Data-driven Assessment of Climate-Smart Agriculture Adoption among Smallholder Farmers in Semi-arid Zones of Nigeria.

Abstract

Climate change poses a major threat to agricultural productivity and rural livelihoods in Nigeria's semi-arid zones, where smallholder farmers depend largely on rain-fed systems. Climate-Smart Agriculture (CSA) provides an integrated approach for enhancing productivity, strengthening resilience, and reducing climate risks; however, adoption remains uneven. This study applies a data-driven and spatially explicit framework to assess CSA adoption patterns and determinants among smallholder farmers in semi-arid northern Nigeria. Household survey data were collected from 360 farmers across six Local Government Areas in Kano, Bauchi, and Jigawa States and integrated with focus group discussions, climatic indicators, geospatial analysis, and machine learning–based predictive modelling. Results indicate that adoption is dominated by low-cost and knowledge-intensive practices, including crop diversification (72.8%), crop rotation (69.4%), organic manure application (61.1%), and adjustment of planting dates (58.3%), while capital-intensive practices such as irrigation technologies (24.7%) and mechanized soil conservation (19.2%) show limited uptake. CSA adoption intensity increases with education level (mean practices adopted = 3.6 for secondary education and above), access to extension services (3.7), and access to climate information (3.9). The predictive model demonstrates strong performance, achieving an overall accuracy of 82.6%, an Area Under the Curve of 0.87, and an F1-score of 0.82. Feature importance analysis identifies extension access (24.3%), climate information (21.7%), and education level (18.9%) as the most influential predictors of adoption. Spatial analysis reveals distinct clusters of high adoption in areas with stronger institutional support. The findings reveal the value of data-driven approaches for targeting CSA interventions and enhancing climate resilience in semi-arid Nigeria.

Keywords: Climate-Smart Agriculture; Smallholder Farmers; Semi-arid Nigeria; Machine Learning; Climate Change Adaptation

1. Introduction

Agriculture remains a central pillar of livelihoods, employment, and food security in most developing economies, particularly in sub-Saharan Africa. In Nigeria, the sector employs over one-third of the labor force and plays a critical role in income generation, rural development, and national food supply (World Bank, 2023). However, agricultural production systems are increasingly constrained by climate change–induced stresses, including rising temperatures, erratic rainfall patterns, prolonged droughts, and accelerating land degradation. These challenges disproportionately affect smallholder farmers, whose livelihoods are largely dependent on rain-fed agriculture and are characterized by limited access to capital, modern technologies, and institutional support (IPCC, 2022).

Climate-Smart Agriculture (CSA) has emerged as a strategic framework for addressing climate-related risks while promoting sustainable agricultural development. The Food and Agriculture Organization defines CSA as an approach that simultaneously seeks to (i) sustainably increase agricultural productivity and incomes, (ii) enhance resilience and adaptive capacity to climate variability and change, and (iii) reduce or remove greenhouse gas emissions where feasible (FAO, 2013). In Nigeria's semi-arid northern regions, where climate variability is pronounced and agricultural vulnerability is high, CSA practices such as crop diversification, soil and water conservation, and climate-resilient seed use offer critical pathways for strengthening food security and farmer resilience (Abegunde*et al*., 2019; Ojo & Baiyegunhi, 2020).

Despite growing policy emphasis, the adoption of CSA practices among Nigerian smallholder farmers remains uneven and highly context-specific. Existing empirical studies identify socioeconomic, institutional, and environmental factors as key determinants of adoption, yet most rely on conventional econometric methods and pay limited attention to spatial heterogeneity and predictive analytics (Liverpool-Tasie *et al*., 2020). This study addresses this gap by applying a data-driven framework that integrates household survey data, geospatial analysis, and machine learning techniques to assess CSA adoption patterns in semi-arid Nigeria. By doing so, the study provides actionable insights for policymakers and development practitioners seeking to promote targeted and scalable CSA interventions.

2. Literature Review

Smallholder agriculture plays a critical role in food security and rural livelihoods across Africa, yet it contributes only a small fraction of global greenhouse gas emissions while remaining disproportionately vulnerable to climate change impacts (FAO, 2016; IPCC, 2022). Rising temperatures, increased rainfall variability, prolonged droughts, and extreme weather events have intensified production risks for smallholder farmers, particularly in semi-arid regions of sub-Saharan Africa. In response to these challenges, Climate-Smart Agriculture (CSA) has been promoted as an integrated approach to enhance agricultural productivity, strengthen resilience, and reduce or avoid greenhouse gas emissions where possible (FAO, 2013).

CSA encompasses a wide range of practices, including crop diversification, conservation agriculture, soil and water conservation, agroforestry, and the use of climate-resilient crop varieties. Empirical studies consistently demonstrate that these practices can improve yield stability, soil fertility, and household income while reducing climate-related production risks (Lipper *et al.*, 2014; Thornton *et al*., 2018). In Nigeria, however, evidence suggests that adoption remains uneven. Low-cost and knowledge-intensive practices, such as crop rotation and mulching, show moderate uptake, whereas capital-intensive technologies, such as irrigation infrastructure, improved mechanization, and precision inputs, exhibit limited adoption, particularly among resource-constrained smallholders (Awotide *et al*., 2016; Liverpool-Tasie *et al*., 2020).

