access to credit	Yes	1.667	21	16.538
	No	98.333	79	83.462
	Total	**100**	**100**	**100**

****, ** indicate significant level at 5% and 1%, respectively between adopters and non-adopters*

Effect of Climatic-Smart Maize Varieties on Maize Farmers' Productivity

Productivity between adopters and non-adopters

The productivity analysis compares the farm size and total output between adopters and non-adopters of CSMVs in Table 2. Farm size is notably smaller among adopters, with a mean of 0.9845 hectares compared to 2.3917 hectares for non-adopters. The difference in farm size (-1.4071 hectares) is statistically significant, as reflected by the t-value of -3.0745. This suggests that adopters of CSMVs tend to operate on smaller farms. A possible explanation is that farmers with smaller plots may be more motivated to adopt improved varieties to maximize productivity within their limited land resources, or they may be more inclined to try new technologies to increase efficiency in line with studies by Feder *et al.* (1985), Doss and Morris (2001), Marenya and Barrett (2007), Langyintuo and Mekuria, (2008) and Simtowe *et al.* (2011). However, this is not in line with Kadafur *et al.* (2020), which implies that the bigger the farm size, the greater the chance of adoption of improved maize varieties. Large farm holding enables farmers practice new technologies without risking his/her farm investment. Also, Kamara *et al.* (2018), reported that farmers with small farm sizes utilize less improved production information.

In terms of total output, adopters have a slightly higher average output of 2,467 kg per ha compared to 2,220 kg per ha for non-adopters. The difference in output, though relatively small (-247 kg), is statistically significant with a t-value of -2.1402. This indicates that despite having smaller farm sizes, adopters of CSMVs are achieving higher levels of productivity. The use of improved, stress-tolerant varieties likely plays a key role in enhancing yields even on smaller plots, which aligns to improve productivity through the adoption of such technologies. These findings suggest that adopting CSMVs has a positive effect on productivity, enabling farmers to achieve higher yields despite operating on smaller farm sizes. The results emphasize the potential for climate-smart varieties to enhance agricultural productivity, especially for smallholder farmers who need to optimize output on limited land. This reinforces the importance of promoting the adoption of these varieties to improve food security and agricultural efficiency.

Table 2: Average productivity between adopters and non-adopters

Variable	Mean adopter	Mean non- adopter	Pooled mean	Difference	T-B Hvalue
Farm size	0.9845	2.3917	0.9360	-1.4071	-3.0745
Total output	2467	2220	2410	-247	-2.1402

The Ordinary Least Squares (OLS) results for factors influencing total maize output among the farmers

The Ordinary Least Squares (OLS) regression results provide insight into the factors influencing total maize output among the farmers (Table 3). The model reveals that adoption of climate-smart maize varieties significantly increases output, with a coefficient of 552.3665 and a p-value of 0.003. This suggests that adopters produce 552.37 kg more maize, on average, compared to non-adopters. The result aligns with the study *by* Oladeji *et al.* (2023), which found that adoption of climate-smart maize varieties led to higher crop yields and increased farm income. This result also aligns with the earlier productivity analysis, emphasizing that adopting improved maize varieties boosts yields, reinforcing the importance of promoting such technologies for increasing agricultural productivity.

Gender has a negative and significant effect on total output, with male farmers producing 322.64 kg less maize than female farmers (p-value = 0.048). This finding could suggest that women are potentially better adopters or more efficient users of the available agricultural resources when it comes to maize production. The finding is consistent with the study by Li *et al.* (2023), which indicate women often exhibit strong resource management skills, contributing to better farm performance when given equal access. Given the significant role women play in agricultural labor, this highlights the need for gender-responsive policies that empower female farmers, ensuring they have equitable access to inputs, training, and resources to maximize their productivity.

Age has a positive and highly significant influence on maize output, with a coefficient of 38.61 (p-value = 0.000). This suggests that older farmers tend to produce more maize, potentially due to their greater experience and accumulated knowledge in farming. This is consistent with findings by Mnukwa *et al. (*2025), that experience plays a critical role in agricultural efficiency, as older farmers often possess better knowledge in sustainable practices, risk management, and resource optimization. However, the effect of household size is negative, though only marginally significant (p-value = 0.097). Larger households may face resource constraints or have competing demands on labor, which might limit their ability to maximize maize output.

