

ADOPTION OF CLIMATE SMART AGRIBUSINESS PRACTICES AND THEIR EFFECTS ON FARM PRODUCTIVITY AND PROFITABILITY IN NORTH CENTRAL NIGERIA

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Abstract

This study examines the adoption of climate smart agribusiness practices and their effects on farm productivity and profitability among smallholder farmers in North Central Nigeria. Primary data were collected from 390 farmers using a multistage sampling technique and structured questionnaires. Descriptive statistics, an adoption intensity index, a Cobb Douglas production function, an Ordinary Least Squares profit model, and an Endogenous Switching Regression model were employed for analysis. The results show a generally moderate to high level of adoption, with practices such as intercropping, crop rotation, and integrated nutrient management being the most widely used. The switching regression estimates reveal the presence of selection bias, which justifies the need for a counterfactual framework. The treatment effect results indicate that adoption significantly increases farm productivity and profitability. Specifically, the average treatment effect on the treated shows that adopters experience about a 30.2 percent increase in productivity and a 42.4 percent increase in profitability relative to what they would have obtained without adoption. The average treatment effect on the untreated further suggests that non adopters would gain substantially if they were to adopt. The findings confirm that adoption operates as a productivity enhancing and income enhancing strategy for smallholder farmers. Adoption nonetheless remains constrained by limited access to credit, extension services, and input markets. The study concludes that scaling up adoption can materially improve farm performance and resilience across the region.

Keywords: Climate smart agriculture; Adoption; Productivity; Profitability; Endogenous switching regression; Nigeria

1. Introduction

Agricultural activity in Nigeria is acutely sensitive to climatic conditions, and smallholder farmers bear the larger share of the burden imposed by erratic weather, prolonged drought, and flooding (Saadu et al., 2024). These climatic stresses exert pronounced negative effects on household food security and on the capacity of rural households to generate income, an effect that is especially severe in regions such as North Central Nigeria where farming forms the backbone of rural livelihoods. In response to these pressures, climate smart agribusiness practices have emerged as a coherent pathway through which farmers can build resilience, sustain productivity, and improve profitability (Gabriel et al., 2023).

Climate Smart Agriculture pursues three interlocking objectives, namely the sustainable increase of agricultural productivity, the strengthening of adaptive capacity in the face of climate change, and the reduction of greenhouse gas emissions where this is feasible. In Nigeria, farmers have taken up a range of such practices that includes crop rotation, conservation tillage, efficient fertiliser application, intercropping, and water harvesting (Saadu et al., 2024). Recent evidence indicates that in North Central Nigeria more than eighty percent of smallholder farmers have already integrated at least one climate resilient trait into their production systems (Gabriel et al., 2023). While headline adoption rates are high, the uptake of knowledge intensive practices such as soil testing, agroforestry, and long term water management remains limited, a shortfall that is widely attributed to constrained access to credit, weak extension support, and insufficient investment capital (Salisu, 2022). Empirical work further suggests that the perceived benefits of adoption, whether expressed as yield gains or income increases, are often uncertain or delayed, which dampens the willingness of farmers to commit fully (Saadu et al., 2024).

Although the benefits of climate smart practices are frequently framed in terms of adaptation and food security, comparatively few studies have rigorously quantified their effect on farm profitability. In North Central Nigeria, where agricultural markets are relatively developed, agribusiness actors that span farmers, aggregators, processors, input dealers, marketers, and transporters stand to benefit substantially if adoption translates into higher returns and improved operational efficiency. There is therefore a pressing need for region specific evidence that links the adoption of climate smart agribusiness practices to profitability. Against this backdrop, the present study assesses the extent and the determinants of adoption among farmers in North Central Nigeria and evaluates how that adoption affects farm productivity and profitability. The conceptual logic that organises the analysis is summarised in Figure 1.

1.1 Statement of the Research Problem

Smallholder farmers in North Central Nigeria confront mounting challenges from climate variability and change that threaten both their livelihoods and the sustainability of agribusiness activity. Although climate smart practices promise to build resilience, raise productivity, and improve environmental sustainability, the extent of their adoption across the region remains uneven and imperfectly understood (Onukwube and Thompson, 2025). Evidence indicates that while many farmers adopt simple practices such as crop rotation and intercropping, the more knowledge intensive and capital intensive practices such as soil testing, agroforestry, and water harvesting attract much lower uptake (Agyekum et al., 2024). This limited adoption persists despite a reported high demand for climate resilient solutions, with farmers citing inadequate credit, limited extension support, and a lack of technical training as the binding constraints (Onukwube and Thompson, 2025).

Beyond the question of adoption lies a critical gap in the understanding of economic impact. Few studies have rigorously quantified how the adoption of climate smart practices translates into improved farm profitability within North Central Nigeria. While research in other Nigerian regions has shown that adoption can raise income and technical efficiency (Saadu et al., 2024), such findings may not generalise to North Central agricultural systems, which differ in their crop and livestock mixes, market access conditions, and agro ecological realities. Institutional and social constraints that limit effective uptake also remain under explored, including capacity weaknesses within extension services and structural barriers such as poor infrastructure and deficient policy incentives (Tsado et al., 2024). Without a deeper understanding of the drivers of adoption and of how adoption affects farm level profitability, interventions aimed at scaling up climate smart agribusiness in the region risk falling short.

1.2 Aim and Objectives

The aim of this study is to analyse the adoption of climate smart agribusiness practices and their effects on farm productivity and profitability in North Central Nigeria. The specific objectives are to describe the socio economic characteristics of farmers in the region, to identify the major climate smart agribusiness practices they adopt, to determine the effects of adopting specific practices on farm productivity and profitability, and to examine the constraints that limit the uptake and effective use of these practices.

1.3 Justification

The justification for this study rests on several empirical grounds. First, despite the widespread recognition of the benefits of climate smart practices, few studies have rigorously quantified their impact on farm level profitability in North Central Nigeria, since most existing research concentrates on food security or yield outcomes without linking adoption to income generation or cost efficiency (Saadu et al., 2024). By evaluating profitability directly, this study provides concrete evidence for farmers, agribusiness actors, and other stakeholders on the economic returns to adoption. Second, North Central Nigeria plays a critical role in national food production and in agribusiness supply chains, so that insights from the region can inform policy formulation, extension planning, and private sector investment. Finally, the study contributes region specific evidence on adoption and its profitability implications, thereby addressing a clear knowledge gap and laying a foundation for future research on sustainable agribusiness in Nigeria.