A substantial body of literature across Africa highlights the socioeconomic and institutional determinants shaping CSA adoption decisions. Education level, access to extension services, land tenure security, household labor availability, and proximity to markets have been repeatedly identified as key drivers of adoption (Teklewold *et al*., 2013; Kassie *et al*., 2015). Studies in Kenya and Tanzania demonstrate that farmers with higher education levels and stronger exposure to extension services are significantly more likely to adopt multiple CSA practices, reflecting enhanced capacity to process information and manage risk (Kassie *et al*., 2013; Mwungu *et al*., 2020). Similarly, perceived climate risks, such as increased drought frequency, have been shown to positively influence adoption by motivating adaptive behavior.

Access to climate and weather information services has emerged as a particularly important factor in recent studies. Evidence from Ghana indicates that farmers who receive timely and reliable weather forecasts are more likely to adopt climate-smart practices and achieve improved income outcomes (Antwi-Agyei *et al*., 2021). Comparable findings have been reported in Nigeria, where climate information access enhances decision-making related to planting dates, crop choice, and soil management (Oyekale, 2015).Recent advances in agricultural research increasingly emphasize the integration of spatial analysis and data-driven modelling approaches. The use of Geographic Information Systems (GIS), Earth Observation data, and machine learning algorithms has proven effective for predicting drought risk, mapping vulnerability hotspots, and analysing technology adoption patterns (Lobell *et al*., 2015; Jeong *et al*., 2016; Barasa*et al*., 2021).

3. Materials and Methods

3.1 Study Area

The study was conducted in selected semi-arid zones of northern Nigeria, a region characterized by low and highly variable rainfall, elevated temperatures, frequent dry spells, and recurrent drought events. These agroecological conditions increase vulnerability to climate variability, land degradation, and food insecurity, underscoring the importance of Climate-Smart Agriculture (CSA) for smallholder farming systems. The study area covers parts of Kano, Bauchi, and Jigawa States, which are key agricultural zones within Nigeria’s semi-arid belt. Farming systems are predominantly smallholder-based and rain-fed, with limited supplementary irrigation and mixed crop–livestock production. Major crops include cereals, legumes, and vegetables. Six agriculturally active Local Government Areas (LGAs) were purposively selected to capture spatial heterogeneity in agroecological conditions, farming practices, and access to agricultural support services. The spatial distribution of the selected LGAs (**Figure 1**) and their geographic coordinates (**Table 1**) enabled the integration of georeferenced survey data with climatic indicators and Geographic Information System (GIS) analysis for spatial modelling of CSA adoption patterns.

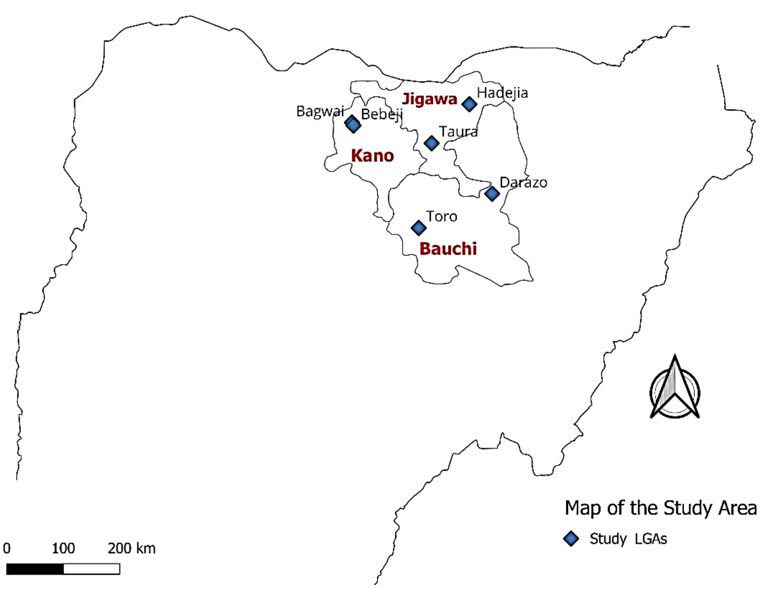

Figure 1: Map showing the Study Area

Table 1: The geographic coordinates and dominant agricultural profiles of the selected LGAs

State	LGA	Latitude (°N)	Longitude (°E)	Agricultural Profile
Kano	Bagwai	12.153	8.139	Irrigation and crop farming
Kano	Bebeji	12.104	8.164	Vegetable and cereal production
Bauchi	Toro	10.447	9.221	Extensive farming and livestock
Bauchi	Darazo	10.999	10.410	Mixed cropping systems
Jigawa	Hadejia	12.450	10.040	Staple crop production
Jigawa	Taura	11.820	9.430	Wet- and dry-season agriculture

