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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 30 one-third of the labor force and plays a critical role in income generation, rural development, and 31 national food supply (World Bank, 2023). However, agricultural production systems are 32 increasingly constrained by climate change–induced stresses, including rising temperatures, 33 erratic rainfall patterns, prolonged droughts, and accelerating land degradation. These challenges 34 disproportionately affect smallholder farmers, whose livelihoods are largely dependent on rain35

fed agriculture and are characterized by limited access to capital, modern technologies, and 36 institutional support (IPCC, 2022). 37 Climate-Smart Agriculture (CSA) has emerged as a strategic framework for addressing climate38 related risks while promoting sustainable agricultural development. The Food and Agriculture 39 Organization defines CSA as an approach that simultaneously seeks to (i) sustainably increase 40 agricultural productivity and incomes, (ii) enhance resilience and adaptive capacity to climate 41 variability and change, and (iii) reduce or remove greenhouse gas emissions where feasible 42 (FAO, 2013). In Nigeria's semi-arid northern regions, where climate variability is pronounced 43 and agricultural vulnerability is high, CSA practices such as crop diversification, soil and water 44 conservation, and climate-resilient seed use offer critical pathways for strengthening food 45 security and farmer resilience (Abegundeet al., 2019; Ojo & Baiyegunhi, 2020). 46 Despite growing policy emphasis, the adoption of CSA practices among Nigerian smallholder 47 farmers remains uneven and highly context-specific. Existing empirical studies identify 48 socioeconomic, institutional, and environmental factors as key determinants of adoption, yet 49 most rely on conventional econometric methods and pay limited attention to spatial 50 heterogeneity and predictive analytics (Liverpool-Tasie et al., 2020). This study addresses this 51 gap by applying a data-driven framework that integrates household survey data, geospatial 52 analysis, and machine learning techniques to assess CSA adoption patterns in semi-arid Nigeria. 53 By doing so, the study provides actionable insights for policymakers and development 54 practitioners seeking to promote targeted and scalable CSA interventions. 55 2. Literature

Review 56 Smallholder agriculture plays a critical role in food security and rural livelihoods across Africa, 57 yet it contributes only a small fraction of global greenhouse gas emissions while remaining 58 disproportionately vulnerable to climate change impacts (FAO, 2016; IPCC, 2022). Rising 59 temperatures, increased rainfall variability, prolonged droughts, and extreme weather events 60 have intensified production risks for smallholder farmers, particularly in semi-arid regions of 61 sub-Saharan Africa. In response to these challenges, Climate-Smart Agriculture (CSA) has been 62 promoted as an integrated approach to enhance agricultural productivity, strengthen resilience, 63 and reduce or avoid greenhouse gas emissions where possible (FAO, 2013). 64

CSA encompasses a wide range of practices, including crop diversification, conservation 65 agriculture, soil and water conservation, agroforestry, and the use of climate-resilient crop 66 varieties. Empirical studies consistently demonstrate that these practices can improve yield 67 stability, soil fertility, and household income while reducing climate-related production risks 68 (Lipper et al., 2014; Thornton et al., 2018). In Nigeria, however, evidence suggests that adoption 69 remains uneven. Low-cost and knowledge-intensive practices, such as crop rotation and 70 mulching, show moderate uptake, whereas capital-intensive technologies, such as irrigation 71 infrastructure, improved mechanization, and precision inputs, exhibit limited adoption, 72 particularly among resource-constrained smallholders (Awotide et al., 2016; Liverpool-Tasie et 73 al., 2020). 74 A substantial body of literature across Africa highlights the socioeconomic and institutional 75 determinants shaping CSA adoption decisions. Education level, access to extension services, 76 land tenure security, household labor availability, and proximity to markets have been repeatedly 77 identified as key drivers of adoption (Teklewold et al., 2013; Kassie et al., 2015). Studies in 78 Kenya and Tanzania demonstrate that farmers with higher education levels and stronger 79 exposure to extension services are significantly more likely to adopt multiple CSA practices, 80 reflecting enhanced capacity to process information and manage risk (Kassie et al., 2013; 81 Mwungu et al., 2020). Similarly, perceived climate risks, such as increased drought frequency, 82 have been shown to positively influence adoption by motivating adaptive behavior. 83 Access to climate and weather information services has emerged as a particularly important 84 factor in recent studies. Evidence from Ghana indicates that farmers who receive timely and 85 reliable weather forecasts are more likely to adopt climate-smart practices and achieve improved 86 income outcomes (Antwi-Agyei et al., 2021). Comparable findings have been reported in 87 Nigeria, where climate information access enhances decision-making related to planting dates, 88 crop choice, and soil management (Oyekale, 2015).Recent advances in agricultural research 89 increasingly emphasize the integration of spatial analysis and data-driven modelling approaches. 90 The use of Geographic Information Systems (GIS), Earth Observation data, and machine 91 learning algorithms has proven effective for predicting drought risk, mapping vulnerability 92 hotspots, and analysing technology adoption patterns (Lobell et al., 2015; Jeong et al., 2016; 93 Barasaet al., 2021). 94

