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Original Research Article

Adoption of climate-smart agricultural practices and its impact on smallholder farming households in some rural areas of North-Western Nigeria

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Abstract

The study determined the impact of climate-smart agriculture (CSA) adoption on crop yield, income, and food security status of smallholder farmers in north-western Nigeria using a sample of 377 farming households. Descriptive statistics, farm budgeting, probit regression model, and treatment effect model were used for data analysis. The result revealed that 82 % of the respondents are adopters of the CSA practices. Significant differences exist in the socioeconomic attributes of the adopters and non-adopters of CSA practices. More so, adopters had significantly larger farm sizes of about 4.0ha compared to 3.4ha for non-adopters. The major CSA practices adopted include crop rotation, application of organic and inorganic fertilisers, and multiple cropping. The major determinants of CSA practices adoption are age, membership of an association, and awareness of climate change impact. The result further shows that CSA adoption will increase technical efficiency scores by 21.9 %, crop income by ₦19,389 ($17.62) per hectare, while the household per capita expenditure on food will also increase by ₦21,938 ($20.0) This implies that the adoption of climate-smart agriculture significantly improved crop yield, income and food security status of smallholder farmers. To sustain the benefits of CSA practices adoption, farmers should be supported so that they do not discontinue its adoption. Credit availability should also be facilitated by the government to enable farmers to obtain relevant agricultural inputs to complement the adoption of CSA practices.

Keywords: climate-smart agriculture; food security; income; smallholder farmers; study zones

INTRODUCTION

The agriculture sector is vital in the eradication of extreme poverty and hunger; it supports the livelihoods of close to 1.5 billion people living in rural area households worldwide (World Bank, 2008). Despite its vital importance, the sector is highly sensitive and susceptible to climate change and variability (Perret, 2006). This is because African agriculture is predominantly rain-fed and hence fundamentally dependent on the vagaries of weather (Zoellick, 2009). According to the Food and Agricultural Organisation (2014), climate change is likely to cause considerable crop yield losses, adversely affecting smallholder livelihoods in Africa. As a result, food security and income generation opportunities for the farming households most reliant on agriculture may be in jeopardy. It is projected that crop yield in Africa may fall by 10–20 % by 2050 or even up to 50 % due to climate change (Nwaobiala and Nottidge, 2013). It is therefore important that measures are taken to mitigate the consequences of climate change.

Climate Smart Agriculture (CSA) is a concept that was coined by the Food and Agricultural Organization and widely endorsed by international development institutions (FAO, 2010; FAO, 2013). It is aimed at sustainable intensification, sound and efficient management of natural resources, and offers an opportunity for climate change funding while seeking to strengthen the livelihoods of small-scale farmers through improved access to services, knowledge, genetic and financial resources, markets, etc. (FAO, 2013). CSA enhances adaptation to climate change and increases food security while productivity practices ensure food sufficiency despite unsuitable climatic conditions. This is achieved through several soil management practices that sequester carbon in the soil, reduce greenhouse gas emissions, and aid intensive production (FAO, 2013). Above all the CSA practices enhance the natural resource base. The most important premise of CSA is the building of healthy soils through increasing the soil organic matter status of the soil (Zheng et al., 2014). Several studies on climate-smart agriculture have been conducted in Nigeria (Ogundele and Jegede, 2011; Akpenpuun et al., 2013; Oluyole, 2013; Tiamiyu et al., 2015; Tiamiyu et al., 2017; Ayanlade et al., 2017; Oyawale et al., 2017 and Oyawale et al., 2020). These studies focused on the effect of climatic variables on agricultural production, the adoption of climate-smart agricultural practices, farmers' perception of climate change, and also their adaptation strategies. Empirical findings from these studies point to the fact that climate change is real and has significantly impacted agricultural production in Nigeria. However, none of these studies assessed the impact of adopting climate-smart agricultural practices on technical efficiency, crop income, and food security status of smallholder farmers in Nigeria. This presents an important research gap since the literature suggests that technical efficiency, crop income, and food security may be influenced by the adoption of climate-smart agricultural practices among farmers. Furthermore, the low level of CSA practices adoption in the region alongside the realities and challenges of climate change is partly due to inadequate empirical evidence on the benefits of CSA practices and farmers' skepticism of the realities of climate change. It is against this background that this study assessed the impact of the adoption of climate-smart agricultural practices on technical efficiency, crop income, and food security status of smallholder farmers in north-western Nigeria.

The specific objectives are to:

i) Determine the level of adoption of climate-smart agriculture by smallholder farmers in Katsina State.
ii) identify the determinants of climate-smart agriculture by smallholder farmers in Katsina State.
iii) determine the impact of climate-smart agricultural practices on technical efficiency, crop income, and food security status among smallholder farmers in Katsina State.

