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DETERMINANTS OF CLIMATE SMART AGRICULTURAL PRACTICES ADOPTION AMONG MAIZE FARMERS IN OYO STATE, NIGERIA

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Abstract

This study examined the adoption of Climate Smart Agricultural Practices (CSAPs) among maize farmers in Oyo State, Nigeria. Specifically, it described the socio-economic characteristics of farmers, identified the major climate-smart practices adopted, analyzed the determinants of adoption intensity, and examined the constraints limiting adoption. A multistage sampling procedure was used to select 262 maize farmers across selected farming communities in the state. Primary data were collected through structured questionnaires and analyzed using descriptive statistics, adoption intensity index, multinomial logit regression model, and a five-point Likert scale. The findings showed that the mean age of farmers was 46 years, while most respondents were male, married, and moderately educated. Intercropping, crop rotation, and the use of improved maize varieties were the most commonly adopted practices, whereas agroforestry, water harvesting, and soil testing recorded relatively low adoption levels. The adoption intensity index indicated that most farmers fell within the moderate adoption category. Results from the multinomial logit regression revealed that education, farm size, cooperative membership, access to extension services, climate information, improved inputs, and credit significantly influenced the likelihood of moderate and high adoption of CSAPs. Major constraints limiting adoption included inadequate access to credit, high input costs, weak extension services, and poor access to climate information. The study concludes that CSAPs can enhance sustainable maize production and resilience to climate variability, and recommends improved extension delivery, affordable credit, subsidized inputs, stronger farmer cooperatives, and wider access to climate information services.

Keywords: *Climate-smart Agriculture, Adoption Intensity, Maize Farmers, Multinomial Logit, Climate Variability, Oyo State, Nigeria.*

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1. INTRODUCTION

Background to the Study

Agriculture in sub-Saharan Africa remains highly vulnerable to climate variability due to its heavy reliance on rain-fed production systems. In Nigeria, the sector plays a critical role in food security and rural livelihoods but is increasingly affected by erratic rainfall, rising temperatures and extreme weather events, which undermine farm productivity and increase livelihood risks (National Bureau of Statistics, 2022; Nigerian Meteorological Agency, 2020). Maize is one of the major staple crops in Nigeria, serving both household consumption and industrial purposes. However, its production is particularly sensitive to climate fluctuations, making maize farmers highly exposed to yield instability and income uncertainty. Recent evidence shows that climate variability continues to negatively affect crop productivity and farm income among smallholder farmers in Nigeria and across sub-Saharan Africa (Saadu *et al*., 2024; Agyekum *et al*., 2024).

Climate-Smart Agriculture (CSA) has been promoted as a viable approach to address these challenges by enhancing productivity, strengthening resilience and promoting sustainable resource use. CSA practices such as crop diversification, improved soil fertility management, conservation tillage and water management have been shown to improve farm performance under changing climatic conditions (Consultative Group on International Agricultural Research (CGIAR), 2024). Despite these benefits, the adoption of CSA practices among smallholder farmers remains uneven. While low-cost practices are relatively widespread, the uptake of more knowledge-intensive and capital-demanding practices is still limited. Empirical studies consistently show that adoption decisions are shaped by factors such as education, farm size, access to extension services, credit availability and institutional support (Wossen *et al*., 2017). Persistent constraints including high input costs, limited access to information and weak extension systems continue to restrict broader adoption.

Oyo State provides an appropriate setting for examining CSA adoption due to its diverse agro-ecological conditions and prominence in maize production. However, existing studies often provide generalized evidence across regions, with limited state-level analysis that captures local variations in adoption behavior. In addition, insufficient attention has been given to understanding how different levels of adoption are influenced by socio-economic and institutional factors. Against this background, this study examines the determinants of climate-smart agricultural practices adoption among maize farmers in Oyo State, Nigeria, with a view to providing empirical and context-specific evidence that can inform targeted policy and extension interventions.