3. Materials and Methods 95 3.1 Study Area 96 The study was conducted in selected semi-arid zones of northern Nigeria, a region characterized 97 by low and highly variable rainfall, elevated temperatures, frequent dry spells, and recurrent 98 drought events. These agroecological conditions increase vulnerability to climate variability, 99 land degradation, and food insecurity, underscoring the importance of Climate-Smart Agriculture 100 (CSA) for smallholder farming systems. The study area covers parts of Kano, Bauchi, and 101 Jigawa States, which are key agricultural zones within Nigeria’s semi-arid belt. Farming systems 102 are predominantly smallholder-based and rain-fed, with limited supplementary irrigation and 103 mixed crop–livestock production. Major crops include cereals, legumes, and vegetables. Six 104 agriculturally active Local Government Areas (LGAs) were purposively selected to capture 105 spatial heterogeneity in agroecological conditions, farming practices, and access to agricultural 106 support services. 1 The spatial distribution of the selected LGAs (Figure 1) and their geographic 107 coordinates (Table 1) enabled the integration of georeferenced survey data with climatic 108 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 230 and climate information as the most influential predictors of CSA adoption intensity. 231 Theme 3: Economic and Institutional Constraints 232 In contrast, FGDs conducted in low-adoption areas revealed persistent barriers related to weak 233 institutional presence, high input costs, and limited market access. Many participants expressed 234 frustration over the absence of extension support, stating that “extension workers rarely come to 235 our community, and we are left to farm on our own.” Financial constraints were also prominent, 236 as reflected in comments such as “even if we want to adopt new methods, we do not have the 237

money to buy improved seeds or fertilizers.” These constraints help explain the spatial clustering 238 of low CSA adoption in remote and underserved areas identified by the predictive models. 239 Theme 4: Social Learning and Collective Action 240 Participation in farmer groups and informal networks emerged as an important mechanism for 241 reducing perceived risk and encouraging experimentation with CSA practices. Farmers 242 emphasized the role of peer learning, noting that “when we learn together as a group, it becomes 243 easier to try new farming practices.” Observing successful adopters within the community was 244 reported to build trust and confidence in CSA technologies. 245 Theme 5: Perceived Benefits of CSA Practices 246 Farmers who had adopted CSA practices highlighted several perceived benefits, including 247 improved yield stability, reduced vulnerability to climate shocks, and better farm-level decision248 making. One participant remarked, “Using these practices has helped us manage dry periods 249 better.” Another stated, “Our harvest is more stable now, even when the rainfall is not good.” 250 These perceived benefits reinforce the sustainability and resilience potential of CSA practices in 251 semi-arid environments. 252 4.5 Predictive Modelling and Spatial Patterns of CSA Adoption 253 4.5.1 Model Performance and Predictive Accuracy 254 The predictive model demonstrated strong performance in distinguishing between low, moderate, 255 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 282 visual representation of these relationships, reinforcing the dominance of institutional and 283 information-related factors in shaping CSA adoption behaviour. 284 Table 6: Relative Importance of Predictors in CSA Adoption Model 285 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 7 286 287 Figure 4: Feature importance plot 288 4.5.3 Spatial Distribution of Predicted CSA Adoption Intensity 289

The predicted CSA adoption index was spatially mapped using Geographic Information System 290 (GIS) techniques to identify geographic patterns and adoption hotspots across the study area. 291 Based on model outputs, farmers were classified into three adoption categories: low, moderate, 292 and high adoption intensity. The spatial distribution of these categories is summarized in Table 293 6, while the geographic clustering of adoption intensity is illustrated in Figure 5. 294 Table 7: Spatial Distribution of Predicted CSA Adoption Intensity 295 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 296 High-adoption clusters are predominantly concentrated in communities with better access to 297 extension services, markets, and climate information infrastructure. These areas also exhibit 298 relatively larger farm sizes and higher levels of educational attainment. In contrast, low-adoption 299 zones are spatially clustered in remote communities characterized by poor road networks, limited 300 institutional presence, and reduced access to formal climate information services, as depicted in 301 Figure 5. 302

303 Figure 5: Spatial Distribution of Predicted CSA Adoption Intensity 304 305 4.5.4 Integration of Quantitative and Qualitative Insights 306 The qualitative findings from the Focus Group Discussions (FGDs) strongly validate and enrich 307 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 (Aryalet 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., 357 2023). 358 Qualitative findings further enrich these results by revealing the lived realities behind observed 359 patterns. Farmers’ perceptions of increasing climate uncertainty echo regional climate 360 assessments that document rising temperatures and rainfall variability across the Sudano361 Sahelian zone (IPCC, 2022; Niang et al., 2014). The emphasis on social learning and farmer 362 groups aligns with social diffusion theory and empirical evidence that peer influence lowers 363 perceived risk and accelerates CSA uptake (Bandiera & Rasul, 2006; Wossen et al., 2017). 364 6. Policy Implications 365 The findings indicate that scaling up Climate-Smart Agriculture (CSA) adoption in semi-arid 366 Nigeria requires targeted, location-specific policy interventions. Priority should be given to 367 strengthening agricultural extension services, expanding access to reliable climate and weather 368 information, and improving farmer education and capacity building. Investments in rural 369 infrastructure and credit access are also essential to overcome adoption barriers for capital370 intensive CSA practices. Furthermore, policymakers should integrate data-driven and spatial 371 decision-support tools into agricultural planning to identify vulnerable communities and 372 efficiently target CSA interventions. 373 7. Conclusion 374