2. Methodology

2.1 The Study Area

The study was conducted in North Central Nigeria, also known as the Middle Belt region, which comprises six states, namely Benue, Kogi, Kwara, Nasarawa, Niger, and Plateau, together with the Federal Capital Territory at Abuja. The region covers a combined land area of approximately 294,428 square kilometres and is one of the largest geopolitical zones in the country. According to the National Population Commission (2006), the region had an estimated population of about 20.3 million, projected to exceed 32.5 million by 2025 at an annual growth rate of 2.8 percent (National Bureau of Statistics, 2022). It lies broadly between latitudes 6 degrees 30 minutes and 11 degrees 20 minutes North and longitudes 3 degrees 30 minutes and 10 degrees 00 minutes East, occupying a central location that links the northern and southern halves of the country and that functions as a strategic corridor for agricultural markets, food distribution, and commodity flows.

The region experiences a tropical savanna climate with distinct wet and dry seasons. The rainy season generally spans April to October while the dry season lasts from November to March. Annual rainfall ranges between 1,000 and 1,600 millimetres, with some highland areas such as Plateau State receiving higher totals, and average temperatures remain warm throughout the year, typically between 24 and 34 degrees Celsius (Nigerian Meteorological Agency, 2020). These conditions support a wide diversity of crop and livestock systems across varying agro ecological belts. Agriculture remains the dominant economic activity, and the region serves as one of the major agribusiness hubs of the country, benefiting from fertile soils, moderate rainfall, and strong linkages to urban markets. Major crops include cassava, yam, rice, maize, sorghum, soybean, groundnut, sesame, and vegetables, while livestock production, particularly poultry, small ruminants, and cattle, contributes significantly to household income and regional food supply (Federal Ministry of Agriculture and Food Security, 2023).

2.2 Sampling Procedure and Sample Size

A multistage sampling technique was employed to select respondents. In the first stage, three states, namely Benue, Nasarawa, and Plateau, were randomly selected from the zone to provide adequate representation of its agro ecological and agribusiness conditions. In the second stage, six Local Government Areas were selected from each state by simple random sampling, giving eighteen areas in total. In the third stage, three farming communities were randomly selected from each area, yielding fifty four communities. In the final stage, farming households were selected from each community using probability proportionate to size sampling based on the number of farming households, so that communities with larger farming populations received proportionally higher representation.

The sample size was determined using the Taro Yamane (1967) formula for finite populations, presented in Equation 1.

$$n = N / [1 + N(e)^2] \quad (1)$$

In this expression n is the required sample size, N is the population of farming households in the selected communities, and e is the level of precision, set at 0.05. The application of this formula yielded a total sample of 390 farming households, which was distributed across states, areas, and communities through

probability proportionate to size sampling in order to ensure representativeness and to minimise sampling bias.

2.3 Data Collection

Primary data were elicited using structured questionnaires administered to farmers across the selected communities. Data were gathered through face to face interviews, which improved the clarity of responses and reduced non response bias, particularly among farmers with limited literacy. Trained enumerators familiar with the local languages assisted with administration and verified responses where necessary, and the instrument was pretested in a nearby community that was not part of the final sample in order to improve data quality.

2.4 Methods of Data Analysis

Descriptive and inferential statistics were used in line with the stated objectives, with each objective matched to an appropriate analytical tool. The first objective was achieved using means, frequency distributions, and percentages. The second was achieved using an adoption intensity index constructed as a weighted score of the practices adopted by each respondent. For the third objective, a Cobb Douglas production function and an Ordinary Least Squares profit model were first estimated to establish baseline relationships between adoption and farm performance. Because adoption decisions are not random and may give rise to selection bias, an Endogenous Switching Regression model was then employed to obtain consistent and unbiased estimates of the impact of adoption on productivity and profitability. For the fourth objective, a five point Likert scale was used to rate the constraints. All analysis was conducted in STATA 15.

2.5 Reliability and Validity

The questionnaire was subjected to both validity and reliability checks. 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. Reliability was tested through a pilot survey conducted in a community outside the study area but with similar socio economic characteristics. Internal consistency was assessed using the Cronbach alpha coefficient, which returned a value of 0.81 for the Likert scale items measuring constraints and 0.78 for the items used in constructing the perception and adoption indices. Both values fall within the acceptable threshold for social science research and indicate good internal consistency.

2.6 Model Specification

The adoption intensity index was used to identify the major climate smart agribusiness practices adopted by farmers, following Tsado et al. (2024). The weighted index for farmer i is expressed in Equation 2.

$$AII_i = \sum_{j=1}^k w_j \cdot d_{ij} \quad (2)$$

Here AII_i is the adoption intensity index for farmer i , ranging from zero to one, d_{ij} equals one if farmer i has adopted practice j and zero otherwise, w_j is the weight assigned to practice j with the weights summing to one, and k is the total number of practices identified. Farmers were subsequently categorised as low adopters where the index falls below 0.33, moderate adopters where it lies between 0.33 and 0.67, and high adopters where it reaches or exceeds 0.67.

To estimate the effect of adoption on productivity, a Cobb Douglas production function was specified with the adoption intensity index included as a technology shifter alongside conventional inputs. The functional form was chosen for its consistency with production economics, its tractability, and its widespread use in smallholder production analysis across Nigeria and sub Saharan Africa (Saadu et al., 2024). The general form is given in Equation 3.

$$Q_i = A \cdot \prod_{n=1}^N X_{ni}^{\alpha_n} \cdot e^{\varepsilon_i} \quad (3)$$

Taking the natural logarithm of both sides linearises the model for estimation, as shown in Equation 4.

$$\ln Q_i = \ln A + \sum_{n=1}^N \alpha_n \ln X_{ni} + \varepsilon_i \quad (4)$$

The explicit log linear form estimated in this study is presented in Equation 5.

$$\ln Q_i = \beta_0 + \beta_1 \ln Land_i + \beta_2 \ln Lab_i + \beta_3 \ln Fert_i + \beta_4 \ln Seed_i + \beta_5 \ln Agrochem_i + \beta_6 AII_i + \beta_7 X_i' \gamma + \varepsilon_i \quad (5)$$

In this specification $\ln Q_i$ is the natural log of total farm output in kilograms, the input terms capture farm size in hectares, labour in man days, fertiliser in kilograms, seed in kilograms, and agrochemical expenditure in naira, AII_i is the continuous adoption intensity index that captures the technology shift effect, $X_i' \gamma$ is a vector of farmer level controls including age, education, extension access, and land tenure, β_0 is the intercept that represents total factor productivity, the coefficients β_1 through β_5 are output elasticities, β_6 is the coefficient of the adoption index, and ε_i is the stochastic error term. The sum of the estimated input elasticities was used to determine returns to scale.