Table 3: OLS Results for factors influencing total maize output among the farmers

Total output	Coef.	Std. Err.	T	P>t
Adoption of CSMV	552.4***	183.5	3.01	0.003
Gender	-322.6**	162.67	-1.98	0.048
Age	38.6***	10.89	3.55	0.000
Hhousehold size	-45.9*	27.576	-1.67	0.097
Farm size	115.04***	27.079	4.25	0.000
Education	128.6	92.498	1.39	0.166
Farming eexperience	.592	1.8628	0.32	0.751
Distance from seed source	50.2***	16.426	3.06	0.002
Cooperative	32.7	20.573	1.59	0.112
Extension contact	102.8	152.36	0.68	0.500
Credit	434.7***	167.89	2.59	0.010
Constant	-53.7	409.17	-0.13	0.896
Number of observations	260			
R-squared	0.2872			
Adj R-squared	0.2556			

*, **, *** *indicate significant level at 10%, 5% and 1%, respectively*

Farm size is a strong positive predictor of maize output, with a significant coefficient of 115.0481 (p-value = 0.000). Larger farm size naturally leads to higher production, indicating that expanding access to land could enhance overall productivity. Distance from seed source is also positively significant (coefficient = 50.21019, p-value = 0.002), which is somewhat counterintuitive but might suggest that farmers farther from seed sources put extra effort into ensuring they maximize the seeds they do obtain, perhaps through better management practices. Access to credit also has a significant positive effect on maize production (coefficient = 434.7744, p-value = 0.010). Farmers with access to credit likely have the financial means to invest in better inputs and farming practices, which enhances their productivity.

Effect of Climate-Smart Maize Varieties on Farmers' Food Security Status

Descriptive statistics of maize farmers' food security status

The food security status of the maize farmers is assessed using the Food Consumption Score (FCS), which categorizes households into three groups: poor, borderline, and acceptable food security (Table 4). The results reveal that a majority of the farmers (61.15%) fall into the borderline category, indicating that while these households are not experiencing severe food insecurity, their diets are inadequate, often lacking diversity and nutritional value. This suggests that many households are vulnerable to slipping into a more severe food insecurity status if any adverse shocks, such as poor harvests or rising food prices, were to occur.

About 21.92% of the households are classified as poor, which indicates a serious level of food insecurity. These households have low dietary diversity and are likely to consume limited quantities of staple foods, with little access to nutritious items such as proteins and vegetables. The high prevalence of food insecurity in this group highlights the need for targeted interventions to improve food access and nutritional intake for these vulnerable farmers. Only 16.92% of the households fall into the acceptable category, signifying that they have an adequate and diverse diet, consuming enough food groups to meet nutritional needs. This small proportion of food-secure households may be those who have adopted more resilient agricultural practices or have better access to resources, such as improved seed varieties, credit, or extension services, which allow them to enhance productivity and food availability.

Table 4: Food security status of maize farmers

FCS_Class	Range	Frequency	Percent
Poor **food consumption score**	FCS < 21	57	21.92
Borderline **food consumption score**	21.1 ≤ FCS ≤ 35	159	61.15
Acceptable **food consumption score**	FCS > 35	44	16.92
Total		260	100.00

Based on World Food Programme, (2008) criteria

Ordered logit regression results of the effect of climate-smart maize varieties on farmers' food security status

The ordered logit regression model was used to examine the effect of CSMVs on farmers' food security status, as measured by the Food Consumption Score (FCS). Adoption of climate-smart maize varieties is a significant and positive predictor of improved food security (coefficient = 1.249801, p-value = 0.002). This finding suggests that farmers who adopt these improved maize varieties are more likely to achieve better food security outcomes. The higher productivity associated with these varieties likely contributes to improved access to food and a more diverse diet, which enhances the household's food security status of some adopters of climate-smart maize varieties. According to Alam *et al*. (2024), adoption can result in increased yield, improved food security, higher income for farmers, and better production outcomes.

Extension contact also has a strong and significant positive effect on food security (coefficient = 1.248294, p-value = 0.000). Farmers who have regular contact with agricultural extension agents likely receive better information about farming practices, technology, and inputs, all of which can contribute to higher productivity and better food security outcomes. This finding underscores the importance of extension services in promoting food security through improved agricultural practices. This result is in line with Amaza *et al.* (2009) who indicated that access to extension agent is a significant factor affecting food security.