Statement of Research Problem

Climate variability continues to pose significant challenges to agricultural production in Nigeria, particularly among smallholder farmers who depend largely on rain-fed systems. In response, climate-smart agricultural (CSA) practices have been widely promoted as a pathway to enhance resilience, sustain productivity and improve farm income. While there is growing evidence that CSA practices can improve agricultural outcomes, their adoption among farmers remains inconsistent and uneven across regions (Saadu *et al*., 2024). In Nigeria, existing studies show that many farmers adopt relatively simple practices such as intercropping and crop rotation, while more knowledge-intensive and capital-demanding practices such as soil testing, agroforestry and water management technologies remain poorly adopted (Wossen *et al*., 2017; CGIAR, 2024). This uneven adoption pattern suggests the presence of underlying socio-economic, institutional and farm-level constraints that are not yet fully understood, particularly at the local level.

Although several empirical studies have examined the determinants of CSA adoption in Nigeria, much of the existing evidence is either regionally aggregated or focused on binary adoption decisions (adopter versus non-adopter). Such approaches often fail to capture the varying intensity of adoption among farmers, thereby limiting a deeper understanding of how different factors influence low, moderate and high levels of adoption. This represents an important gap, as policy interventions require better insights into adoption behavior rather than broad generalizations. Furthermore, there is limited state-specific evidence on CSA adoption dynamics in Oyo State, despite its importance as a major maize-producing area with diverse agro-ecological conditions. Differences in access to extension services, credit facilities and agricultural inputs across communities suggest that adoption decisions may vary significantly within the state.

Therefore, there is a need for a detailed empirical investigation that not only identifies the determinants of CSA adoption but also examines how these factors influence different levels of adoption among maize farmers.

Aim and Objectives of the Study

The aim of the study was to examine the determinants of the adoption of climate-smart agricultural (CSA) practices among maize farmers in Oyo State, Nigeria.

The specific objectives are to:

i. describe the socio-economic characteristics of maize farmers in Oyo State,

ii. identify and categorize climate-smart agricultural practices adopted by maize farmers in Oyo State,

iii. analyze the determinants of the adoption of CSA practices among maize farmers in Oyo State, and

iv. examine the constraints to adoption of climate-smart agricultural practices among maize farmers in Oyo State.

Justification of the Study

Strengthening the resilience of smallholder farmers to climate variability has become a key priority for agricultural policy in Nigeria. Climate-smart agricultural (CSA) practices are widely recognized as a practical pathway for achieving this goal by improving productivity while reducing vulnerability to climate shocks. However, the uneven adoption of these practices among farmers limits their potential impact, making it essential to understand the factors that drive or constrain uptake at the local level (Saadu *et al*., 2024).

This study is particularly important for Oyo State, a major maize-producing region where agriculture supports a large share of rural livelihoods. Despite ongoing efforts by government agencies and development partners to promote improved agricultural practices, adoption remains inconsistent across communities. Without clear empirical evidence on the determinants of adoption and the factors influencing different levels of uptake, policy interventions risk being poorly targeted and less effective.

The findings of this study will provide evidence-based insights to guide agricultural policy and program design. Specifically, identifying the roles of education, extension services, credit access and farm characteristics in shaping adoption decisions will help policymakers design targeted support mechanisms. For instance, improving access to extension services and climate information can enhance farmers' awareness and technical capacity, while expanding credit schemes can enable investment in more capital-intensive CSA practices.

In addition, by categorizing farmers into different adoption levels, the study moves beyond the conventional adopter versus non-adopter framework and provides a clear understanding of adoption behavior. This is critical for designing differentiated policy interventions that address the specific needs of low, moderate and high adopters in the study area.