To assess whether adoption translates into higher profitability after controlling for farm and household characteristics, a log linear profit model was estimated with net farm profit per hectare as the dependent variable. Profit was computed as total revenue minus total variable cost per hectare, as defined in Equation 6.

$$\pi_i = TR_i - TVC_i = (P_{qi} \cdot Q_i) - \sum_n (P_{ni} \cdot X_{ni}) \quad (6)$$

Here TR is total revenue, TVC is total variable cost, P_{qi} is the farm gate price of output, Q_i is total output, and P_{ni} and X_{ni} are respectively the prices and quantities of variable inputs. Given the skewed nature of profit distributions in smallholder data, the natural log transformation was applied to positive profit values, and the profitability model is specified in Equation 7.

$$\ln \pi_i = \alpha_0 + \alpha_1 AII_i + \alpha_2 \ln FarmSize_i + \alpha_3 \ln FarmInc_i + \alpha_4 Edu_i + \alpha_5 ExtAccess_i + \alpha_6 Credit_i + \alpha_7 FarmerAssoc_i + \alpha_8 Gender_i + \alpha_9 Age_i + \alpha_{10} OffFarmInc_i + \alpha_{11} \ln InputCost_i + \alpha_{12} MktAccess_i + \mu_i \quad (7)$$

The dependent variable is the natural log of net farm profit per hectare, and the regressors comprise the adoption index, farm size, farm income, education, extension access, credit, farmer association membership, gender, age, off farm income, input cost, and distance to the nearest output market, with μ_i as the error term.

To account for the potential selection bias that arises from the non random adoption of climate smart practices, an Endogenous Switching Regression model was employed. The framework jointly models the adoption decision and the outcome equations under two regimes, adopters and non adopters, while allowing for

correlation between the unobserved factors that influence both adoption and farm performance. The adoption decision is modelled as a latent variable, as shown in Equations 8 and 9.

$$A_i^* = Z_i \gamma + \varepsilon_i \quad (8)$$

$$A_i = 1 \text{ if } A_i^* > 0, \text{ and } A_i = 0 \text{ otherwise} \quad (9)$$

Here A_i is the adoption status, Z_i is a vector of variables that influence adoption, γ is the parameter vector, and ε_i is the error term. The variables in the selection equation comprise age, education, household size, farming experience, farm size, extension access, credit access, farmer association membership, and access to climate information, the last of which serves as the identifying instrument. Separate outcome equations are specified for the two regimes. For adopters the productivity and profitability equations are given in Equations 10 and 11, and for non adopters in Equations 12 and 13.

$$\ln Q_{1i} = X_{1i} \beta_1 + \sigma_{1\varepsilon} \lambda_{1i} + \mu_{1i} \quad (10)$$

$$\ln \pi_{1i} = X_{1i} \alpha_1 + \sigma_{1\varepsilon} \lambda_{1i} + v_{1i} \quad (11)$$

$$\ln Q_{0i} = X_{0i} \beta_0 + \sigma_{0\varepsilon} \lambda_{0i} + \mu_{0i} \quad (12)$$

$$\ln \pi_{0i} = X_{0i} \alpha_0 + \sigma_{0\varepsilon} \lambda_{0i} + v_{0i} \quad (13)$$

In these equations $\ln Q$ is the natural log of total farm output, $\ln \pi$ is the natural log of farm profit per hectare, X_i is the vector of explanatory variables, β and α are the parameters to be estimated, λ is the inverse Mills ratio that corrects for selectivity, and μ and v are error terms. The model permits the estimation of actual and counterfactual outcomes, from which the average treatment effect on the treated and the average treatment effect on the untreated are derived in Equations 14 and 15.

$$ATT = E(Y_1 | A=1) - E(Y_0 | A=1) \quad (14)$$

$$ATU = E(Y_1 | A=0) - E(Y_0 | A=0) \quad (15)$$

To ensure proper identification of the switching regression model, access to climate information was used as an exclusion restriction. The variable was included in the adoption equation but excluded from the outcome equations. The justification is that access to weather forecasts, seasonal advisories, and agro climatic information shapes the decision to adopt by improving awareness of climate related risk and adaptation opportunity, yet it does not directly affect productivity or profitability once adoption and the conventional production factors are controlled for.

3. Results and Discussion

3.1 Socio Economic and Demographic Characteristics

The socio economic and demographic characteristics of the sampled farmers are presented in Table 1. The results reveal that the majority of farmers, some 35.13 percent, fall within the 41 to 50 year age bracket, with a mean age of 44 years, which confirms a predominantly middle aged farming population of the kind widely documented in Nigerian agricultural surveys (Gabriel et al., 2023). The implication for adoption is double edged, since older farmers may command greater asset wealth and farming capital yet tend to be less receptive to knowledge intensive innovations that depart substantially from established routines (Tsado et al., 2024). Male respondents constituted 76.41 percent of the sample against 23.59 percent female, a composition that reflects the structural gender

dynamics of smallholder agriculture in the region, where land ownership, credit access, and participation in farmer organisations are disproportionately concentrated among male headed households. Most respondents were married, at 78.46 percent, with a mean household size of six persons, a figure characteristic of rural North Central Nigeria that carries mixed implications, since larger households supply family labour that lowers hiring costs yet impose greater food and income demands that can divert resources from farm investment (Saadu et al., 2024).

The educational profile shows that a combined 65.39 percent of respondents had attained secondary or tertiary education, with a mean of nine years of schooling and only 12.31 percent reporting no formal education, a level above the national rural average. Education is a critical enabler of adoption, since better educated farmers are more able to process extension messages, interpret agronomic recommendations, and engage with market information (Agyekum et al., 2024). Farming was the primary occupation for 80.00 percent of respondents, and farming experience averaged nineteen years, with the largest proportion in the eleven to twenty year bracket, indicating a population with considerable practical knowledge of local agro ecological systems. The mean farm size was 1.87 hectares, with 41.54 percent cultivating between one and two hectares and a notable 21.54 percent cultivating less than one hectare, which underscores the smallholder character of farming in the area and is consistent with the national smallholder average documented by the Federal Ministry of Agriculture and Food Security (2023).

Access to extension services was reported by 54.87 percent of farmers, with those reached receiving a mean of three visits per year. Although this access rate exceeds some rural averages, the low frequency of visits implies that the quality and intensity of support remain insufficient. Only 44.10 percent of respondents reported access to credit, with a mean amount of 84,600 naira among those reached, a constraint of particular consequence for capital intensive practices such as drip irrigation, soil testing, and mechanised conservation tillage. Annual farm income averaged 298,400 naira, with the largest group earning between 100,000 and 300,000 naira, figures that reflect the constrained profitability of smallholder production and that provide further justification for examining the income effects of adoption.