THEORETICAL FRAMEWORK OF CSA

This study borrows from the theoretical framework of the theory of utility. As stated by Terdoo and Adekola (2014), deciding whether or not to adopt any CSA practice falls under utility and profit-maximisation theoretical frameworks. The theory of utility explains the behaviour of individuals on the basis that individuals can consistently rank their choices based on their preferences. With the theory of utility, what is deemed necessary about utility concerning choice/s being made is whether an option has a higher utility than another and not the measure of the difference between the available options. The consideration of choices made on which agricultural practices to be adopted by farmers hangs on the concept of ordering available options based on the benefits they receive from the practices. There is the assumption that economic agents, including small-scale farmers, adopt CSA practices when the expected utility or net benefit is significantly higher than when they do not adopt them. As utility cannot be directly observed, the activities of economic agents could be observed through their choices. Consider a rational farmer whose aim is to maximise the proceeds from production over a specific period and has a set of CSA practice z options to choose from. The farmer decides to adopt CSA practice z if the utility from z is perceived to be more than that from other options (assume, M) this relationship is expressed as Equation (i)

$$Uiz = (\beta^{!}\, z\, Xi + \varepsilon z) > UiM\, (\beta^{i}\, K\, X_i + \varepsilon j),\ M \neq z \qquad \text{(i)}$$

where Uiz and Uim denote the perceived utility by farmer i from CSA practice options z and m, respectively; Xi is a vector of regressors that influence the CSA practice option the farmer chooses; εz and Xn are parameters of the independent variables; and "z and "m are the error terms, which based on an econometric assumption are independently and identically distributed (Hill et al., 2018)

$$Y_{iz} = 1 \text{ if } Uiz > 0 \text{ and } Y_{iz} = 0 \text{ if } U_{iz} < 0 \qquad \text{(ii)}$$

In the generated formula, Y is a binary dependent variable valued as 1 when the farmer opts for a CSA practice and 0 if otherwise. The probability that farmer i will choose CSA practice option z among the set of adaptation options could be expressed as Equation (iii)

$$
\begin{aligned}
&(X = 1/X)_{-\varepsilon m > 0/x} = P\,(U_{ij} > U_{im/X}) = P(\beta^{1}\, z\, X_i + \varepsilon z - \beta z\, Xi - \\
&- \varepsilon z - \beta^{1} MX_i - = P(\beta z\, Xi + \varepsilon z - \beta^{1} MX_i - \varepsilon zm > 0/X) = \\
&= P(\beta x\, Xi + \varepsilon x > 0/X) = F(\beta x\, Xi) \qquad \text{(iii)}
\end{aligned}
$$

where P is a probability function; $\varepsilon^* = \varepsilon z$ is a random disturbance term; $\beta^* = (\beta' z - \beta' m)$ is a vector of unknown parameters that can be explained as the net influence of the determinants of the choice of CSA practice; and $F(\beta^*\, Xi)$ is a cumulative distribution of ε^* estimated at β^* $\beta' Xi$ (Hill et al., 2018).

According to Issahaku and Abdulai (2019), a practice can be regarded as 'climate-smart' if it falls within the three main climate-smart agricultural goals set by the FAO (2013) which are as follows.

(a) Increasing agricultural productivity and incomes on a sustainable basis.
(b) Adopting and building climate change resilience.
(c) Reducing greenhouse gas emissions.

The following were climate-smart agricultural goals set by FAO (2013) and their practices

(a) Increasing Agricultural Productivity and Incomes on Sustainable Basis

i) Diversifying cropping practices
ii) Crop rotation
iii) Mixed farming
iv) Usage of wetland FADAMA
v) High yielding cultivators
vi) Agroforestry
vii) Adjusting of planting date

(b) Adoption and Building Climate Change Resilience

i) Planting drought-resistant varieties
ii) Relocation from climate risk
iii) Multiple cropping
iv) Recycling of waste products
v) Improvement in farmers' management skills
vi) Agro-forestry
vii) Zero tillage
viii) Diversifying cropping practices

(c) Reducing Greenhouse Gas Emission

i) Conservation tillage
ii) Cover crop
iii) Application of organic and inorganic fertilisers
iv) Agro-forestry
v) Usage of wetland FADAMA

This implies that only farmers observed to be practicing climate-smart agricultural practices that cut across all the three main objectives of climate-smart agriculture will be considered adopters of climate-smart agriculture. This means that partial adopters or farmers using CSA practices that cut across one or two objectives of CSA as stated by FAO (2013) will not be considered adopters of CSA practices in this study. A similar approach was adopted by Olawuyi and Mushines (2018) for a study on the adoption of conservation agricultural practices in Nigeria.