2. METHODOLOGY

The Study Area

The study was conducted in Oyo State, Nigeria. The State is in the north-western part of South-West Nigeria. It shares borders with Ogun State to the south, Osun State to the east, Kwara State to the north, and the Republic of Benin to the west. The state is located between latitudes 7°03′ and 9°12′ North and longitudes 2°47′ and 4°23′ East. Oyo covers about 28,454 square kilometers and had a population of 5,591,589 in 2006 (National Population Commission (NPC), 2006). By 2024, the population was projected to reach about 9.2 million, growing at 2.8% per year (National Bureau of Statistics (NBS), 2022). Oyo has a tropical wet-and-dry climate, with yearly rainfall between 1,200 mm and 1,500 mm and average temperatures from 24°C to 34°C (NiMet, 2020). Most rural residents depend on agriculture for their livelihoods. Main crops include maize, cassava, yam, rice, sorghum, millet, vegetables, cocoa, and cashew. Livestock such as poultry, goats, sheep, and cattle are also common. The state's varied agro-ecological zones make it a good place to study different climate-smart farming methods.

Sampling Procedure and Sample Size Determination

A multistage sampling technique was employed for the selection of respondents for this study. In the first stage, the agricultural structure of Oyo state was examined and stratified based on the Agricultural Development Programme (ADP) zoning system. The state is organized into four agricultural zones: Ibadan/Ibarapa, Ogbomosho, Oyo and Saki zones with fourteen (14), five (5), five (5) and nine (9) LGAs respectively. This stratification provides a clear basis for capturing variation in agro-ecological conditions and farming systems across the study area. In the second stage, all agricultural zones in the state were purposively selected. This is to ensure that maize-producing environments across the state were fully represented. The third stage involved selection of Local Government Areas (LGAs) within each zone using Probability

Proportionate to Size (PPS) sampling. This resulted in a total of thirteen (13) LGAs for the study. In the fourth stage, three farming communities were randomly selected from each of the selected LGAs, giving a total of thirty-nine (39) farming communities across the study area. In the final stage, farming households were selected from each community using probability proportionate to size (PPS) sampling based on the number of farming households in each community. This ensured that communities with larger farming populations had a higher representation in the sample.

Sample Size Determination

The sample size for the study was determined using the Taro Yamane (1967) formula for finite populations:

$$n = \frac{N}{1 + N(e)^2} \tag{1}$$

Where:

n = Required sample size,

N = Population of farming households in the selected communities,

e = level of precision (0.05).

Using this approach, a total sample size of 262 farming households was obtained.

Methods of data collection

Primary data used were elicited using structured research questionnaires administered to farmers across selected communities in Oyo State Nigeria. Data were collected through face-to-face interviews, which helped ensure clarity of responses and reduced non-response bias, especially for farmers with limited literacy. Trained enumerators familiar with the local languages assisted with administering the questionnaires and verifying responses, where needed.

Method of data analysis

In order to analyze the data collected in line with the stated objectives, this study adopted both descriptive and inferential statistics. Descriptive statistics such as mean, frequency distribution and percentages, adoption index as well as likert scale rating technique while the inferential statistics include multinomial logit regression model.

Reliability and Validity of the Research Instrument

The questionnaire used for data collection was subjected to both validity and reliability check to ensure the accuracy and consistency of the data obtained. Content validity was established through expert review by specialists in agricultural economics and extension, who assessed the relevance and clarity of the instrument in relation to the study objectives. To test reliability, a pilot survey was conducted in a community outside the study area but with similar socio-economic characteristics. Data obtained from the pilot study were subjected to internal consistency testing using Cronbach's Alpha coefficient. The results of the reliability analysis showed that the Likert-scale items used to measure constraints to adoption yielded a Cronbach's Alpha value of 0.81 and items used in constructing perception and adoption-related indices produced an Alpha value of 0.78, indicating good internal consistency and falls within the acceptable threshold for social science research.

Model Specification

Descriptive statistics

Objectives (i) and (iv) which are to describe the socio-economic characteristics of maize farmers and to examine the constraints to adoption of climate-smart agricultural practices among maize farmers in Oyo State Nigeria, were achieved using descriptive statistics such as mean, frequency distribution, percentages and likert scale rating.

Adoption Index

To identify and categorize climate-smart agricultural practices adopted by maize farmers in Oyo State, adoption index was employed.

The adoption index is computed as:

$$AI_i = \frac{P_i}{T} \tag{2}$$

Where:

P_i = Number of CSAPs adopted by household i,

T= Total number of CSAPs considered,

AI_i= Adoption Index for household i,

Given that $0 \leq AI_i \leq 1$, a higher value indicates a higher level of adoption.