Table 1. Socio Economic and Demographic Characteristics of Respondents

Variable	Frequency	Percent	Mean +/- SD
Age: 20 to 30	43	11.03	
Age: 31 to 40	98	25.13	
Age: 41 to 50	137	35.13	44 +/- 9.6
Age: 51 to 60	82	21.03	
Age: above 60	30	7.69	
Gender: Male	298	76.41	
Gender: Female	92	23.59	
Married	306	78.46	
Household size: 4 to 6	154	39.49	6 +/- 2.3
No formal education	48	12.31	

Variable	Frequency	Percent	Mean +/- SD
Secondary education	149	38.21	9 +/- 4.3
Tertiary education	106	27.18	
Primary occupation: Farming	312	80.00	
Experience: 11 to 20 yr	148	37.95	19 +/- 8.7
Farm size: 1.0 to 2.0 ha	162	41.54	1.87 +/- 1.12
Income 100k to 300k	147	37.69	298,400 +/- 214,600
Extension access: Yes	214	54.87	
Credit access: Yes	172	44.10	

Source: Data analysis (2026). SD denotes standard deviation.

3.2 Major Climate Smart Agribusiness Practices Adopted

Table 2 presents the practices adopted by farmers in the study area, and the results reveal a clear and consistent gradient that runs from practices that are simple, low cost, and knowledge light to those that are capital intensive, knowledge intensive, or dependent on institutional support, a pattern extensively documented in the climate smart agriculture literature for sub Saharan Africa (Agyekum et al., 2024). The full gradient is visualised in Figure 1. Intercropping recorded the highest individual adoption rate at 81.54 percent, followed closely by crop rotation at 75.90 percent, a finding consistent with Gabriel et al. (2023), who reported that more than eighty percent of North Central smallholders had integrated at least one climate resilient trait, with simple diversification strategies being the most prevalent. Improved and organic fertiliser application at 69.49 percent and composting and organic manure use at 63.59 percent ranked third and fourth, in line with evidence that the integration of organic and inorganic nutrient sources is increasingly promoted by extension programmes in the region.

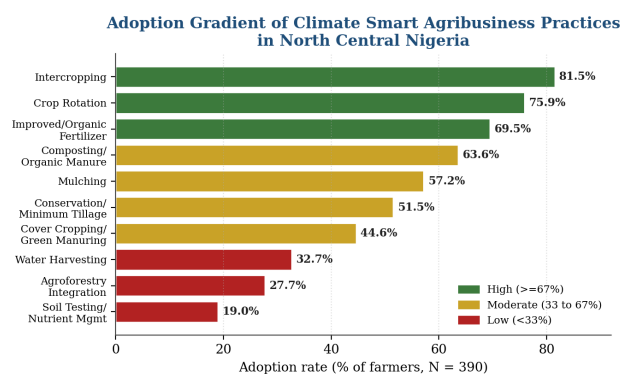


Figure 1: Adoption gradient of climate smart agribusiness practices across the sampled farmers.

Source: Data analysis (2026).

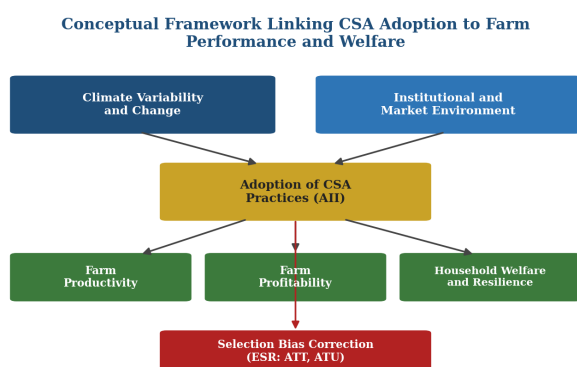


Figure 2: Conceptual framework linking adoption to farm performance and household welfare.

Source: Authors' conceptual synthesis.

Mulching at 57.18 percent and conservation or minimum tillage at 51.54 percent both achieved moderate adoption, which reflects a degree of traction for these soil health practices but also suggests that nearly half of the sampled farmers continue to rely on conventional tillage and leave soils bare between seasons, practices that contribute to moisture loss and erosion under the variable rainfall that characterises the region. Cover cropping and green manuring at 44.62 percent similarly attracted moderate uptake, the lower rate relative to intercropping likely reflecting knowledge gaps around cover crop management and the perceived opportunity cost of land allocated to non food species. Water harvesting at 32.67 percent and agroforestry integration at 27.69 percent registered low adoption, since the capital and knowledge requirements of earth bunds, check dams, and micro catchment systems place them beyond the reach of most smallholders who lack credit and technical advisory support, a finding that corroborates Salisu (2022). Soil testing and site specific nutrient management recorded the lowest rate of all, at 18.97 percent, a result that is particularly concerning given that soil testing is foundational to evidence based fertiliser application and long term fertility management.

Table 2. Climate Smart Agribusiness Practices Adopted by Farmers

Practice	Weight	Adopters	% Adoption	Level
Intercropping	0.07	318	81.54	High
Crop Rotation	0.08	296	75.90	High
Improved/Organic Fertiliser	0.09	271	69.49	High
Composting/Organic Manure	0.10	248	63.59	Moderate
Mulching	0.09	223	57.18	Moderate
Conservation/Minimum Tillage	0.10	201	51.54	Moderate
Cover Cropping/Green Manuring	0.10	174	44.62	Moderate
Water Harvesting	0.12	143	32.67	Low
Agroforestry Integration	0.12	108	27.69	Low
Soil Testing/Nutrient Mgmt	0.13	74	18.97	Low

Source: Data analysis (2026). Multiple responses allowed; percentages relative to N = 390. High at or above 67 percent; Moderate 33 to 67 percent; Low below 33 percent.

3.3 Effects on Farm Productivity

Table 3 presents the Cobb Douglas production function results for the effect of adoption on farm productivity. The model achieves an R squared of 0.742, indicating that the specified variables explain approximately seventy four percent of the variation in log farm output, a strong fit for a cross sectional production function on smallholder data, and the F statistic of 96.84 confirms the joint significance of the regressors. Diagnostic tests confirm the absence of significant heteroskedasticity, of functional form misspecification, and of multicollinearity. The relative magnitude of the estimated effects is illustrated in Figure 3.

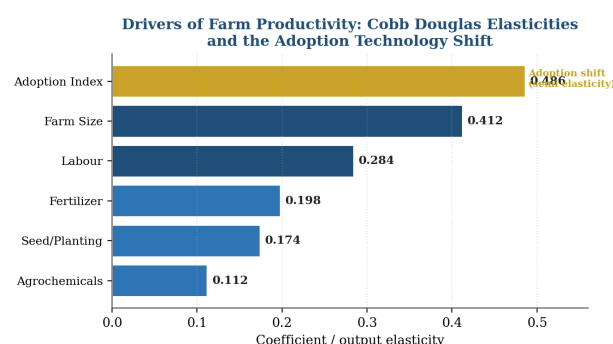


Figure 3: Cobb Douglas output elasticities and the adoption technology shift effect on productivity.