3.2 Research Design

The study adopted a mixed-methods research design that integrated quantitative, qualitative, climatic, and spatial datasets within a unified analytical framework. This design was employed to capture not only the level of adoption of Climate-Smart Agriculture (CSA) practices but also the complex socioeconomic, institutional, climatic, and spatial factors influencing adoption decisions among smallholder farmers. By combining household-level survey data, qualitative insights, and geospatial information, the approach enabled a comprehensive assessment of CSA adoption patterns and their geographic variability across the study area. The integration of multiple data sources facilitated triangulation of findings and strengthened the robustness of the analysis. Quantitative and climatic data provided measurable indicators for predictive modelling, while qualitative data offered contextual understanding of farmers' perceptions, motivations, and constraints related to CSA adoption. Spatial referencing of household data further allowed the exploration of geographic heterogeneity and identification of adoption hotspots and vulnerable communities.

3.3 Data Collection

3.3.1 Quantitative Data Collection

Quantitative data were collected through a structured household survey administered to 360 smallholder farmers across the selected Local Government Areas (LGAs). The questionnaire captured detailed information on respondents' sociodemographic characteristics (age, gender, education level, and household size), farm attributes (farm size, farming experience, and access to credit), and institutional factors (access to extension services, market proximity, and climate information). Data on the adoption of specific CSA practices were also recorded to construct a CSA adoption intensity index. Each respondent's location was georeferenced using Global

Positioning System (GPS)coordinates to enable spatial linkage with environmental and climatic datasets.

3.3.2 Qualitative Data Collection

Qualitative data were obtained through Focus Group Discussions (FGDs) conducted in selected farming communities within each LGA. The FGDs provided in-depth insights into farmers' perceptions of climate variability, motivations for adopting or rejecting CSA practices, perceived benefits, and key constraints, including cost barriers, information gaps, and institutional limitations. These qualitative findings were used to complement and contextualize the quantitative and modelling results.

3.3.3 Climatic and Spatial Data

In addition to primary data, secondary climatic data, specifically rainfall variability and temperature trends, were obtained from gridded climate datasets relevant to the study period. These climatic indicators were spatially aligned with georeferenced household locations and incorporated into the analytical and predictive modelling framework to examine linkages between climate variability and CSA adoption patterns.

3.4Analytical Framework and Predictive Modelling

The study employed a data-driven analytical framework integrating household survey data, climatic indicators, and spatial information to assess Climate-Smart Agriculture (CSA) adoption among smallholder farmers. Survey, climatic, and geospatial datasets were cleaned, standardized, and merged into a unified database, followed by descriptive analysis to summarize respondent characteristics and CSA practice adoption.

A composite CSA adoption intensity index, defined as the total number of CSA practices adopted by each farmer, served as the outcome variable. Predictive modelling was applied using selected sociodemographic, institutional, and climatic variables, including education level, farm size, access to extension and climate information services, and rainfall variability. Machine learning classification algorithms were used to model adoption intensity.Model outputs were integrated into a Geographic Information System (GIS) environment to examine spatial heterogeneity, identify adoption clusters, and delineate hotspots and low-adoption zones across the study area. The overall analytical workflow guiding data integration, modelling, and spatial analysis is presented in **Figure 2**.