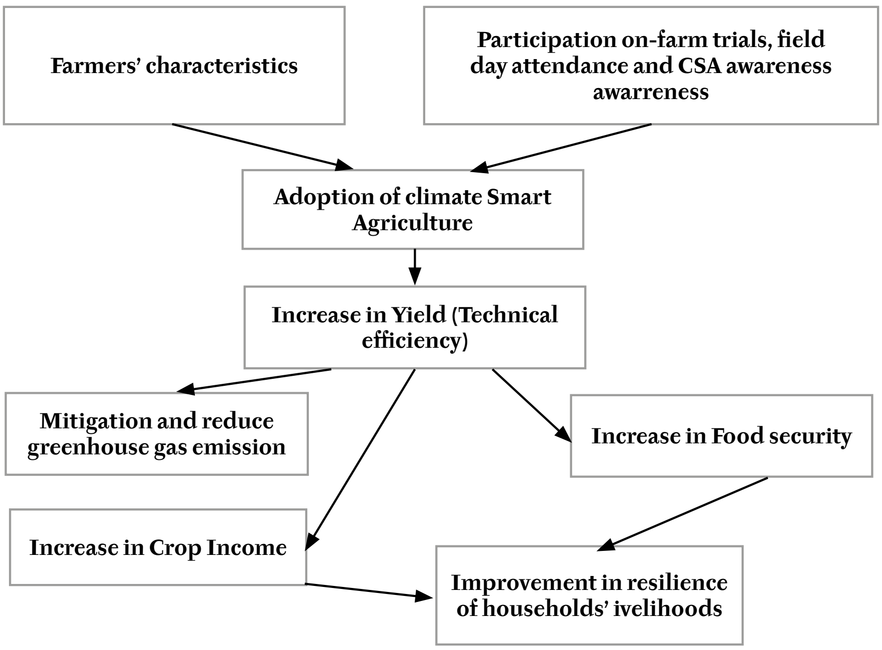

Figure 1. Conceptual Framework diagram which shows the relationship between CSA and technical efficiency, crop income, and food security.

CONCEPTUAL FRAMEWORK OF CSA

The pathways through which the CSA can impact farmers' technical efficiency, crop income and food security status among smallholder farmers are presented in Figure 1. The Adoption of CSA depends on the farmers' characteristics such as gender, education, farming experience, frequency with contact extension agents, past participation in farm trials, and field day attendance awareness. An immediate effect of CSA practice adoption is an increase in yield which will in turn lead to an increase in crop income to farmers. An increase in crop income can enhance or improve food security status at the household level (Immediate effect). On the other hand, farming households' ability to mitigate and reduce greenhouse gas emissions is enhanced. It is expected that the total of the immediate effects will in the long run lead to a more resilience farming household and system that will sustain the food system

MATERIAL AND METHODS

The field survey was carried out in Katsina State, which is located in the northwestern region of Nigeria where farming is the major occupation (Figure 2). The northwestern region is described as a relatively hot climate with seasonal rainfall and a marked dry season (Soneye, 2014). Katsina State comprises thirty-four (34) Local Government Areas (LGAs). The state covers an area of 24,192 km^2 and is located between latitudes 12°15N and 12.250°N and longitudes 7°30E and 7.50°E. The population of the State is 7,831,300 (NPC, 2016). The State shares borders with the Niger Republic to the North, Jigawa, and Kano State to the East, Kaduna State to the South, and Zamfara State to the West. The state has scrub vegetation with wooded savannah in