Source: Data analysis (2026).

Among the conventional inputs, farm size records the highest output elasticity at 0.412, indicating that a one percent increase in cultivated area is associated with a 0.41 percent increase in total output, holding other inputs constant. Labour at 0.284 and fertiliser at 0.198 follow, consistent with the labour and nutrient intensive cropping systems typical of the region. The sum of the conventional input elasticities, at 1.180, indicates mildly increasing returns to scale, a result consistent with Nigerian smallholder evidence that finds scale economies at the farm sizes typical of the area (Saadu et al., 2024). The coefficient on the adoption intensity index is positive, large, and highly significant at 0.486. Because the index enters as a continuous variable on a zero to one scale, the coefficient is interpreted as a semi elasticity, so that a move from zero adoption to full adoption of all weighted practices is associated with a 48.6 percent increase in total output, holding conventional inputs and farmer characteristics constant. This substantial technology shift confirms that adoption acts as a significant upward shifter of the production frontier, in line with the thirty to sixty percent productivity gains documented in sub Saharan African impact studies (Teklu et al., 2024). Among the controls, extension access and credit access were both positive and significant, confirming their dual role as enablers of adoption and as independent determinants of productivity, while gender and education were also positively significant and age exerted a small negative effect consistent with the lower productivity of older and less technologically engaged farmers.

Table 3. Effect of Adoption on Farm Productivity (Cobb Douglas)

Variable	Coef.	Std. Err.	t	p
ln Farm Size	0.412	0.048	8.58	<0.001
ln Labour	0.284	0.052	5.46	<0.001

Variable	Coef.	Std. Err.	t	p
ln Fertiliser	0.198	0.038	5.21	<0.001
ln Seed/Planting	0.174	0.041	4.24	<0.001
ln Agrochemicals	0.112	0.034	3.29	0.001
Adoption Index	0.486	0.074	6.57	<0.001
Age	-0.008	0.004	-2.00	0.046
Gender	0.094	0.042	2.24	0.026
Education	0.018	0.006	3.00	0.003
Extension Access	0.112	0.038	2.95	0.003
Credit Access	0.088	0.041	2.15	0.032
Constant (ln A)	4.214	0.312	13.51	<0.001
R-squared = 0.742	Adj = 0.734	F = 96.84	RTS = 1.180	

Source: Data analysis (2026). Robust standard errors. Returns to scale increasing; max VIF 3.18; no heteroskedasticity or misspecification detected.

3.4 Effects on Farm Profitability

Table 4 presents the log linear regression results for the effect of adoption on farm profitability. The model explains 68.4 percent of the variation in log net farm profit per hectare, and all diagnostic tests confirm model adequacy, with no evidence of heteroskedasticity, no functional form misspecification, and a maximum variance inflation factor of 3.42 that lies well below the conventional threshold of ten. The relative contribution of each determinant is shown in Figure 4. The adoption intensity index was the largest and most significant coefficient in the model, at 0.724. Interpreted as a semi elasticity, this indicates that a move from zero to full adoption is associated with a 72.4 percent increase in net farm profit per hectare, holding all other factors constant, a finding consistent with Saadu et al. (2024), who reported that adoption significantly improved per capita farm income among smallholders in North West Nigeria.

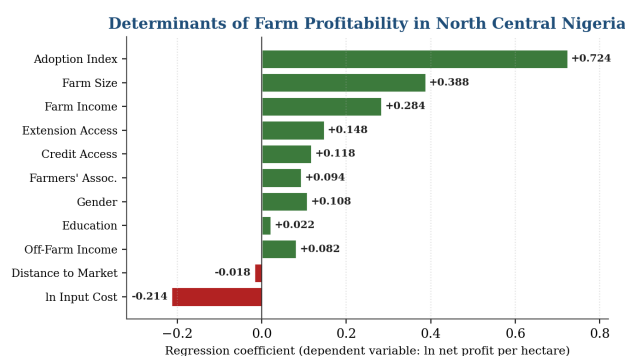


Figure 4: Determinants of farm profitability, showing positive enablers and cost side drags.

Source: Data analysis (2026).

Farm size at 0.388 and farm income at 0.284 were the next most influential positive determinants, confirming the scale and revenue base effects expected from larger and more productive farms. Extension access and credit access were both positive and significant, reinforcing the finding that institutional connectivity enables not only adoption but also the efficient use of the inputs and market opportunities that convert adoption into profit.

Membership of farmer associations contributed positively, reflecting the collective bargaining, bulk procurement, and output marketing advantages available to organised farmers. Input cost exerted a negative and significant effect on net profit, in line with the a priori expectation that higher input expenditure compresses margins, and distance to the nearest input market also significantly reduced profitability, reflecting the transaction cost burden imposed by poor market access. Taken together, these results add an economic efficiency dimension to the market access constraint that the descriptive statistics had already foreshadowed.

Table 4. Effect of Adoption on Farm Profitability (Log Linear OLS)

Variable	Coef.	Std. Err.	t	p
Adoption Index	0.724	0.112	6.46	<0.001
ln Farm Size	0.388	0.058	6.69	<0.001
ln Farm Income	0.284	0.062	4.58	<0.001
Education	0.022	0.009	2.44	0.015
Extension Access	0.148	0.048	3.08	0.002
Credit Access	0.118	0.052	2.27	0.024
Farmers' Association	0.094	0.044	2.14	0.033
Gender	0.108	0.051	2.12	0.035
Age	-0.009	0.004	-2.25	0.025
Off-Farm Income	0.082	0.046	1.78	0.076
ln Input Cost	-0.214	0.041	-5.22	<0.001
Distance to Market	-0.018	0.005	-3.60	<0.001
Constant	4.618	0.484	9.54	<0.001
R-squared = 0.684	Adj = 0.673	F = 62.14	VIF 3.42	

Source: Data analysis (2026). Robust standard errors. Dependent variable is ln net profit per hectare.

3.5 Endogenous Switching Regression Estimates

Table 5 presents the selection equation that models the factors influencing the adoption decision. Education was positive and significant, indicating that better educated farmers are more likely to adopt, as also reported by Kassie et al. (2015). Farming experience was weakly positive, suggesting that experience slightly raises the probability of adoption, a result that contrasts with Deressa et al. (2009), where experience sometimes reduced adoption through risk aversion and attachment to traditional practices. Farm size showed a strong positive effect, confirming that larger farmers are more likely to adopt. The institutional variables were highly significant, since access to extension services strongly increased adoption and credit access was also positive, consistent with Kassie et al. (2015). Membership of farmer associations positively influenced adoption, corroborating Wossen et al. (2017) on the importance of social capital and collective learning, and access to climate information emerged as the strongest predictor, reinforcing the findings of Ragasa et al. (2014) that timely and reliable climate information improves adoption decisions.