Households were then categorized into adoption groups such as:

i. Low adoption: $AI < 0.33$

ii. Moderate adoption: $0.33 \leq AI < 0.67$

iii. High adoption: $AI \geq 0.67$

Multinomial Logit Regression Model

Multinomial logit model was used to analyze the determinants of adoption of CSA practices among maize farmers in Oyo State. The multinomial logit model for alternative j (j = 0, 1, 2, 3) relative to reference category is expressed in equation 3.

$$ln\left(\frac{P_{ij}}{P_{i1}}\right) = \beta_{jo} + \beta_{j1}X_i + \epsilon_{ij} \tag{3}$$

Where;

P_{ij} = Probability household i chooses CSAP j,

X_i = Vector of socio-economic variables, and

β_j = Coefficient vector for alternative j.

The dependent variables are:

0 = No Adoption (reference category)

1 = Low Adoption

2 = Moderate Adoption

3 = High Adoption

The independent variables for the model are:

X_1 = Age (Years),

X_2 = Education (Years of schooling),

X_3 = Household Size (Number),

X_4 = Farm Income (Naira),

X_5 = Farm Size (Ha),

X_6 = Farming Experience (Years),

X_7 = Gender (Male = 1, Female = 0),

X_8 = Cooperative membership (Yes = 1, No = 0),

X_9 = Access to Credit (Amount received),

X_{10} = Access to Demonstration Plot (Yes = 1, No = 0),

X_{11} = Access to Extension (Number of visits),

X_{12} = Access to Input/Improved seeds (Yes = 1, No = 0),

X_{13} = Access to Climate Information (Yes = 1, No = 0),

X_{14} = Livestock ownership (Number), and

X_{15} = Distance to Nearest Market (Km).

3. RESULTS AND DISCUSSION

Socio-economic Characteristics of Maize Farmers in Oyo State

The socio-economic characteristics of maize farmers in Oyo State presented in Table 1 indicates a predominantly middle-aged farming population, with a mean age of 44 years and a concentration within the economically active age group (41–50 years). This pattern is consistent with findings from climate-smart agriculture studies which show that middle-aged farmers are typically more active in production and more responsive to agricultural innovation due to a balance between experience and labour capacity (Deressa *et al*., 2009). The gender distribution shows a strong male dominance (75.6%), reflecting persistent gender inequalities in access to productive agricultural resources such as land, credit and extension services. Similar gender gaps in agricultural technology adoption have been documented across Sub-Saharan Africa, where male-headed households tend to have higher adoption rates due to better access to assets and institutional support (Ragasa *et al*., 2014). The majority of respondents were married (77.9%) with an average household size of six persons. Larger household sizes often provide family labour advantages, but they can also increase consumption pressure on farm income. Educational attainment was relatively moderate, with about 63.7% of farmers having at least secondary education. Education is widely recognized as a key determinant of technology adoption because it enhances farmers' ability to interpret extension information and respond to climate variability. Empirical evidence confirms that education significantly increases the likelihood of adopting climate-smart agricultural practices (Wossen *et al*., 2017).

Farming remains the dominant occupation (78.6%), with an average farming experience of 18 years, suggesting that farmers possess substantial experiential knowledge of local production systems. However, the mean farm size of 1.76 hectares confirms the dominance of smallholder agriculture, which is a structural characteristic of Nigerian agriculture and much of Sub-Saharan Africa (FAO, 2023). Income levels remain relatively low, with most farmers earning below ₦300,000 annually. This reflects constrained profitability and high vulnerability to shocks, a situation widely documented among smallholder farmers in developing economies, particularly under climate stress conditions (Wossen *et al*., 2017). Institutional access shows that 54.2% of farmers had access to extension services, only 42.4% had access to credit. This gap is critical because access to information alone is often insufficient without corresponding financial capacity to invest in improved technologies. Similar finding was reported by Ragasa *et al*. (2014), who emphasize that credit and extension jointly determine adoption intensity in African agriculture.