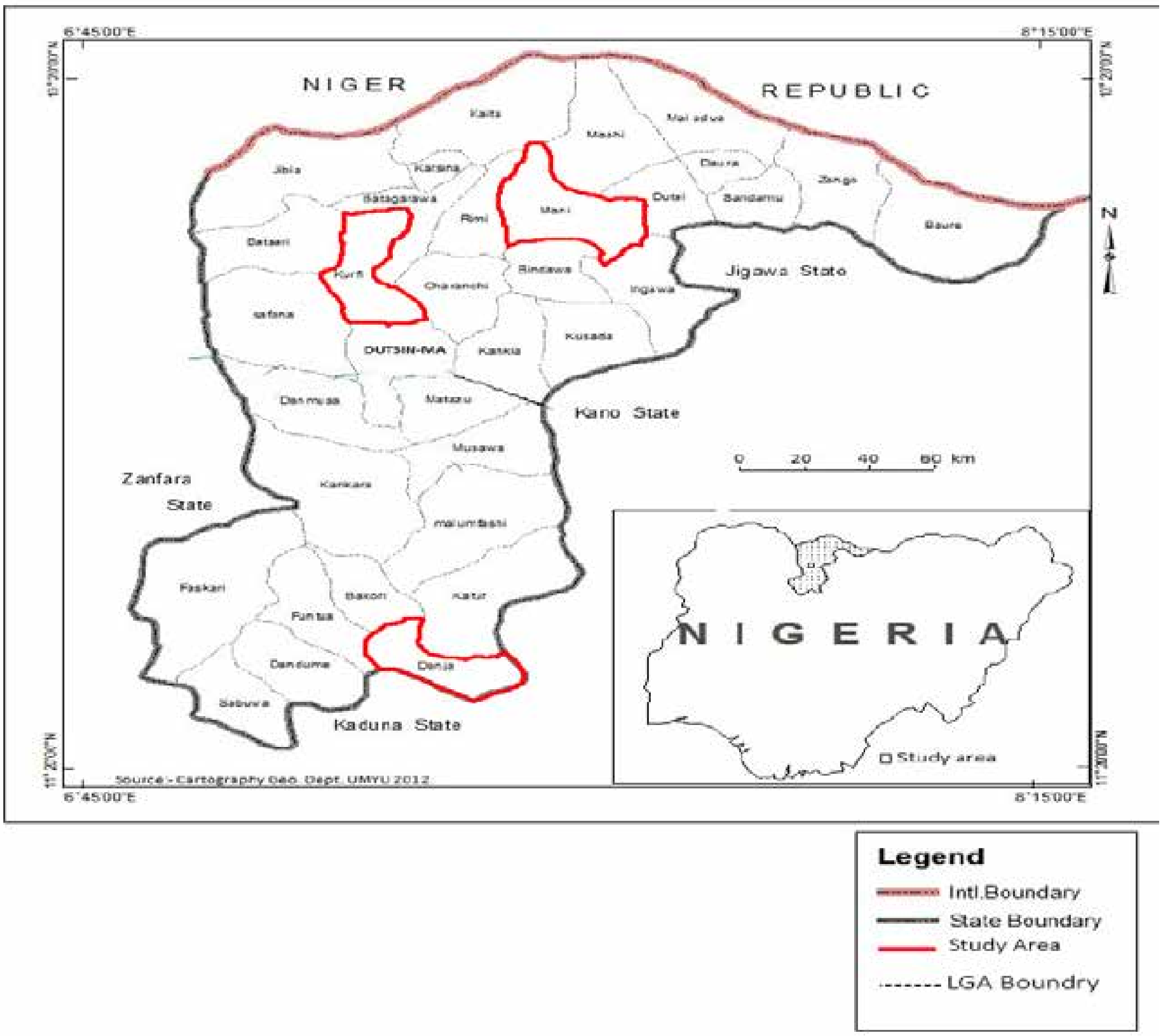

Figure 2. Map of Katsina State

the south. Average rainfall and temperature are about 600 mm *per annum* and 26 °C, respectively. The climate in the state makes the farmers cultivate a wide range of crops such as cereals, legumes, and vegetables, the farmers also rear livestock such as cattle, goats, sheep, poultry etc. Katsina State is mainly populated by Hausa, Fulani, and other minor tribes.

Sampling procedure and data collection

In the absence of an experimental setting, observational data were used for the study. The smallholder farming households in the study area constitute the population for the study. A cross-sectional sample survey design was adopted for the study. The study area (Katsina State) was stratified into three agricultural development zones namely; Ajiwa, Funtua, and Dutsinma zones, and a random selection of one LGA from each of the three agricultural zones in Katsina was done using balloting. The following LGAs, Kurfi, Mani, and Danja were selected in the initial stage. Furthermore, in each LGA, the major farming communities were identified via a reconnaissance survey with the assistance of farmers and extension agents. Twenty communities were identified in Kurfi LGA, whereas 25 and 30 were identified in Mani and Danja LGAs, respectively. Raosoft sample size calculator was used to determine the appropriate sample size from the population of farming households in the selected communities and a sample size of 377 households was recommended for the study as shown in Table 1. The data for the study were collected using a structured questionnaire during the 2021/2022 farming season. The questionnaire contains demographic information such as age, farming experience, educational level, household size, extension contact, membership of association, and farm size. Production information such as inputs used (land, seed, labor, fertilisers, and agrochemical) and output obtained.