Table 5. Selection Equation (Probit Model for Adoption Decision)

Variable	Coef.	Std. Err.	z
Age	-0.005	0.004	-1.25
Education	0.038	0.016	2.38
Household Size	0.021	0.014	1.50
Farming Experience	0.017	0.009	1.89
Farm Size	0.274	0.068	4.03
Extension Access	0.496	0.132	3.76
Credit Access	0.421	0.168	2.51
Farmer Association	0.287	0.141	2.04
Climate Information (instrument)	0.563	0.149	3.78
Constant	-1.842	0.512	-3.60

Source: Data analysis (2026).

Table 6 reports the productivity outcome equation, which compares the determinants of farm productivity between adopters and non adopters within the switching framework. Across both regimes the production elasticities are positive and significant, but they are consistently higher for adopters, which signals genuine productivity gains associated with adoption. Farm size exhibited the strongest effect in both groups, with a slightly higher elasticity among adopters, suggesting that land remains a key asset whose productivity is enhanced under climate smart systems. Labour also contributed positively and more strongly among adopters, in line with evidence that adoption improves labour efficiency through better farm management. Fertiliser and seed inputs showed the same pattern, reflecting better quality input use among adopters, consistent with Suri (2011) on technology complementarities in smallholder systems. The contrast between the two regimes is summarised in Figure 5.

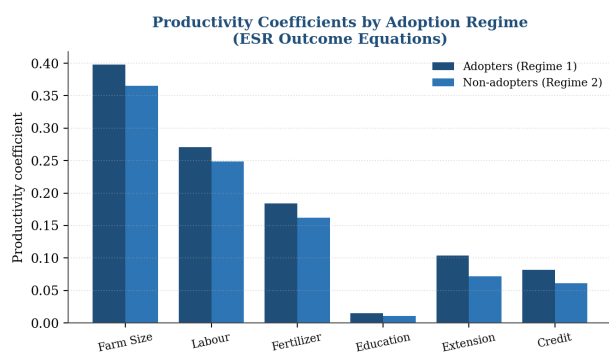


Figure 5: Productivity coefficients by adoption regime from the switching regression outcome equations.

Source: Data analysis (2026).

Human capital variables behaved as expected, with education exerting a stronger influence among adopters and extension access reinforcing the role of advisory services in translating adoption into measurable productivity gains. Credit access was significant only among adopters, which suggests that credit is more productivity enhancing when it is combined with climate smart practices, a reading that supports Kassie et al. (2015), who argue that credit alone does not improve productivity unless it is accompanied by improved production technology. The broad implication is that while conventional inputs remain important in

both groups, their returns are consistently higher among adopters, which provides empirical support for the complementary role of climate smart practices in enhancing input efficiency.

Table 6. Outcome Equation: Productivity Model (Coefficients with Standard Errors)

Variable	Adopters	Non adopters
ln Farm Size	0.398 (0.052)	0.365 (0.061)
ln Labour	0.271 (0.049)	0.249 (0.055)
ln Fertiliser	0.184 (0.037)	0.162 (0.041)
ln Seed	0.168 (0.039)	0.149 (0.043)
ln Agrochemicals	0.106 (0.032)	0.094 (0.037)
Education	0.015 (0.006)	0.011 (0.006)
Extension Access	0.104 (0.036)	0.072 (0.039)
Credit Access	0.082 (0.038)	0.061 (0.041)
Constant	4.102 (0.301)	3.864 (0.342)

Source: Data analysis (2026). Standard errors in parentheses.

The profitability outcome equation in Table 7 shows clear differences between the two regimes, with adopters consistently recording stronger and more significant returns from the key production and institutional variables. Farm size was positively significant in both regimes though slightly higher among adopters, indicating that scale contributes to profitability in both systems but that climate smart practices enhance the efficiency with which land generates returns. Farm income also showed a stronger effect among adopters, suggesting that adoption is associated with improved revenue generating capacity. Input cost had a negative and significant effect in both groups, with a slightly stronger adverse impact among non adopters, which suggests that climate smart practices partially cushion farmers against rising input costs through improved input efficiency and better resource management.

Among the human capital and institutional variables, education was positive and significant in both regimes and stronger among adopters, while extension access was more influential among adopters. Credit access was significant only among adopters, suggesting that financial services translate more effectively into profitability when they are combined with climate smart practices, and membership of farmer associations was likewise significant only for adopters, which highlights the importance of collective action in improving market access and procurement efficiency. The consistent superiority of the adopter coefficients supports the hypothesis that adoption improves the efficiency and profitability of smallholder farming systems in the region.

Table 7. Outcome Equation: Profitability Model (Coefficients with Standard Errors)

Variable	Adopters	Non adopters
ln Farm Size	0.372 (0.057)	0.341 (0.062)
ln Farm Income	0.261 (0.061)	0.228 (0.066)
ln Input Cost	-0.201 (0.039)	-0.226 (0.044)
Education	0.019 (0.008)	0.014 (0.008)

Variable	Adopters	Non adopters
Extension Access	0.139 (0.046)	0.091 (0.049)
Credit Access	0.109 (0.049)	0.078 (0.052)
Farmer Association	0.088 (0.041)	0.063 (0.045)
Gender	0.101 (0.049)	0.072 (0.052)
Age	-0.008 (0.004)	-0.006 (0.005)
Distance to Market	-0.017 (0.005)	-0.014 (0.006)
Constant	4.521 (0.472)	4.188 (0.503)

Source: Data analysis (2026). Standard errors in parentheses.

Table 8 reports the selectivity correction parameters from the switching model, which capture the extent and direction of selection bias. The correlation coefficient for adopters was negative and significant, indicating negative selection into adoption, which implies that unobserved factors associated with lower potential outcomes in the absence of adoption influence the decision to adopt. In practical terms, adopters may have been initially disadvantaged in unobservable characteristics, but adoption helped them improve outcomes beyond what they would otherwise have achieved. For non adopters the correlation coefficient was positive and significant, indicating positive selection, which implies that non adopters possess unobserved characteristics associated with relatively better outcomes under non adoption, so that the failure to adopt is not purely random but is partly driven by latent heterogeneity. The significance of both correlation parameters confirms the presence of selection bias and justifies the use of the switching framework rather than a naive comparison of adopters and non adopters. The variance parameters were both positive and significant, and the slightly higher variance among adopters points to greater heterogeneity of outcomes, which may reflect differences in the intensity of adoption, in management efficiency, or in complementary investment.