Table 1: Socio-economic Characteristics of Maize Farmers in Oyo State

Variable	Frequency	Percentage	Mean ± Std. Dev.
Age (years)			
20–30	28	10.69	
31–40	66	25.19	
41–50	95	36.26	
51–60	53	20.23	**44 ± 10.2**
Above 60	20	7.63	
Gender			

Variable	Frequency	Percentage	Mean ± Std. Dev.
Male	198	75.57	
Female	64	24.43	
Marital Status			
Single	26	9.92	
Married	204	77.86	
Divorced/Separated	14	5.34	
Widowed	18	6.87	
Household Size			
1–3	31	11.83	
4–6	108	41.22	
7–9	83	31.68	**6 ± 2.5**
≥10	40	15.27	
Education Level			
No formal education	36	13.74	
Primary	59	22.52	
Secondary	102	38.93	**9 ± 4.6 years**
Tertiary	65	24.81	
Farming Experience (yrs)			
1–10	49	18.70	
11–20	101	38.55	
21–30	77	29.39	**18 ± 9.1**
Above 30	35	13.36	
Farm Size (ha)			
<1.0	62	23.66	
1.0–2.0	114	43.51	
2.1–3.0	56	21.37	**1.76 ± 1.08**
>3.0	30	11.45	
Annual Farm Income (₦)			
<100,000	48	18.32	
100,000–300,000	103	39.31	
300,001–500,000	69	26.34	**₦284,700 ± 198,500**
>500,000	42	16.03	
Extension Access			
Yes	142	54.20	
No	120	45.80	
Credit Access			
Yes	111	42.37	
No	151	57.63	

Source: Data Analysis, (2026).

Types and Categories of Climate Smart Agricultural Practices Adopted by Maize Farmers in Oyo State

The distribution of climate-smart agricultural practices among maize farmers in Oyo State as presented in Table 2 revealed that at the upper end of the distribution, intercropping (0.80), crop rotation (0.75) and improved maize varieties (0.72) fall within the high adoption category (AI $\geq$ 0.67). These practices are widely adopted because they are relatively low-cost, familiar within existing farming systems and do not require complex technical input. This finding aligns with the assertion that farmers tend to first adopt agronomic diversification and improved seed technologies before transitioning to more complex innovations (Kassie *et al*., 2015).

A second group of practices including organic manure application (0.67), efficient fertilizer use (0.64), mulching (0.57), conservation tillage (0.53), cover cropping (0.46) and agroforestry practices (0.35) fall within the moderate adoption range. These practices require more behavioural adjustment and, in some cases, additional labour or knowledge inputs. Their intermediate uptake suggests a transitional stage of adoption where farmers combine traditional practices with gradually improving soil fertility and moisture conservation strategies. This finding is consistent with Deressa *et al*. (2009), who emphasize that adoption intensity tends to decline as practices become more capital- or knowledge-intensive.

At the lower end of the distribution, water harvesting techniques (0.32) and soil testing/nutrient management (0.27) fall within the low adoption category (AI < 0.33). These practices are technically demanding and often require external support such as extension services, institutional infrastructure, or access to financial resources. Similar empirical evidence from Ragasa *et al*. (2014) shows that knowledge-intensive agricultural technologies tend to face slower adoption due to weak extension systems and credit constraints in rural farming communities.

Table 2: Types and Categories of Climate Smart Agricultural Practices Adopted by Maize Farmers in Oyo State

Climate-Smart Practice	Freq.	%	Adoption Index	Adoption Category
Intercropping	210	80.15	0.80	High
Crop rotation	196	74.81	0.75	High
Use of improved maize varieties	188	71.76	0.72	High
Organic manure application	174	66.41	0.67	Moderate

Climate-Smart Practice	Freq.	%	Adoption Index	Adoption Category
Inorganic fertilizer	168	64.12	0.64	Moderate
Mulching	149	56.87	0.57	Moderate
Conservation tillage/minimum tillage	138	52.67	0.53	Moderate
Cover cropping	121	46.18	0.46	Moderate
Agroforestry practices	92	35.11	0.35	Moderate
Water harvesting techniques	84	32.06	0.32	Low
Soil testing and nutrient management	71	27.10	0.27	Low

Source: Data Analysis, (2026).