Analytical techniques

A simple descriptive, probit regression model and a treatment effect model were used for the data analysis. The data envelopment analysis was used to estimate technical efficiency from crop production so that the variations in units for different crop outputs could be accommodated.

Probit regression model

This model was used for the study because the dependent variable (adoption of CSA practices) is categorical. In the Probit regression model; the dependent variable takes the value of "1", for adopters of CSA practices and "0", if otherwise. The explicit form of the model is as follows:

$$Y = a + X_1b_1 + X_2b2 + X_3b_3 + X_4b_4 + X_5b_5 + X_6b_6 + X_7b_7 + + X_8b_8 + X_9b_9 + X_{10}b_{10} + X_{11}b_{11+}\mu\ldots i$$

where

Y = Climate-smart agricultural practices adoption (1 = adopter, 0 = No adopter)

Independent variables are

X_1 = Age of household head (years)

X_2 = Gender of households (male = 1, female = 0)

X_3 = Awareness of climate change impact

X_4 = Household size (number)

X_5 = Educational status of household (years)

X_6 = Farming experience of household head (years)

X_7 = Farm size (hectares)

Table 1. Distribution of the farmers selected in the study area

Katsina State Agricultural Zones	Selected LGAs	Selected Community/ Villages	Number of Households Farmers Identified	Number of Households Farmers Selected
Zone (i) Ajiwa	Mani	Muduru	1245	27
		Bagiwa	1085	23
		Kwatta	1185	25
		Magami	1125	24
		Jani	1200	26
Zone (ii) Funtua	Danja	Jiba	1300	28
		Tandama	1400	30
		Kahutu	1230	26
		Dabai	1300	28
		Yakaji	1000	23
		Tsangamawa	1150	24
Zone (iii) Dutsin-ma	Kurfi	Tsauri	1100	23
		Rawayau	950	20
		Barkiya	1130	24
		Tamawa	1200	26
Total	**3**	**3**	**17700**	**377**

Source: Field Survey, 2021

X_8 = Access to Membership of farm association (yes = 1, no = 0)
X_9 = Off-farm income (naira)
X_{10} = Access to agricultural credit (yes = 1, no = 0)
X_{11} = Access with extension agent (yes = 1, no = 0)
μ = Error term

These variables were selected from previous studies on the determinants of the adoption of CSA practices in Nigeria (Ojoko et al., 2017; Onyeneke et al., 2018; Oyawole et al., 2019 Jellason et al., 2021; Okpokiri, et al., 2021; Victory et al., 2022). These studies have shown that the selected variables can significantly influence the adoption behaviour of smallholder farmers hence the rationale for their inclusion in the probit regression model.

Endogenous treatment effect model

To obtain a consistent estimate of the impact of CSA practices adoption on the outcomes of interest (yield of crops, crop income, and food security status) an endogenous treatment effect model was used to account for endogeneity between the adoption of CSA practices and outcomes. This is because the bias related to unobservable characteristics of the farmers cannot be controlled using Propensity Score Matching (Adebayo et al., 2018). The treatment effects estimators determine the experimental-type causal effects from the observational data. An Endogenous treatment effects model is used to determine an accurate causal effect if the selection-dependent variable is binary and endogenous. Given that the outcomes (technical efficiency used as a proxy for crop yield, crop income, and food security) depend on some characteristics of individual farmers and households (X_i) and a dummy variable for the selection variable which is CSA adoption (A_i), the outcome variable (technical efficiency, income, and food security) can be expressed as:

$$TE_i = \beta i X_i + \delta k A_i + \beta_f \lambda j + \eta_i \quad \text{(ii)}$$

$$CI_i = \beta i X_i + \delta k A_i + \beta_f \lambda j + \varphi_i \quad \text{(iii)}$$

$$FS_i = \beta i X_i + \delta k A_i + \beta_f \lambda j + \psi_i \quad \text{(iv)}$$

where TEi, CI_i, and FS_i are the technical efficiency (a proxy for outputs of all crops produced), crop income, and food security status for the respondents, respectively. X_i is a vector of household characteristics which include
X1 = Age of the house respondent (years)
X_2 = Gender of the respondent (male = 1, female = 0)
X_3 = Awareness of climate change impact (yes = 1, no = 0)
X_4 = Household size of the respondent (numbers)
X_5 = Educational status of the respondent (years)
X_6 = Farming experience of the respondent (years)
X_7 = Farming size (hectares)
X_8 = Off-farm income (naira)
X_9 = Access to agricultural credit (yes = 1, no = 0)
X_{10} = access to extension agent (yes = 1, no = 0)
X_{11} = Membership of farm association (yes = 1, no = 0)
X_{12} = Inverse mills ratio
Z_1 = past participation in an on-farm trial (yes = 1, no = 0)
Z_2 = Field day attendance (yes = 1, no = 0)
A_i is the CSA practice adoption status; λu is the Inverse Mills Ratio (IMR); η_i, φ_i and ψ_i are the error term; and βi, βj and δk are parameters to be estimated.