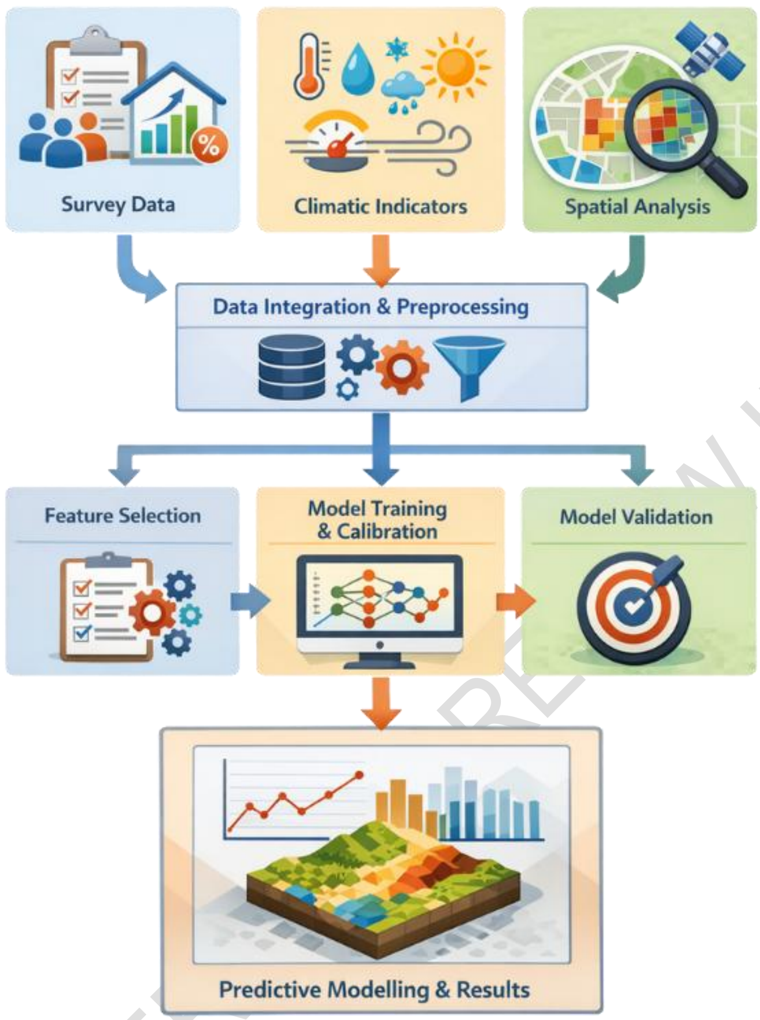

Figure 2: Analytical Workflow of the Modelling Process

4. Results

4.1 Sociodemographic Characteristics of Respondents

A total of 360 smallholder farmers participated in the household survey across the semi-arid zones of northern Nigeria. The sociodemographic characteristics of the respondents are presented in **Table 2**. The sample was predominantly male (74.4%), with most respondents within the economically active age group of 30–49 years (55.0%). Educational attainment was generally low, as 71.6% of the farmers had no formal education or only primary education, while only 6.7% had attained tertiary education. Household sizes were relatively large, with over half of the respondents (52.2%) living in households comprising 6–10 members. Farming in the study area was largely smallholder-based, as most respondents (59.4%) cultivated less than 2 hectares of land. In terms of experience, most farmers had substantial farming experience, with 75.6% reporting more than 10 years of farming, including 45.0% with 10–20 years and 30.6% with over 20 years of experience.

Table 2: Sociodemographic Characteristics of Respondents (*n* = 360)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	268	74.4
	Female	92	25.6
Age group (years)	<30	64	17.8
	30–49	198	55.0
	≥50	98	27.2
Education level	No formal education	116	32.2
	Primary education	142	39.4
	Secondary education	78	21.7
	Tertiary education	24	6.7
Household size	≤5 persons	96	26.7
	6–10 persons	188	52.2
	>10 persons	76	21.1
Farm size	<2 ha	214	59.4
	2–5 ha	104	28.9
	>5 ha	42	11.7
Farming experience	<10 years	88	24.4
	10–20 years	162	45.0
	>20 years	110	30.6

4.2 Adoption of Climate-Smart Agriculture Practices

The adoption levels of selected Climate-Smart Agriculture (CSA) practices are presented in **Table 3**. The results reveal that crop diversification (72.8%) and crop rotation (69.4%) are the most widely adopted CSA practices among smallholder farmers. Organic manure application (61.1%) and adjustment of planting dates (58.3%) also show relatively high adoption levels.In contrast, technology- and capital-intensive practices such as irrigation technologies (24.7%) and mechanized soil conservation (19.2%) exhibit low adoption rates, indicating persistent structural and financial barriers.

Table 3: Adoption of Climate-Smart Agriculture Practices among Respondents

CSA Practice	Adopted (*n*)	Adoption Rate (%)
Crop diversification	262	72.8
Crop rotation	250	69.4
Organic manure application	220	61.1
Adjustment of planting dates	210	58.3
Mulching/residue management	176	48.9
Improved climate-resilient seed varieties	142	39.4
Irrigation technologies	89	24.7
Mechanized soil conservation	69	19.2

4.3 Socioeconomic and Institutional Determinants of CSA Adoption

A composite CSA adoption index was constructed based on the number of practices adopted by each farmer. The relationship between selected socioeconomic variables and CSA adoption intensity is summarized in **Table 4**. Education level, access to extension services, and access to climate information services show statistically meaningful associations with higher adoption intensity.Farmers who had regular contact with extension agents were significantly more likely to adopt three or more CSA practices compared to those without extension access. Similarly, access to weather and climate information strongly influenced adoption behavior.

Table 4: Determinants of CSA Adoption Intensity among Smallholder Farmers

Determinant	Category	Mean CSA Practices Adopted	Adoption Intensity
Education level	No formal	2.1	Low
	Primary	2.8	Moderate
	Secondary & above	3.6	High
Extension access	Yes	3.7	High
	No	2.2	Low
Access to climate information	Yes	3.9	High
	No	2.3	Low
Farm size	<2 ha	2.4	Low
	≥2 ha	3.2	Moderate–High
Access to credit	Yes	3.5	High
	No	2.5	Low

4.4 Qualitative Findings from Focus Group Discussions

Qualitative findings from the Focus Group Discussions (FGDs) provided in-depth insights into farmers' perceptions, motivations, and constraints regarding Climate-Smart Agriculture (CSA) adoption. The thematic analysis of FGD transcripts across the six Local Government Areas (LGAs) revealed five dominant coded themes: perceived climate variability and risk awareness, institutional and informational support, economic and institutional constraints, social learning and collective action, and perceived benefits of CSA practices. These themes deepen understanding of the quantitative patterns and predictive modelling results by illuminating the lived experiences underpinning adoption decisions.