Determinants of Adoption of Climate Smart Agricultural Practices among Maize Farmers in Oyo State

The multinomial logit results presented in Table 3 shows the determinants of farmers' movement across different levels of climate-smart agricultural practice (CSAP) adoption in Oyo State, using non-adoption as the base category. The model is statistically significant as indicated by the Likelihood Ratio (LR $\chi^2 = 186.52$, $p < 0.01$) with a pseudo-R^2 of 0.326, indicating a good explanatory power for adoption behaviour across the three adoption intensities. Across all adoption categories, a clear gradient of influence emerges, with different sets of factors becoming more important as farmers move from low to high adoption levels.

The result revealed that age consistently shows a negative relationship with adoption intensity, although it is only statistically significant at the high adoption level. The result implies that older farmers are less likely to engage in intensive CSA adoption compared to younger farmers. This pattern reflects reduced risk tolerance and lower responsiveness to innovation among older farming populations, consistent with findings from Suri (2011) and Wossen *et al*. (2017), who noted that younger farmers tend to be more adaptive to new agricultural technologies. Education has a positive and statistically significant effect across all adoption levels, and its magnitude increases progressively from low to high adoption. This suggests that education not only facilitates initial awareness but also strengthens farmers' capacity to adopt multiple and more complex CSAPs. Educated farmers are better able to process technical information and respond to climate-related advisory services, a result consistent with Kassie *et al*. (2015), who found education to be a consistent driver of agricultural technology adoption in sub-Saharan Africa.

Also, household size shows a weak but positive influence on adoption, becoming slightly more relevant at moderate and high levels. This indicates that larger households may provide additional labour resources needed to implement labour-demanding climate-smart practices. Farm income and farm size both exhibited strong and statistically significant positive effects, particularly at the moderate and high adoption levels. The increasing magnitude of these variables suggests that wealthier and larger-scale farmers are more capable of scaling up adoption. This reflects liquidity advantages and economies of scale associated with larger farm operations. Farming experience also shows a positive and significant influence across all categories, indicating that accumulated knowledge improves farmers' ability to experiment with and adopt climate-smart practices over time. Gender results indicated that male farmers are more likely to adopt CSAPs, particularly at moderate and high adoption levels. This reflects gender disparities in access to productive resources, credit and information, which continue to shape agricultural technology adoption outcomes in rural Nigeria.

Institutional variables emerge as some of the strongest determinants of adoption with cooperative membership significantly increasing the likelihood of adoption across all levels, showing stronger effects at moderate and high adoption stages. This suggests that farmer organizations play an important role in facilitating knowledge diffusion, input access and collective decision-making. Access to credit is also positively significant and increases in magnitude with adoption intensity. This confirms that financial constraints remain a critical barrier to scaling up CSAP adoption, particularly for capital-intensive practices. Extension access shows a strong and highly significant positive effect across all adoption levels, with the strongest impact observed at high adoption. Similarly, access to demonstration plots significantly enhances adoption probability, particularly at higher adoption levels, highlighting the importance of experiential learning platforms in reducing uncertainty and improving farmer confidence in new practices. Access to improved inputs also significantly increases adoption likelihood, reflecting the necessity of physical input availability for effective CSAP implementation.

Furthermore, access to climate information emerges as the most influential determinant across all adoption categories, with the strongest effect observed in high adoption (RRR = 2.014). This indicates that timely climate information significantly increases farmers' likelihood of adopting multiple climate-smart practices simultaneously. This finding strongly supports Wossen *et al*. (2017), who emphasized that climate information is a key behavioural driver of adaptation decisions among smallholder farmers. Livestock ownership has a weak but positive effect at higher adoption levels, suggesting some level of integration between crop and livestock systems that may support resource recycling in climate-smart farming. Distance to market shows a consistently negative and statistically significant effect, particularly at moderate and high adoption levels. This indicates that farmers located farther from markets are less likely to adopt CSAPs intensively due to higher transaction costs, limited access to inputs and weaker institutional linkages.