Table 8. Selectivity Correction Terms

Parameter	Estimate	Std. Err.
rho_1 (Adopters)	-0.312	0.148
rho_0 (Non adopters)	0.287	0.136
sigma_1	0.742	0.061
sigma_0	0.695	0.058

Source: Data analysis (2026). Coefficients significant at conventional levels.

Table 9 presents the counterfactual treatment effects, which capture the impact of adoption on both productivity and profitability while correcting for selection bias. The average treatment effect on the treated was positive and significant for both productivity and profitability, implying that farmers who adopted achieved about 30.2 percent higher productivity and 42.4 percent higher profitability than they would have obtained had they not adopted. The average treatment effect on the untreated was also positive and significant, indicating that non adopters would have realised meaningful gains had they adopted, and the magnitude of this effect points to substantial unrealised gains and to a wide scope for scaling up adoption across the study area. The

comparison of the two effects is depicted in Figure 6. A comparison of the two measures shows that both groups stand to benefit from adoption, although adopters realise slightly higher gains, which suggests that while selection into adoption is not random, the technology is broadly welfare enhancing across farmer types.

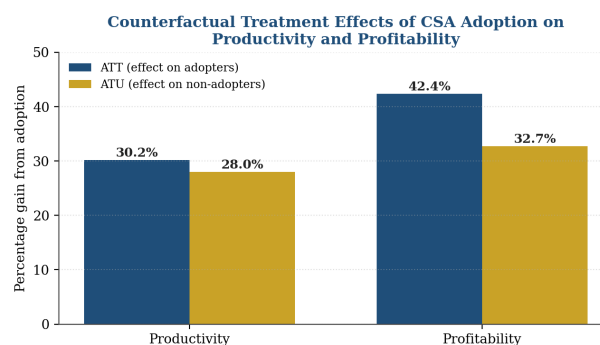


Figure 6: Counterfactual treatment effects of adoption on productivity and profitability.

Source: Data analysis (2026).

The practical significance of these gains is considerable. Given the average annual farm income of 298,400 naira among the sampled farmers, a productivity gain of 30.2 percent represents a substantial improvement in farm performance and household welfare that could translate into additional marketable surplus and enhanced food availability. Because smallholders in the region typically operate on less than two hectares and remain vulnerable to climatic shocks, gains of this magnitude are economically meaningful and contribute toward food security and livelihood resilience, in agreement with the sub Saharan evidence that climate smart practices generate significant productivity improvements among resource constrained farmers (Teklu et al., 2024). The accompanying 42.4 percent gain in profitability demonstrates that these productivity improvements are not merely increases in physical output but translate into tangible economic benefits capable of strengthening household income and reducing vulnerability to climate related production risk.

Table 9. Treatment Effects (Counterfactual Analysis)

Effect	Productivity	Profitability
ATT (effect on adopters)	0.302	0.424
ATU (effect on non adopters)	0.280	0.327

Source: Data analysis (2026). Both effects significant at the ten percent level; standard errors 0.081 and 0.094 for ATT and 0.089 and 0.101 for ATU.

Two further checks reinforce confidence in these estimates. To assess robustness, alternative model specifications were examined using different information related variables as exclusion restrictions, and the signs, magnitudes, and significance levels of the treatment effects remained largely unchanged, which suggests that the positive effects of adoption are not driven by a particular instrument but reflect a stable underlying relationship between adoption and farm performance. A sensitivity assessment that re estimated the model using access to demonstration plots and the frequency of climate advisory exposure as alternative instruments produced treatment effects that varied only marginally,

remaining within the range of twenty seven to thirty three percent for productivity and thirty nine to forty five percent for profitability. The stability of these estimates indicates that the treatment effects are not highly sensitive to instrument selection, which strengthens the causal interpretation of the reported impacts.

3.6 Constraints Limiting Uptake and Effective Use

Table 10 presents the severity ratings for the twenty constraint items, ranked in descending order of mean score, and the corresponding severity profile is visualised in Figure 7. The results reveal a spectrum of severity in which thirteen items were rated as very severe or severe and only two fell below the moderate threshold, confirming that the barriers to adoption in North Central Nigeria are pervasive, multi dimensional, and systematically concentrated in the financial, institutional, and infrastructural domains. Limited access to credit and finance ranked as the single most severe constraint, with a mean of 4.28 and a combined very severe and severe rating of 80.5 percent, a finding consistent with the mounting evidence that smallholder financial exclusion is the most binding structural barrier to the uptake of productivity enhancing technology (Salisu, 2022; Onukwube and Thompson, 2025). Inadequate access to extension services ranked second and the high cost of inputs ranked third, confirming the capital intensity of practices that lie beyond the simple diversification tier.

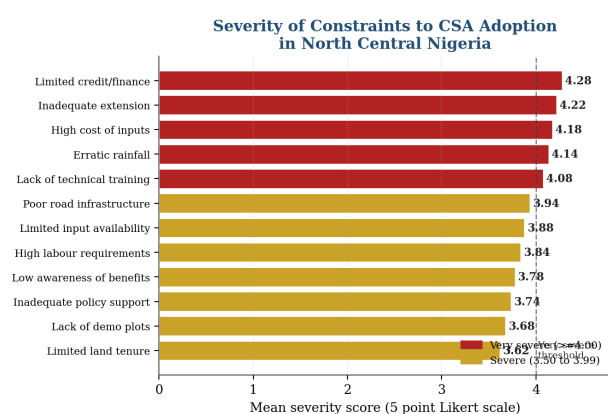


Figure 7: Severity of the leading constraints to adoption, ranked by mean Likert score.

Source: Field survey (2025).

Erratic rainfall and climate variability ranked fourth, a finding that adds an important agro ecological dimension to the constraint landscape, since even where financial and institutional barriers are eased the inherent climatic risk of rainfed smallholder agriculture imposes an additional layer of uncertainty that dampens adoption, particularly for infrastructure requiring practices whose returns are closely tied to consistent rainfall. The lack of access to technical training ranked fifth, reflecting the knowledge intensity of many practices and the absence of accessible community level training. Together, the top five constraints of credit, extension, input cost, climate risk, and technical training define a mutually reinforcing cluster of financial and institutional barriers that systematically prevent farmers from moving beyond the simple and low cost practices that dominate the current adoption portfolio. Constraints related to market infrastructure, labour, and awareness form a secondary tier, while socio cultural constraints such as negative cultural attitudes, gender barriers, and storage inadequacy are

present but relatively less binding, which suggests that the primary leverage points for intervention are structural and institutional rather than attitudinal.