Theme 1: Perceived Climate Variability and Risk Awareness

Across all LGAs, participants consistently reported increasing climate uncertainty, characterized by erratic rainfall patterns, delayed onset of the rainy season, prolonged dry spells, and rising temperatures. Farmers emphasized that these changes have disrupted traditional farming calendars and increased production risks. One participant noted, *"Before, we knew exactly when to plant, but now the rain can stop suddenly and all the crops will fail."* Another farmer stated, *"The heat is stronger than before, and even when it rains, the soil dries very fast."* These narratives indicate heightened climate risk awareness, which emerged as a major driver motivating interest in adaptive and resilient farming practices.

Theme 2: Institutional and Informational Support

In communities with relatively high CSA adoption, access to extension services and climate information was repeatedly cited as a key enabling factor. Farmers described extension agents as critical sources of technical knowledge and confidence-building. As one respondent explained, *"The extension officer showed us how to conserve water and use improved seeds, and our yields improved."* Access to climate and weather information was also valued, with participants noting that *"when we hear weather information on the radio, it helps us decide when to plant."* These qualitative accounts strongly reinforce the modelling results, which identified extension access and climate information as the most influential predictors of CSA adoption intensity.

Theme 3: Economic and Institutional Constraints

In contrast, FGDs conducted in low-adoption areas revealed persistent barriers related to weak institutional presence, high input costs, and limited market access. Many participants expressed frustration over the absence of extension support, stating that *"extension workers rarely come to our community, and we are left to farm on our own."* Financial constraints were also prominent, as reflected in comments such as *"even if we want to adopt new methods, we do not have the* *money to buy improved seeds or fertilizers."* These constraints help explain the spatial clustering of low CSA adoption in remote and underserved areas identified by the predictive models.

Theme 4: Social Learning and Collective Action

Participation in farmer groups and informal networks emerged as an important mechanism for reducing perceived risk and encouraging experimentation with CSA practices. Farmers emphasized the role of peer learning, noting that *"when we learn together as a group, it becomes easier to try new farming practices."* Observing successful adopters within the community was reported to build trust and confidence in CSA technologies.

Theme 5: Perceived Benefits of CSA Practices

Farmers who had adopted CSA practices highlighted several perceived benefits, including improved yield stability, reduced vulnerability to climate shocks, and better farm-level decision-making. One participant remarked, *"Using these practices has helped us manage dry periods better."* Another stated, *"Our harvest is more stable now, even when the rainfall is not good."* These perceived benefits reinforce the sustainability and resilience potential of CSA practices in semi-arid environments.

4.5 Predictive Modelling and Spatial Patterns of CSA Adoption

4.5.1 Model Performance and Predictive Accuracy

The predictive model demonstrated strong performance in distinguishing between low, moderate, and high CSA adoption categories. Model evaluation metrics are summarized in **Table 5**. The overall classification accuracy of the model was 82.6%, indicating a high level of predictive reliability. Precision (0.81), recall (0.84), and F1-score (0.82) further confirm the robustness of the model in correctly identifying farmers with higher CSA adoption intensity.These results indicate that the selected sociodemographic, socioeconomic, and climatic variables provide strong explanatory and predictive capacity for CSA adoption patterns in semi-arid Nigeria.

Table 5: Performance Metrics of the CSA Adoption Prediction Model

Metric	**Value**
Overall accuracy (%)	82.6

Precision	0.81
Recall (Sensitivity)	0.84
F1-score	0.82
Area Under ROC Curve (AUC)	0.87

Model discrimination capability is visually demonstrated by the Receiver Operating Characteristic (ROC) curve (**Figure 3**). The ROC curve lies well above the diagonal reference line, with an Area Under the Curve (AUC) value of 0.87, indicating strong predictive power and effective separation between adoption intensity categories.