The implications of these findings is that CSA adoption in Oyo State is not random but systematically driven by a combination of human capital, resource endowment, institutional access and information flow. While education and experience primarily influence entry into adoption, financial access, extension services and climate information are the key drivers of intensive adoption. The dominance of climate information and extension access highlights the central role of knowledge systems in shaping climate adaptation behaviour among maize farmers.

Table 3: Determinants of Adoption of Climate Smart Agricultural Practices among Maize Farmers in Oyo State

Variable	Low Adoption	Moderate Adoption	High Adoption
Age	0.992 (0.008)	0.985 (0.011)	0.978* (0.012)
Education	1.041** (0.017)	1.086*** (0.021)	1.132*** (0.026)
Household Size	1.018 (0.015)	1.027* (0.016)	1.035* (0.018)
Farm Income	1.012 (0.009)	1.038** (0.014)	1.061*** (0.017)
Farm Size	1.124* (0.062)	1.318*** (0.074)	1.487*** (0.088)
Farming Experience	1.031* (0.018)	1.049** (0.021)	1.072** (0.025)
Gender	1.092 (0.081)	1.184* (0.094)	1.276** (0.108)
Cooperative Membership	1.148* (0.086)	1.296** (0.102)	1.418*** (0.117)
Access to Credit	1.211* (0.098)	1.412** (0.121)	1.639*** (0.144)
Extension Access	1.338** (0.105)	1.524*** (0.128)	1.781*** (0.156)
Demonstration Plot Access	1.276** (0.102)	1.467*** (0.118)	1.692*** (0.143)
Input/Improved Seeds Access	1.193* (0.091)	1.358** (0.109)	1.601*** (0.136)
Climate Information Access	1.402*** (0.112)	1.689*** (0.135)	2.014*** (0.168)
Livestock Ownership	1.006 (0.004)	1.011 (0.006)	1.018* (0.007)
Distance to Market	0.964 (0.021)	0.921** (0.028)	0.884*** (0.032)
Constant	0.412*** (0.118)	0.276*** (0.104)	0.184*** (0.087)
Log Likelihood = -312.47			
LR Chi-square =			

Variable	Low Adoption	Moderate Adoption	High Adoption
186.52***			
Pseudo $R^2 = 0.326$			

Source: Data Analysis, (2026).

Note: Standard errors are in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Constraints to Adoption of Climate Smart Agricultural Practices among Maize Farmers in Oyo State

The results presented in Table 4 reveal that constraints to the adoption of climate-smart agricultural practices (CSAPs) among maize farmers in Oyo State are predominantly structural, financial, and institutional in nature, with most variables falling within the severe constraint category.

The most critical constraint is inadequate access to credit and finance (mean = 4.42), ranked first. This indicates that liquidity constraints remain the strongest barrier preventing farmers from investing in climate-smart technologies. Without access to affordable credit, farmers are unable to purchase improved inputs, invest in soil management practices or adopt water-saving technologies. This finding is consistent with empirical evidence from Wossen *et al*. (2017), who emphasized finance as a binding constraint to agricultural technology adoption in sub-Saharan Africa. Closely following is the high cost of improved inputs (mean = 4.31), ranked second. This suggests that even when inputs are available, their affordability remains a major limitation. This reinforces the argument that adoption decisions are strongly shaped by input market inefficiencies and cost barriers. The poor access to extension services (mean = 4.18) ranked third, highlighting the critical role of advisory systems. This implies that farmers are not receiving sufficient technical guidance on how to effectively implement climate-smart practices. This finding aligns with Ragasa *et al*. (2014), who noted that weak extension systems significantly slow down technology diffusion in African agriculture. Limited access to climate information (mean = 4.06) and inadequate training (mean = 4.01) further reinforce the importance of knowledge systems. Farmers require timely weather forecasts and practical training to confidently adopt and sustain CSAPs, especially under increasing climate variability.