Given that, a farmer self-selects to adopt CSA practices, the same unobservable factors such as farmers' innate abilities and motivations may simultaneously influence adoption decisions and the outcomes (technical efficiency, crop income, and food security). The error term μ in Equation (i), and the error term $\eta_i\ \varphi_i\ \psi_i$ in any of the Equations (ii) (iii), or (iv) may be correlated such that corr ($\varepsilon_{i,} \eta_i \varphi_i \psi_i \neq 0$), leading to potential endogeneity of the adoption variable in the analysis. The Ordinary Least Squares (OLS) model will produce biased and inconsistent estimates if it is used to estimate the effect of CSA practice adoption on technical efficiency, crop income, and food security when there is self-selection bias.

A treatment effects model proposed by Zhihao et al. (2024) was used to determine the impact of CSA adoption on crop yield (proxied with technical efficiency estimates), crop income, and food security in this study. The Endogenous treatment effects model estimates the CSA practice adoption decision equation (i) and the outcome equations (ii) (iii) and (iv). The treatment effect corrects for hidden or unobservable bias by removing the selection bias due to the observed and unobserved covariates. In addition, the exposure to treatment becomes random, conditional on the inclusion of the Inverse Mills Ratio (IMR), and the factors determining the outcome (technical efficiency, crop income, and food security status) were identified in the second stage, respectively (Hassan et al., 2018).

For proper identification of the model, the treatment effects model requires that there is at least one variable in the X_i of the adoption or selection equation that does not appear in the X_j of the outcome equations (the factors determining the outcomes (crop yield, crop income, and food security) are identified in the second stage (Hassan et al., 2018). The additional variable in the outcome equation serves as an instrumental variable to

Table 2. Quantitative attributes of adopters and non-adopters of CSA practices

Description of Variables	Adopters	Non-Adopters	Differences
Age (years)	45.6 (7.89)	42.1 (9.44)	0.04**
Household size (persons)	17.2 (6.67)	13.6 (7.02)	0.02**
Farming experience (years)	21.9 (8.92)	15.6 (11.60)	0.00***
Highest educational level (years)	5.4 (5.15)	5.2(3.82)	0.41
Farm size (numbers)	4.0 (1.34)	3.4 (1.69)	0.04**

Notes: Figures outside the parenthesis are means while the ones in the parenthesis are standard deviations. ***, **, * Denotes significance at the 1%, 5% and 10%, respectively.
Source: Field Survey, 2021

Table 3. Qualitative attributes of adopters and non-adopters of CSA practices

Variables	Chi-Square Value	P-Value
Gender	1.016	0.313
Access to Credit	4.1503	0.042**
Access to Extension Service	0.8369	0.36
Access to Membership of Ass.	16.57	0.000***
Off-farm income	0.1195	0.730
Awareness of Climate Change	10.2424	0.001***
Past Participation in Farm Trials	13.1368	0.000***
Field Day Attendance	4.0595	0.044**

Note: ***, **, * Denotes significance at the 1, 5, and 10%, respectively.
Source: Field Survey, 2021

control for endogeneity problems due to unobservable factors (e.g. farmers' innate abilities and motivation) that may bias the impact of CSA adoption on the outcome variables directly. In this study, previous participation in an on-farm trial and field day attendance were used as identifying instruments. This is in line with the submission of Ghimire and Shrestha (2015) that farmers are more likely to adopt CSA practices if they have participated in on-farm trials and have attended field days in the past.

RESULTS AND DISCUSSION

Socioeconomic characteristics of respondents

The quantitative socioeconomic characteristics of adopters and non-adopters are presented in Table 2. The results show that the majority of the respondents are males and polygamous, with an average household size of about 17 and 13 persons for adopters and non-adopters of CSA practices, respectively. Farming is the main occupation of all categories of the respondents. The majority (82%) of the respondents are adopters of CSA practices. The average age of the adopters and non-adopters was 45 and 42 years, respectively, whereas the average number of years for schooling was 5.4 years and 5.2 years for adopters and non-adopters, respectively, indicating that either group of farmers had not completed primary education but the majority had Quranic education. The average farming experience was 21 years and 15 years for adopters and non-adopters, respectively. More so, adopters had significantly larger farm sizes of about 4 ha compared to 3.4 ha for non-adopters.