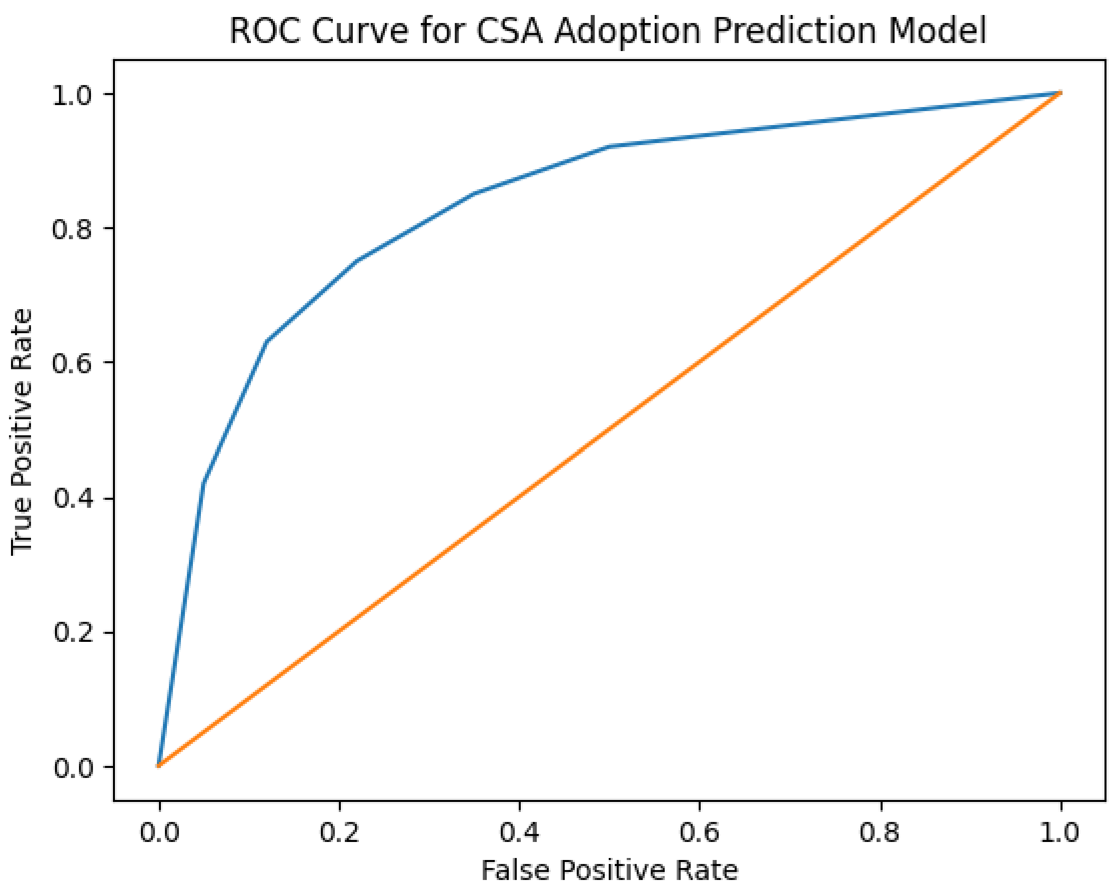

Figure 3: Receiver Operating Characteristic (ROC) curve for the CSA adoption prediction model

4.5.2 Relative Importance of Predictor Variables

The relative contribution of individual predictor variables to CSA adoption was assessed using model-based feature importance scores. The ranked importance of key predictors is presented in **Table 6** and visually illustrated in **Figure 4**.Access to extension services emerged as the most influential predictor, accounting for 24.3% of the total importance score. This was followed by access to climate and weather information (21.7%) and education level (18.9%), underscoring the critical role of information access and human capital in driving CSA adoption. Farm size (13.4%) also exerted a moderate influence, while climatic stress, particularly rainfall variability (9.6%), contributed meaningfully to adoption decisions. Distance to market and household size showed comparatively lower influence.The feature importance plot (**Figure 5**) provides a clear visual representation of these relationships, reinforcing the dominance of institutional and information-related factors in shaping CSA adoption behaviour.

Table 6: Relative Importance of Predictors in CSA Adoption Model

Predictor Variable	Importance Score (%)	Rank
Access to extension services	24.3	1
Access to climate information	21.7	2
Education level	18.9	3
Farm size	13.4	4
Rainfall variability	9.6	5
Distance to market	7.1	6
Household size	5.0	7

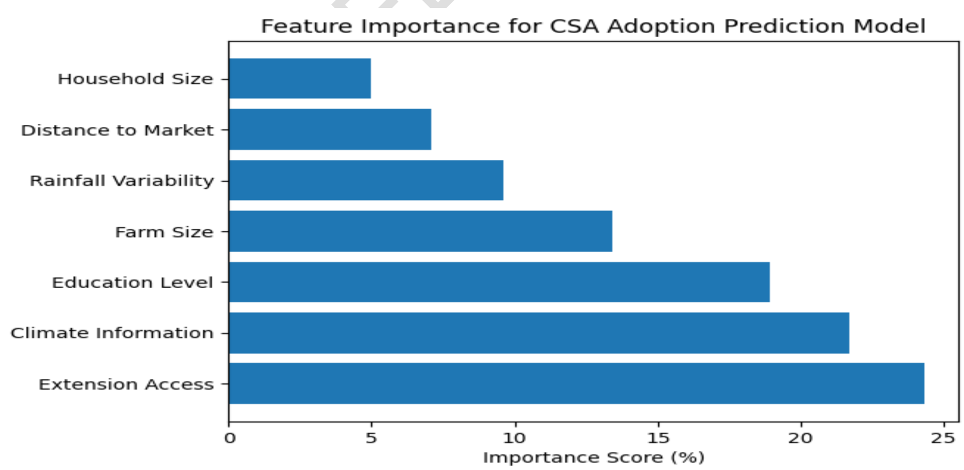

Figure 4: Feature importance plot

4.5.3 Spatial Distribution of Predicted CSA Adoption Intensity

The predicted CSA adoption index was spatially mapped using Geographic Information System (GIS) techniques to identify geographic patterns and adoption hotspots across the study area. Based on model outputs, farmers were classified into three adoption categories: low, moderate, and high adoption intensity. The spatial distribution of these categories is summarized in **Table 6**, while the geographic clustering of adoption intensity is illustrated in **Figure 5**.