Infrastructure-related constraints such as poor roads and transport systems (mean = 3.92) and distance to input markets (mean = 3.48) also feature prominently. These factors increase transaction costs, reduce input availability and limit market participation, thereby discouraging adoption. Institutional and socio-structural constraints such as land tenure insecurity, weak farmer organizations and gender-related barriers fall within the moderate category. While not the most binding, they still influence adoption decisions indirectly by limiting access to resources and collective support systems.

Table 4: Constraints to Adoption of Climate-Smart Agricultural Practices among Maize Farmers in Oyo State

Constraint	Mean Score	SD	Rank	Decision
Inadequate access to credit/finance	4.42	0.78	1	Severe
High cost of improved inputs	4.31	0.81	2	Severe
Poor access to extension services	4.18	0.84	3	Severe
Limited access to climate information	4.06	0.86	4	Severe
Inadequate training on CSA practices	4.01	0.89	5	Severe
Poor road and transport infrastructure	3.92	0.91	6	Severe
Limited access to improved seeds/inputs	3.85	0.88	7	Severe
High labour requirement for CSA practices	3.78	0.90	8	Severe
Lack of demonstration plots	3.69	0.93	9	Severe
Low awareness of CSA benefits	3.64	0.95	10	Severe
Land tenure insecurity	3.52	0.97	11	Moderate
Distance to input markets	3.48	0.94	12	Moderate
Negative perception of risk/uncertainty	3.41	0.92	13	Moderate
Weak farmer organization/cooperatives	3.36	0.89	14	Moderate
Gender-related constraints	3.21	0.91	15	Moderate
Inadequate storage facilities	3.05	0.88	16	Moderate

Source: Data Analysis, (2026).

4. CONCLUSION AND RECOMMENDATIONS

Conclusion

This study assessed the adoption of Climate Smart Agricultural Practices (CSAPs) among maize farmers in Oyo State, Nigeria. The findings revealed that maize farmers in the study area are relatively active and economically productive, with most respondents being within the economically active age group and having moderate farming experience and formal education. The study further showed that farmers adopted a combination of climate-smart agricultural practices, although the level of adoption varied across practices. Practices such as intercropping, crop rotation and use of improved maize varieties recorded relatively high adoption rates, while more technical and capital-intensive practices such as agroforestry, water harvesting and soil testing were less adopted. The adoption intensity analysis indicated that most maize farmers were moderate adopters of climate-smart agricultural practices, suggesting that awareness and use of CSAPs exist but are yet to reach optimal levels.

The multinomial logit regression results showed that education, farm size, cooperative membership, access to extension services, access to credit, access to improved inputs and climate information significantly influenced adoption intensity among maize farmers. The study also established that inadequate finance, high input costs, limited extension services and poor access to climate information remain major barriers to the adoption of climate-smart agricultural practices. These constraints continue to limit farmers' capacity to fully adopt sustainable agricultural technologies needed to improve resilience and productivity under changing climatic conditions.

Recommendations

Based on the findings of this study, the following recommendations are made:

1. Government and financial institutions should improve farmers' access to affordable credit facilities through low-interest agricultural loan schemes and flexible collateral arrangements. This will help farmers overcome financial barriers associated with the adoption of climate-smart technologies.

2. Extension services should be strengthened and expanded by increasing the number of extension agents, improving training programmes and promoting regular farmer-extension interactions. This will improve farmers' awareness and technical knowledge of climate-smart agricultural practices.

3. Subsidized access to improved seeds, fertilizers and other climate-smart inputs should be enhanced to reduce the high-cost burden faced by maize farmers and encourage wider adoption of sustainable practices.

4. Farmer cooperatives and producer associations should be strengthened and supported since cooperative membership significantly influenced adoption intensity.

5. Climate information dissemination systems should be improved through radio programmes, mobile phone platforms and community-based early warning systems to enable farmers make timely and climate-informed production decisions.

6. Policies and intervention programmes should promote practical demonstration plots and farmer field schools where farmers can observe the benefits of climate-smart agricultural practices directly. This will improve farmers' confidence and willingness to adopt new practices.

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