This study demonstrates the value of a data-driven and integrative analytical framework for 375 assessing Climate-Smart Agriculture (CSA) adoption among smallholder farmers in semi-arid 376 Nigeria. By combining household survey data, qualitative insights, climatic indicators, spatial 377 analysis, and predictive modelling, the study provides a comprehensive understanding of CSA 378 adoption patterns and their key determinants. The results reveal that adoption is strongly 379 influenced by institutional and informational factors, particularly access to extension services 380 and climate information, while significant geographic disparities persist across the study area. 381 The integration of quantitative and qualitative evidence highlights the importance of contextual 382 and location-specific approaches to scaling CSA practices. The findings reveal the potential of 383 predictive analytics and geospatial tools to support targeted policy interventions, enhance institutional support, and promote resilient and sustainable agricultural development under increasing climate variability.

References

Abdul-Rahaman, A., Issahaku, G., & Zereyesus, Y. A. (2021). Improved rice variety adoption and farm productivity in Ghana. Food Security, 13, 1–15.

Abegunde, V. O., Sibanda, M., & Obi, A. (2019). Determinants of the adoption of climate-smart agricultural practices by small-scale farming households in South Africa. Climate Change, 155, 1–17.

Acheampong, P. P., et al. (2018). Determinants of climate-smart agriculture adoption in Ghana. International Journal of Climate Change Strategies and Management, 10(4), 537–556.

Antwi-Agyei, P., Nyantakyi-Frimpong, H., & Dougill, A. J. (2021). The role of climate information in agricultural adaptation in Ghana. Climate Risk Management, 32, 100281.

Antwi-Agyei, P., Stringer, L. C., & Dougill, A. J. (2018). Livelihood adaptations to climate variability. Environmental Science & Policy, 89, 38–49.

Aryal, J. P., Rahut, D. B., Maharjan, S., & Erenstein, O. (2018). Factors affecting the adoption of multiple climate-smart agricultural practices in the Indo-Gangetic Plains of India. Natural Resources Forum, 42(2), 141–158. https://doi.org/10.llll/1477-8947.12152

Awotide, B. A., Karimov, A. A., & Diagne, A. (2016). Agricultural technology adoption, commercialization and smallholder rice farmers’ welfare in rural Nigeria. Agricultural and Food Economics, 4(1), 3.

Barasa, P. M., Botai, C. M., & Botai, J. O. (2021). A review of climate-smart agriculture research and applications in Africa. Agricultural Systems, 193, 103211.

FAO. (2013). Climate-Smart Agriculture Sourcebook. Food and Agriculture Organization of the United Nations.

FAO. (2016). The State of Food and Agriculture: Climate Change, Agriculture and Food Security. FAO.

FAO. (2018). The future of food and agriculture: Alternative pathways to 2050. Food and Agriculture Organization of the United Nations.

IPCC. (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability. Cambridge University Press.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., & Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. 416 Land Use Policy, 42, 400–411. 417 Lipper, L., Thornton, P., Campbell, B. M., et al. (2014). Climate-smart agriculture for food 418 security. Nature Climate Change, 4, 1068–1072. 419 Liverpool-Tasie, L. S. O., Reardon, T., & Belton, B. (2020). “Essential non-essentials”: COVID420 19 policy missteps in Nigeria rooted in persistent myths about African food supply chains. 421 Applied Economic Perspectives and Policy, 43(1), 205–224. 422 NBS. (2022). General Household Survey Panel. Abuja. 423 Ojo, T. O., & Baiyegunhi, L. J. S. (2020). Determinants of climate change adaptation strategies 424 and its impact on the net farm income of rice farmers in south-west Nigeria. Land Use Policy, 425 Elsevier, vol. 95(C). 426 Prestele, R., & Verburg, P. H. (2020). The overlooked spatial dimension of climate-smart 427 agriculture. Global Change Biology, 26, 1045–1054. 428 Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural 429 practices in rural Ethiopia. Journal of Agricultural Economics, 64(3), 597–623. 430 Thornton, P. K., Whitbread, A., Baedeker, T., et al. (2018). A framework for priority-setting in 431 climate smart agriculture research. Agricultural Systems, 167, 161–175. 432

World Bank. (2023). Employment in agriculture (% of total employment) – Nigeria. World Bank 433 Data. 434

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