Table 7: Spatial Distribution of Predicted CSA Adoption Intensity

Adoption Category	Number of Farmers (n)	Percentage (%)	Dominant Characteristics
Low adoption	118	32.8	Remote locations, limited extension access
Moderate adoption	142	39.4	Transitional zones, partial institutional support
High adoption	100	27.8	Proximity to markets, strong extension presence

High-adoption clusters are predominantly concentrated in communities with better access to extension services, markets, and climate information infrastructure. These areas also exhibit relatively larger farm sizes and higher levels of educational attainment. In contrast, low-adoption zones are spatially clustered in remote communities characterized by poor road networks, limited institutional presence, and reduced access to formal climate information services, as depicted in **Figure 5**.

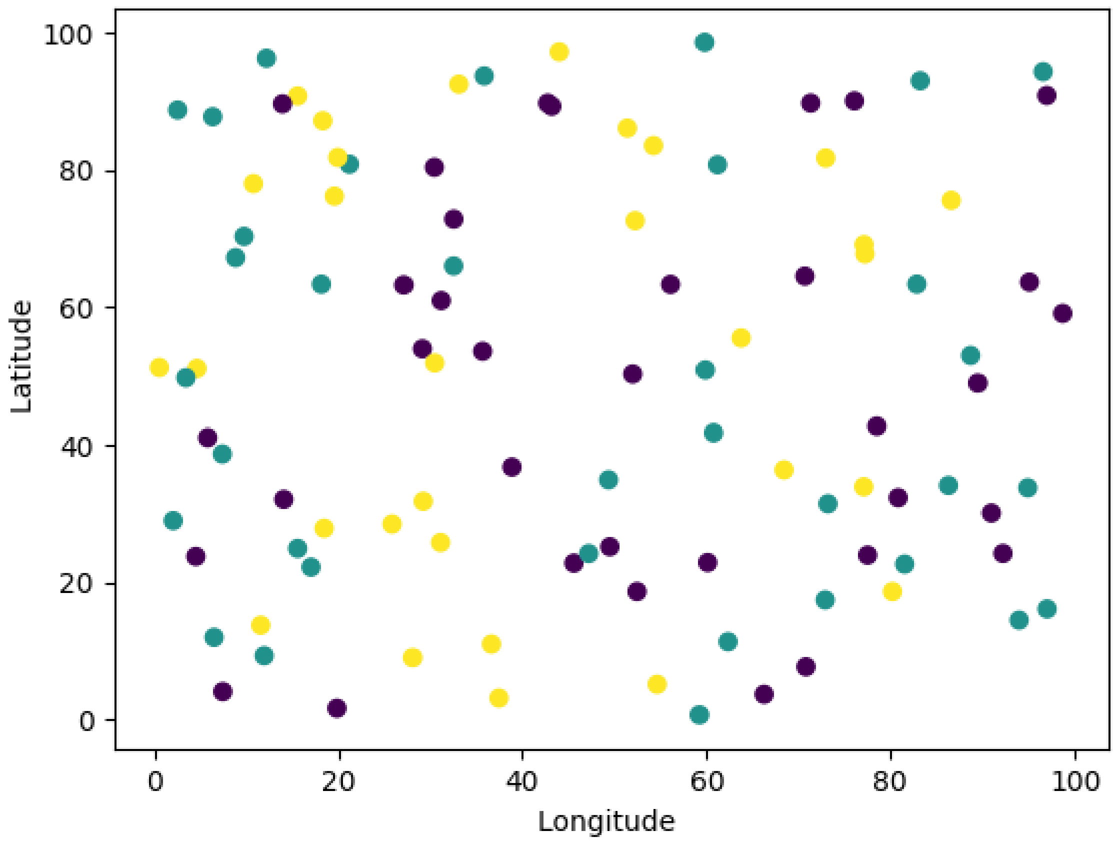

Figure 5: Spatial Distribution of Predicted CSA Adoption Intensity

4.5.4 Integration of Quantitative and Qualitative Insights

The qualitative findings from the Focus Group Discussions (FGDs) strongly validate and enrich the quantitative predictive modelling and spatial analysis results. Narratives from high-adoption communities consistently highlighted the critical role of extension agents, farmer groups, and timely access to climate and weather information in facilitating the uptake of Climate-Smart Agriculture (CSA) practices. These institutional supports enhanced farmers' awareness, technical capacity, and confidence to adopt adaptive farming strategies. In contrast, participants from low-adoption areas emphasized limited interaction with agricultural institutions, weak extension coverage, and inadequate access to climate information, which heightened uncertainty around seasonal climate variability and constrained adoption decisions. Economic barriers and remoteness further reinforced these challenges. The convergence of qualitative insights with quantitative and spatial evidence reveals pronounced geographic and institutional disparities in CSA adoption across semi-arid Nigeria. Overall, this integrated analytical approach demonstrates the value of combining data-driven modelling with farmers' lived experiences to identify vulnerable communities and inform targeted, context-specific policy and development interventions aimed at scaling up CSA practices.