Education has a significant negative effect on food security (coefficient = -0.4152674, p-value = 0.043), which is counterintuitive. One possible explanation for this result could be that more educated individuals may diversify into non-farm activities, reducing their reliance on farming as a primary source of food and income. This shift may affect their food security status, especially if off-farm employment opportunities are inconsistent or insufficient. Oyinbo and Jonathan (2013) found that education was positive and significant at 1% level, implying that the higher the educational level, the more food secure the farmers and vice versa. This is because education enhances the productivity of the respondents and the respondents tend to be better informed and have better food management techniques that will ensure equitable all-round supply of food

Participation in cooperative societies also shows a negative relationship with food security (coefficient = -0.1027331, p-value = 0.024). While cooperative membership is often expected to improve access to resources and support networks, this result might suggest that some cooperatives are ineffective in improving members' food security. It could be a sign that these organizations need to focus more on ensuring that all members benefit equitably from the services they provide.

Table 5: Ordered Logit Regression Results for the effect of climate-smart maize varieties on farmers' food security status

Variable	Coef.	Std. Err.	Z	P>Z
Adoption of CSMV	1.24***	.395	3.16	0.002
Gender	.177	.353	0.50	0.616
Age	.041*	.023	1.75	0.081
Hhsize	-.086	.059	-1.46	0.144
Farm size	.017	.056	0.30	0.762
Education	-.415**	.205	-2.02	0.043
Farming experience	.001	.003	0.53	0.599
Distance from seed source	.008	.035	0.25	0.804
Cooperative	-.102**	.045	-2.25	0.024
ExtensionContact	1.25***	.335	3.73	0.000
Credit	-.148	.372	-0.40	0.690
Number of observation	260			
LR chi^2 (11)	28.44			
Pseudo R^2	0.305			
Log likelihood	-228.64			

, **, * indicate significant level at 10%, 5% and 1%, respectively*

Marginal Effect of ordered logit regression Results from the effect of climate-smart maize varieties on farmers' food security status

The marginal effects analysis revealed several significant determinants of food security among farmers cultivating climate-smart maize varieties. Notably, adoption of climate-smart maize varieties was associated with a 19.6% reduction in the likelihood of falling into the poor food security category and a 16.6% increase in the likelihood of attaining acceptable food security. This underscores the positive impact of adopting improved, climate-resilient technologies on household food security. This aligns with findings from Oyetunde-Usman and Shee (2023), who reported that the adoption of drought-tolerant maize varieties (a type of CSMV) positively influences household welfare and food security in Nigeria. Their study emphasizes that such adoption, especially when combined with practices like manure application, enhances food security outcomes

Similarly, access to agricultural extension services had a significant and positive influence. Farmers with extension contact were 19.6% less likely to be food insecure and 16.6% more likely to enjoy acceptable food security, indicating the critical role of advisory services in promoting good agricultural practices and improving welfare outcomes. The finding is consistent with the study by *Saadu et al.* (2024), which found that access to extension services significantly improves the adoption of climate-smart agricultural practices, thereby enhancing food security among smallholder farmers in North-Western Nigeria.

Table 6. Marginal Effects (dy/dx) Results for the effect of climate-smart maize varieties on farmers' food security status

Variable	**dy/dx** (Poor)	**dy/dx** (Borderline)	**dy/dx** (Acceptable)	**p-value**
Adoption	-0.1961**	0.0301	0.1660	0.001
Gender	-0.0278	0.0043	0.0236	0.617
Age	-0.0065	0.0010	0.0055	0.079
Hhsize	0.0136	-0.0021	-0.0115	0.141
Farm_size	-0.0027	0.0004	0.0023	0.762
Education	0.0652**	-0.0100	-0.0552**	0.042
FarmingExperience	-0.0003	0.0000	0.0003	0.598
DistanceFromSeedSource	-0.0014	0.0002	0.0012	0.804
Cooperative	0.0161**	-0.0025	-0.0136**	0.022
ExtensionContact2	-0.1959***	0.0301	0.1658	0.000
Credit	0.0233	-0.0036	-0.0197	0.691

, **, * indicate significant level at 10%, 5% and 1%, respectively*

Interestingly, education level showed a counterintuitive effect: it was associated with a 6.5% increase in the likelihood of poor food security and a 5.5% decrease in acceptable food security. This suggests that higher education may not directly translate into better food security, possibly because more educated farmers are engaged in off-farm employment or may not focus on farming as their primary livelihood. This contrasts with the findings of the study by Oke *et al*. (2023), which indicated that higher educational qualifications positively influence food security among catfish farming households. The discrepancy might be due to differences in the nature of farming activities or the possibility that more educated individuals engage less in farming, affecting their food security status.