Table 10. Constraints to Adoption of Climate Smart Agribusiness Practices

Constraint Item	Mean	Rating	Rank
Limited access to credit/finance	4.28	Very Severe	1
Inadequate access to extension	4.22	Very Severe	2
High cost of inputs	4.18	Very Severe	3
Erratic rainfall and climate variability	4.14	Very Severe	4
Lack of access to technical training	4.08	Very Severe	5
Poor road and transport infrastructure	3.94	Severe	6
Limited input availability in markets	3.88	Severe	7
High labour requirements	3.84	Severe	8
Low awareness of benefits	3.78	Severe	9
Inadequate policy support and subsidies	3.74	Severe	10
Lack of demonstration plots	3.68	Severe	11
Limited land tenure security	3.62	Severe	12
Perceived high risk of returns	3.58	Severe	13
Distance to input markets	3.52	Moderate	14
Low farmer organisational capacity	3.44	Moderate	15
Inadequate soil testing infrastructure	3.38	Moderate	16
Negative cultural attitudes	3.18	Moderate	17
Gender based barriers	3.08	Moderate	18
Inadequate storage for organic inputs	2.94	Not Severe	19
Competition with food crops for land	2.82	Not Severe	20

Source: Field survey (2025). Mean at or above 4.00 Very Severe; 3.50 to 3.99 Severe; 3.00 to 3.49 Moderate; below 3.00 Not Severe.

4. Conclusion and Recommendations

This study provides empirical evidence on the role of climate smart agribusiness practices in improving farm productivity and profitability among smallholder farmers in North Central Nigeria. The findings show that while adoption levels are relatively high for low cost practices, the more knowledge intensive and capital intensive practices remain less widely adopted. The switching regression results confirm that adoption decisions are not random and are shaped by observable and unobservable factors such as farm size, education, extension access, and credit access. After correcting for selection bias, the counterfactual analysis demonstrates that adoption leads to significant gains in both productivity and profitability, that adopters outperform non adopters, and that non adopters themselves stand to gain considerably were they to transition into adoption.

Five recommendations follow from the evidence. First, since climate information significantly influences the decision to adopt, scaling up access to timely and reliable weather and climate advisory services can accelerate uptake. Second, because distance to market depresses profitability, investment in rural roads, storage

facilities, and market linkages is needed to reduce transaction costs and raise the returns to adoption. Third, given the weight of input cost as a constraint, input subsidy programmes or cost sharing mechanisms for climate smart technologies such as improved seed and organic fertiliser should be expanded, particularly for resource poor farmers. Fourth, since credit access emerged as a key determinant of both adoption and profitability, policy should promote tailored financing schemes for smallholders, including low interest loans and flexible collateral requirements. Fifth, because membership of farmer associations positively influenced adoption and profitability, strengthening these groups can improve access to inputs, credit, and market information while supporting collective learning and the diffusion of technology.

Declarations

The authors declare that there is no conflict of interest regarding the publication of this paper. The study was self funded by the authors. Ethical approval was obtained from the relevant institutional review framework, informed consent was obtained from all respondents prior to data collection, participants were assured of the confidentiality and anonymity of their responses, and participation was entirely voluntary.

References

- [1] Agyekum, K., Ansah, I. G. K. and Kuwornu, J. K. M. (2024). Adoption of climate smart agricultural practices and its impact on farm performance in sub Saharan Africa. *Agricultural Systems*, 215, 103905.
- [2] Consultative Group on International Agricultural Research (2024). Climate smart agriculture and sustainable intensification: global research insights. CGIAR Research Program on Climate Change, Agriculture and Food Security.
- [3] Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T. and Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, 19(2), 248 to 255.
- [4] Federal Ministry of Agriculture and Food Security (2023). Annual agricultural performance report. Abuja, Nigeria: Federal Ministry of Agriculture and Food Security.
- [5] Gabriel, S. C., Ojo, M. A. and Yusuf, A. B. (2023). Climate smart agriculture adoption among smallholder farmers in North Central Nigeria. *Journal of Agricultural Extension*, 27(2), 45 to 58.
- [6] Kassie, M., Teklewold, H., Jaleta, M., Marenja, P. and Erenstein, O. (2015). Understanding the adoption of a portfolio of sustainable intensification practices in eastern and southern Africa. *Land Use Policy*, 42, 400 to 411.
- [7] Mbah, C. N., Ezeaku, P. I. and Opara, C. C. (2024). Agroforestry systems and soil fertility improvement in savanna agroecosystems of Nigeria. *Agroforestry Systems*, 98(1), 113 to 128.
- [8] National Bureau of Statistics (2022). Nigeria gross domestic product report. Abuja, Nigeria: National Bureau of Statistics.
- [9] National Bureau of Statistics (2024). Agricultural performance survey report. Abuja, Nigeria: National Bureau of Statistics.
- [10] National Population Commission (2006). Population and housing census of the Federal Republic of Nigeria. Abuja, Nigeria: National Population Commission.
- [11] Nigerian Meteorological Agency (2020). Climate review bulletin. Abuja, Nigeria: Nigerian Meteorological Agency.
- [12] Onukwube, H. N. and Thompson, D. (2025). Institutional constraints and adoption of climate smart agriculture in Nigeria. *African Journal of Agricultural Economics*, 10(1), 77 to 92.
- [13] Ragasa, C., Berhane, G., Tadesse, F. and Taffesse, A. S. (2014). Gender differences in access to extension services and agricultural productivity. *Journal of Agricultural Education and Extension*, 20(5), 437 to 468.
- [14] Saadu, M. A., Ibrahim, H. Y. and Bello, A. (2024). Climate smart agriculture and farm income among smallholder farmers in Northern Nigeria. *Journal of Agricultural Economics and Development*, 13(1), 25 to 39.
- [15] Salisu, A. A. (2022). Determinants of climate smart agriculture adoption in the Middle Belt of Nigeria. *Journal of Sustainable Agriculture*, 14(3), 112 to 126.
- [16] Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1), 159 to 209.
- [17] Teklu, B. M., Kassie, M. and Shiferaw, B. (2024). Impacts of climate smart agricultural practices on productivity and income in sub Saharan Africa. *World Development*, 175, 106512.
- [18] Tsado, J. H., Abdullahi, A. and Mohammed, S. (2024). Extension service delivery and climate smart agriculture adoption in Nigeria. *Journal of Agricultural Extension and Rural Development*, 16(1), 1 to 12.
- [19] Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., Feleke, S., Olanrewaju, A. and Manyong, V. (2017). Impacts of extension access and cooperative membership on technology adoption and household welfare. *Journal of Rural Studies*, 54, 223 to 233.
- [20] Yamane, T. (1967). *Statistics: An Introductory Analysis* (2nd ed.). New York: Harper and Row.