The result in Table 3 further shows that significant differences exist in the qualitative attributes of the two categories of respondents. However, no significant differences were observed in gender, access to extension services, and off-farm income among the respondents. This implies that the two groups are heterogeneous and are significantly different from one another justifying the need to correct for potential selection bias in the analysis to estimate consistent and unbiased impacts of CSAP adoption on crop yield, income, and food security.

Adoption of CSA practices

The level of adoption of CSA practices is presented in Table 4. The result shows that considering all the CSA practices as a whole, crop rotation, application of organic and inorganic fertilisers, and multiple cropping are the most common and widely adopted practices for coping with the effects of climate change among farmers in the study area. A similar observation was made by Ojoko et al. (2017). However, the findings further show that recycling of waste products and agro-forestry were the least practices adopted by farmers in the study area. The farmers prefer to plant trees such as mango, guava, pawpaw, and cashew trees that generate income for

Table 4. Level of adoption of climate smart agricultural practices

	CSA Practices	Frequency	Percentage	Rank
	Productivity-enhancing CSAPs			
1	Crop rotation	377	100	1st
2	Diversify cropping practices	354	93.89	2nd
3	Used of wetland (Fadama)	173	45	3rd
4	High yielding cultivators	173	45.88	4th
5	Adjusting planting date	60	15.92	5th
6	Mixed farming	49	12.99	6th
7	Agro-forestry	34	9.01	7th
	Resilience building CSAPs			
8	Multiple cropping	366	97.8	1st
9	Zero tillage	140	37.16	2nd
10	Planting drought-resistant varieties	37	9.81	3rd
11	Improvement of farm management skills	26	6.90	4th
12	Relocation from risk areas	23	6.10	5th
13	Recycling of waste product	20	5.30	6th
	Greenhouse Gas Mitigation CSAPS			
14	Application of organic and inorganic fertilisers	377	100	1st
15	Cover crop	166	44	2nd
16	Conservation tillage	26	6.90	3rd

Source: Field Survey, 2021

a long time. This finding is supported by Tiamiyu et al. (2018) who also evaluated the level of CSA adoption in Nigeria.

Outcome indicators for adopters and non-adopters of CSA practices

The result from Table 5 shows that there is a significant difference in all three outcome indicators between adopters and non-adopters of CSA practices. However, without conducting a formal impact evaluation this is not enough evidence to conclude that the adoption of CSA practices will lead to a higher production efficiency, crop income, and *per capita* expenditure on food in the study area.

Determinants of adoption of CSA practices

The results of the probit model for the determinants of CSA practices adoption decisions are presented in Table 6. The result shows that collectively all the estimated coefficients are statistically significant since the likelihood Ratio (LR) statistically has a $p < 0.01$. The pseudo R^2 value is 33 % which is acceptable for cross-sectional data, confirming that the model fits the data well (Wooldridge, 2009). The age of the household head, membership in farmers´ associations, and awareness of climate change are statistically significant in influencing household decisions to adopt CSA practices. The age of the household head had a negative but significant influence on the adoption of CSA practices. This finding suggests that older farmers are conservative and are not disposed to the adoption of CSA practices, implying that the younger farmers are more likely to try out new practices and bear the risk associated with the adoption of new technology (Awotide et al., 2012) similarly corroborated the findings of Leavy and Smith (2010) and Duyen et al. (2020), who found that older farmers were more risk averse and less likely to make long-term investments in the farm than younger farmers. Membership in farmers' associations was positive and significantly influenced the adoption of CSA practices suggesting that farmers who are members of farmers' associations are more likely to be the adopters of CSA practices. This

Table 5. T-test for outcome indicators

Description of outcome indicators	Adopters	Non-adopters	P values
Technical efficiency	0.86	0.542	0.005***
Average Crop income (₦)	221355.20	171550.00	0.017**
Per capita food expenditure (₦)	52808.23 ($48.0)	43495.00 ($39.5)	0.033**

Note: *, **, *** = significant at 10 %, 5 %, 1 %, respectively.
Source: Field Survey, 2021

Table 6. Determinants of adoption of CSA practices

Variables	Coefficient	Marginal Effect
Age	–0.03 (0.02) **	–0.004
Gender	–2.0 (0.55)	–0.13
Household size	0.04 (0.49)	0.01
Farming experience	0.03 (0.32)	0.01
Highest educational level	–0.03(0.53)	–0.006
Access to extension service	0.56(0.34)	0.23
Access to credit	0.99 (0.26)	0.26
Off Farm income	–0.07 (0.90)	–0.02
Membership of the farm association	1.02 (0.03) **	0.25
Farm sizes	0.04 (0.78)	0.01
Awareness of climate change Impact	1.65 (0.005) ***	0.53
Constant	–0.289	
Number of observations	377	
Log-likelihood	–30.39	
LR Chi^2 (12)	33.49	
Prob > Chi^2	0.0000	
Pseudo R^2	0.33	