Furthermore, membership in cooperatives was linked to a 1.6% increase in poor food security and a 1.36% decrease in acceptable food security. While cooperatives are generally expected to improve outcomes through collective action, this result may reflect that more vulnerable farmers tend to join cooperatives in search of support, or that some cooperatives are not functioning effectively to improve members' food security.

CONCLUSION AND RECOMMENDATIONS

There was high level of adoption of the CSMV among the farmers and that could be attributed the availability of information through extension services, access to credit, and the influence of education and younger farmers in the region. The result reveals that adoption of climate-smart maize varieties significantly increases output, with a coefficient of 552.37 and a p-value of 0.003. Gender was negative and significant on total output and could suggest that women are potentially better adopters or more efficient users of the available agricultural resources when it comes to maize production. The results reveal that a majority of the farmers (61.15%) fall into the borderline category, indicating that while these households are not experiencing severe food insecurity, their diets are inadequate, often lacking diversity and nutritional value. Adoption of climate-smart maize varieties was significant and positive predictor of improved food security (coefficient = 1.249801), suggesting that farmers who adopt these improved maize varieties are more likely to achieve better food security outcomes. It is recommended that agricultural institutions and non-governmental organizations (NGOs) should focus on promoting adoption of improve maize varieties, ensuring women and older farmers are adequately supported, and provide access to credit and land to boost agricultural efficiency in order to improve productivity.

REFERENCES

Adesina, O. S., and Loboguerrero, A. M. (2021) Enhancing food security through climate-smart agriculture and sustainable policy in Nigeria. In: Leal Filho, W.; Luetz, J.; Ayal, D. (eds) Handbook of climate change management. Cham (Switzerland): *Springer Nature*, 17p. ISBN: 978-3-030-22759- https://doi.org/10.1007/978-3-030-22759-3_338-1

Alam, M. J., Sarma, P. K., Begum, I. A., Connor, J., Crase, L., Sayem, S. M., et al. (2024). Agricultural extension service, technology adoption, and production risk nexus: evidence from Bangladesh. *Heliyon*, 10(14), e34226. doi: https://.org.10.1016/j.heliyon.2024.e34226

Alhassan, Y. J., Sanchi, I. D., Ikpe, E., and Norbert, S. (2022) Assessment of climate smart agricultural practices (CSAP) adopted by crop farmers in adapting to climate change and environmental issues in Zamfara State, Nigeria. *Discoveries in Agriculture and Food Sciences,* 10(5), 58-70. https://doi.org/10.14738/dafs.105.14347

Amaza, P., Abdoulaye, T., Kwaghe, P., and Tegbaru, A. (2009). Changes in Household Food Security and Poverty Status in PROSAB Area of Southern Borno State, Nigeria Promoting Sustainable Agriculture in Borno State (PROSAB). International Institute of Tropical Agriculture, Ibadan, Nigeria. 40 pp. ISBN 978-131-341-2

Ani, K., Anyika, V., and Mutambara, E. (2022). The impact of climate change on food and human security in Nigeria. *International Journal of Climate Change Strategies and Management*, 14. 148-167. https://doi.org/10.1108/IJCCSM-11-2020-0119 .

Babuga, U. S., Garba, A., and Dandawo, H. (2021). Socio-economic characteristics of maize farmers in Bauchi State, Nigeria. *African Scholar Publications and Research International*, 19(2), 319-324. ISSN: 2010-1086

Chete, O. (2021). Factors influencing adoption of improved maize seed varieties among smallholder farmers in Kaduna State, Nigeria. *Journal of Agricultural Extension and Rural Development,* 13(1), 107-114. http://dx.doi.org/10.5897/JAERD2019.1032.