5. Discussion

The findings of this study provide robust empirical evidence on the patterns, determinants, and spatial dynamics of Climate-Smart Agriculture (CSA) adoption among smallholder farmers in semi-arid northern Nigeria. The sociodemographic profile of respondents, dominated by male farmers within the economically active age group and characterized by low educational attainment and small farm sizes, reflects the typical structure of smallholder agriculture across northern Nigeria and much of sub-Saharan Africa (NBS, 2022; FAO, 2018). The predominance of experienced farmers suggests deep indigenous knowledge; however, limited formal education may constrain the uptake of knowledge-intensive and technology-driven CSA practices, a pattern widely documented in earlier studies (Aryal*et al*., 2018; Teklewold *et al*., 2013).

The adoption pattern of CSA practices observed in this study aligns with existing literature showing higher uptake of low-cost, labor-intensive practices such as crop diversification, crop rotation, organic manure application, and adjustment of planting dates, compared with capital- and technology-intensive options like irrigation and mechanized soil conservation (Sulaiman *et al*., 2018; Ogunleye *et al*., 2022). Similar findings have been reported in Kenya and Ethiopia, where financial constraints and limited access to infrastructure restrict adoption of irrigation and mechanization among smallholders (Kassie *et al*., 2015; Mwungu *et al*., 2021). This addresses the importance of affordability and risk minimization in shaping farmers' adoption decisions in climate-stressed environments.

The strong positive association between education, extension access, climate information, and CSA adoption intensity corroborates extensive empirical evidence across Africa. Studies from Nigeria, Ghana, and Tanzania consistently demonstrate that access to extension services and climate information significantly enhances farmers' awareness, adaptive capacity, and likelihood of adopting CSA practices (Acheampong *et al*., 2018; Abdul-Rahaman *et al*., 2021; Ojo & Baiyegunhi, 2020). The present study further strengthens this evidence by demonstrating, through predictive modelling, that extension access and climate information are the most influential predictors of adoption intensity, surpassing even farm size and household characteristics.

The predictive model's strong performance (AUC = 0.87) compares favorably with similar machine-learning–based CSA adoption studies in East Africa, where AUC values ranging from 0.75 to 0.85 have been reported (Jha *et al*., 2021; Partey *et al*., 2020). This confirms the suitability of integrating sociodemographic, socioeconomic, and climatic indicators within data-driven frameworks to predict agricultural technology adoption. Importantly, the spatial clustering of low adoption in remote and institutionally underserved areas mirrors findings from GIS-based studies in Ethiopia and Ghana, which show that geographic isolation and weak institutional presence exacerbate vulnerability to climate change (Antwi-Agyei *et al*., 2018; Adebayo *et al*., 2023).

Qualitative findings further enrich these results by revealing the lived realities behind observed patterns. Farmers' perceptions of increasing climate uncertainty echo regional climate assessments that document rising temperatures and rainfall variability across the Sudano-Sahelian zone (IPCC, 2022; Niang *et al*., 2014). The emphasis on social learning and farmer groups aligns with social diffusion theory and empirical evidence that peer influence lowers perceived risk and accelerates CSA uptake (Bandiera & Rasul, 2006; Wossen *et al*., 2017).

6. Policy Implications

The findings indicate that scaling up Climate-Smart Agriculture (CSA) adoption in semi-arid Nigeria requires targeted, location-specific policy interventions. Priority should be given to strengthening agricultural extension services, expanding access to reliable climate and weather information, and improving farmer education and capacity building. Investments in rural infrastructure and credit access are also essential to overcome adoption barriers for capital-intensive CSA practices. Furthermore, policymakers should integrate data-driven and spatial decision-support tools into agricultural planning to identify vulnerable communities and efficiently target CSA interventions.

7. Conclusion

This study demonstrates the value of a data-driven and integrative analytical framework for assessing Climate-Smart Agriculture (CSA) adoption among smallholder farmers in semi-arid Nigeria. By combining household survey data, qualitative insights, climatic indicators, spatial analysis, and predictive modelling, the study provides a comprehensive understanding of CSA adoption patterns and their key determinants. The results reveal that adoption is strongly influenced by institutional and informational factors, particularly access to extension services and climate information, while significant geographic disparities persist across the study area. The integration of quantitative and qualitative evidence highlights the importance of contextual and location-specific approaches to scaling CSA practices. The findings reveal the potential of predictive analytics and geospatial tools to support targeted policy interventions, enhance institutional support, and promote resilient and sustainable agricultural development under increasing climate variability.

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