Note: ***, **, * Denotes significance at the 1, 5, and 10%, respectively.
Source: Field Survey, 2021

Table 7. Impact adoption of climate-smart agricultural practices on technical efficiency, crop income and per capita food expenditure

Variables	Technical Efficiency		Crop income		Per-capita food expenditure	
	Coefficient	S.E.M.	Coefficient	S.E.M.	Coefficient	S.E.M.
Age	–4.32	10.332	–120.36	79.39	2.1038	7.3044
Farming experience	0.59	8.75	19.15	59.88	10.87	8.31
Extension contact	120.77	0.13	659.75	1316.96	460.65*	200.23
Education	494.02***	199.29	11.02	94.919	–6.76	13.64
Farm size	214.89***	25.88	2165.79***	167.17	167.74***	23.46
Household size	41.18**	17.69	–899.81***	115.22	223.07***	16.07
Off-farm income	0.19*	0.0969	2072.89*	1178.91	645.03	147.92
Access to credit	–1.85	297.1	–2254.20	1749.74	140.29	267.43
adoption of CSA	0.219**	256.5	19389.45***	3371.97	21938.12	367.08
participation in on-farm trials	0.15***	0.04	0.08	0.05	0.66***	0.07
Constant	0.24	0.04	0.26	0.04	0.26	0.26
Lambda			18138.86	2011.89	3022.55	217.38
Rho	0.738	0.019	0.68	0.054		
Sigma	4270.54	95.32	26375.85	978.41	3927.18	125.2
Prob> Chi^2	0.0000	0.0000	0.0000			
Wald chi^2	**487.76**		**486.29**		**315.06**	

Note: ***, **, * Denotes significance at the 1, 5, and 10%, respectively.
Source: Field Survey, 2021

outcome is consistent with the findings of Ghimire and Houng (2015) and Duyen et al. (2020). The awareness of climate change impact also has a positive and significant influence on farmers' decision to adopt CSA practices. This means that creating awareness and providing information on climate change can be instrumental in encouraging farmers to adopt the CSA practices.

Impact of adoption of climate-smart agricultural practices

To be sure that the estimated impacts on crop yield, crop income, and food security are due to the adoption of CSA practices and not a result of any other unobservable characteristics of the farmers, a linear regression with an endogenous treatment effects model was used. Participation in on-farm trials was used as an instrument that certified the exclusive restriction. This variable can influence CSA practices adoption but does not have any effect on crop yield, crop income, and food security except through the adoption of CSA practices.

The average treatment effect on the treated (ATT) of being an adopter of CSA practices was estimated on crop yield, crop income, and food security and also included other covariates. The result of the analysis is presented in Table 7. The adoption of CSA practices increased the crop yield which was measured using the Technical Efficiency scores by 21.9 percent. The increase was significant at ($p < 0.05$). On the other hand, crop income and the per capita food expenditure increased by N19389 (\$17.62) and N21938 (\$20.00), respectively. By implication, the adoption of CSA practices can lead to an increase in crop yield and income generated from crop production. However, while the increase in crop income was significant at ($p < 0.01$), the increase in per capita on food was not significant at ($p = 0.10$). The findings above are in line with similar work by Kuworno and Owusu (2012) and Muchara et al. (2014). The authors noted that the adoption of improved technology is key to a rural economy, alleviating poverty and enhancing the livelihood of farming households in Nigeria.

CONCLUSION AND RECOMMENDATIONS

The adoption of climate-smart agricultural practices such as crop rotation, complementary application of organic and inorganic fertilisers as well as multiple cropping can significantly improve crop yield, income, and food security status of farming households. The study generated empirical evidence to support the need to adopt CSA practices by smallholder farmers in Nigeria. However, it is important to note that other productivity-enhancing factors such as enhanced market access, timely and adequate supply of credit, and farm inputs such as seeds and fertilisers must be in place to sustain the gains of climate-smart agricultural practices adoption. The creation of awareness and organisation of training on the use of CSA will enhance the adoption of CSA practices and this will be invaluable for mitigating the effects of the climate change effect on the livelihood of rural farming households in Nigeria. A major limitation of the study is the non-random assignment of the respondents to both treatment and control groups. Further research using a randomised evaluation design will be useful in providing additional insights.

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