Doss, C. R., and Morris, M. L. (2001). How does gender affect the adoption of agricultural innovations? The case of improved maize technology in Ghana. *Agricultural Economics,* 25(1), 27–39. https://doi.org/10.1111/j.1574-0862.2001.tb00233.x

FAO, (2018). Climate-smart agriculture training manual − A reference manual for agricultural

FAOSTAT, (2022). Maize production statistics in Africa. Food and Agriculture Organization of the United Nations. https://www.fao.org/faostat/en/#data

Feder, G., Just, R. E., and Zilberman, D. (1985). Adoption of agricultural innovations in developing countries: A survey. *Economic Development and Cultural Change*, 33(2), 255–298. https://doi.org/10.1086/451461

Kadafur, I. M., Idrisa, Y. L. and Shehu, A. (2020). Adoption of improved maize varieties in northern guinea savannah of Borno State, Nigeria. *Journal of Agricultural Extension*, 24 (1), 34-41. ISSN(e): 24086851; ISSN(Print); 1119944X

Kamara, A. Y., Oyinbo, O., Manda, J., Kamara, A., Idowu, E. O., and Mbavai, J. J. (2023). Beyond average: are the yield and income impacts of adopting drought-tolerant maize varieties heterogeneous? *Climate and Development*,
DOI: https://10.1080/17565529.2023.2178840 .

Kamara, A. Y., Kamai, N., Kanampiu, F., Kamsang, L., and Kamara, A.Y. (2018). Gender analysis of soybean adoption and impact. IITA, Ibadan, Nigeria. 57pp. ISBN 978-978-131-353-0.

Langner, J. A., Zanon, A. J., Streck, N. A., Reiniger, L. R. S., Kaufmann, M. P., and Alves, A. F. (2019). Maize: Key agricultural crop in food security and sovereignty in a future with water scarcity. *Revista Brasileira de Engenharia Agricola e Ambiental*, 23(9), 648–654. https://doi.org/10.1590/1807-1929/agriambi.v23n9p648-654

Langyintuo, A. S., and Mekuria, M. (2008). Assessing the influence of neighborhood effects on the adoption of improved agricultural technologies in developing agriculture. *Agricultural Economics,* 38(3), 271–284. https://doi.org/10.1111/j.1574-0862.2008.00294.x

Li, J., Ma, W., and Zhu, H. (2023). A systematic literature review of factors influencing the adoption of climate-smart agricultural practices. *Mitigation and Adaptation Strategies for Global Change, 29*(2). https://doi.org/10.1007/s11027-023-10098-x

Marenya, P. P., and Barrett, C. B. (2007). Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. *Food Policy*, 32(4), 515–536. https://doi.org/10.1016/j.foodpol.2006.10.002

Mnukwa, M. L., Mdoda, L., and Mudhara, M. (2025). Assessing the adoption and impact of climate-smart agricultural practices on smallholder maize farmers' livelihoods in Sub-Saharan Africa: A systematic review. *Frontiers in Sustainable Food Systems, 9*. https://doi.org/10.3389/fsufs.2025.1543805.

Oderinde, F. O., Akano, O. I., Adesina, F. A., and Omotayo, A. O. (2022). Trends in climate, socioeconomic indices and food security in Nigeria: Current realities and challenges ahead Research. *Frontiers in Sustainable Food Systems*. Open Access. dol: https://doi.org.10.3389/fsufs.2022.940858

Oke, F. O., Kareem, I. A., Bamigbade-Sanni, S. A., Akerele, D., and Oose, M. O. (2023). Impact assessment of cooperatives on food security among catfish farming households in Oyo State, Nigeria. *African Journal of Food, Agriculture, Nutrition and Development,* 23(4). http://ajfand.net/AJFAND/copyrightstatement.html.

Oladeji, O., Kolade, O., Fasakin, I. J., Sowunmi, F., and Abdoulaye, T. (2023). Factors influencing the adoption intensity of climate-smart maize varieties among rural farming households in Southern Guinea Savannah of Nigeria. *FARA Research Report,* 7(35), 441-452. https://doi.org/10.59101/frr072

Opeyemi, G., Opaluwa, H.I., Adeleke, A.O., Ugbaje, B. (2021). Effect of climate smart agricultural practices on farming households′ food security status in Ika north east Local Government Area, Delta State, Nigeria. *Journal of Agriculture and Food Sciences*, 19(2), 30-42. http://dx.doi.org/10.4314/jafs.v19i2.4

Oyetunde-Usman, Z., and Shee, A. (2023). Adoption of drought-tolerant maize varieties and interrelated climate smart agricultural practices in Nigeria. *Agric and Food Secure,* 12, 43 (2023). https://doi.org/10.1186/s40066-023-00429-1

Oyinbo, O., and Jonathan, J. (2013). Socioeconomic analysis of the food security status of maize farming households in giwa local government area of Kaduna State, Nigeria. *Journal of Management and Science*, 3(4), 458-462. https://doi.org/10.26524/jms.2013.58

Oyinbo, O., Mbavai, J. J., Shitu, M. B., Kamara, A. Y., Abdoulaye, T., and Ugbabe, O. O. (2019). Sustaining the beneficial effects of maize production in Nigeria: Does adoption of short season maize varieties matter? *Experimental Agriculture*, 55(6), 885-897. https://doi.org/DOI: https://doi.org/10.1017/S0014479718000467

Ren, C., Liu, S., Grinsven, H., Reis, S., Jin, S., and Liu, H., and Gu, B. (2019). The impact of farm size on agricultural sustainability. *Journal of Cleaner Production*, 220. https://doi.org.10.1016/j.jclepro.2019.02.151 .

Saadu, B., Ibrahim, H. Y., Nazifi, B., and Mudashiru, A. (2024). Adoption of climate-smart agricultural practices and its impact on smallholder farming households in some rural areas of North-Western Nigeria. *Agricultura Tropica et Subtropica,* 57(OV), 23–34. https://doi.org/10.2478/ats-2024-0003

SDG, (2022). Sustainable development goal SDG (2022). 64pp

Simtowe, F., Asfaw, S., Alene, A., Shiferaw, B., Abate, T., and Silim, S. (2011). Determinants of agricultural technology adoption: The case of improved pigeonpea varieties in Tanzania. *Quarterly Journal of International Agriculture*, 50(4), 325–345. http://dx.doi.org/10.22004/ag.econ.155537

Tofa, A. I., Kamara, A. Y., Babaji, B. A., Akinseye, F. M., and Beeley, J. F. (2021). Assessing the use of a drought-tolerant variety as adaptation strategy for maize production under climate change in the savannas of Nigeria. *Scientific Reports* 11, 8983. https://doi.org/10.5539/jas.v8n7p153

Usman, H. A., Saminu, Z., Egwuma, H., Abdoulaye, T., Oyekunle, M., Yisa, F., Oladimeji, Y. U., Magaji, B. D., Hussaini, A. S., and Bagya, B. S. (2022). Analysis of drought tolerant maize varieties (DTMVS) production in drought-prone savanna agroecologies of Nigeria: a gender perspective. *Nigerian Journal of Rural Economy and Society,* 8(1and2), 61-76.

Villacis, A., Mayorga, J., and Mishra, A. (2022). Experience-based food insecurity and agricultural productivity in Nigeria. *Food Policy*, 113. 1-39pp. http://doi.org.102286.10.1016/j.foodpol.2022.102286 .

Wossen T., Abdoulaye T., Alene A., Feleke S., Menkir, A., and Manyong V. (2017). Measuring the impacts of adaptation strategies to drought stress: The case of drought tolerant maize varieties. *Journal of Environmental Management*, 203(1), 106–113. https://doi.org/10.1016/j.jenvman.2017.06.058

Wossen, T., Menkir, A., Alene, A., Abdoulaye, T., Ajala, S., Badu-Apraku, B., Gedil, M., Mengesha, W., and Meseka S. (2023). Drivers of transformation of the maize sector in Nigeria. *Global Food Security*, https://doi.org/10.1016/j.gfs.2023.100713

Wudil, A. H., Ali, A., Aderinoye-Abdulwahab, S., Raza, H. A., Mahmoud, H. Z., and Sannoh, A. B. (2023). Determinants of food security in Nigeria: Empirical evidence from beneficiaries and non-beneficiaries rice farmers of the Kano River Irrigation Project. *Front. Sustain. Food Syst. Sec. Land, Livelihoods and Food Security*. doi: https://.org.10.3389/fsufs.2023.999932 .