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Determinants of the Joint Adoption of Climate-Smart Agriculture Practices by Agro-Pastoralists in Sokoto State, Nigeria

Abstract. This study examined the determinants of the joint adoption of climate-smart agriculture practices by agro-pastoralists in Sokoto State, Nigeria. A multi-stage sampling technique was used to select 428 agro-pastoralists who were surveyed using a structured questionnaire. The data were subjected to multivariate probit, ordered probit regression, and factor analysis. The climate-smart practices considered were water, nutrients, carbon, the weather, and crop-smart activities. The results show that the majority of the agro-pastoralists were male (85%), married (90%), and had formal education (55%). The mean score for age, farming experience, household size, and farm size was 44.81 years, 22.26 years, 10.25 persons, and 7.33 hectares, respectively. The multivariate model revealed that land tenure, extension contact, awareness of climate incidences, farming systems, sources of credit, gender, perception, and association membership significantly influenced the joint adoption of climate-smart agricultural practices. This study advocates that resources and conditions that promote the joint adoption of climate-smart practices should be identified to facilitate the dissemination and effective adoption of technologies.

Keywords: agro-pastoralists, water-smart, nutrient-smart, carbon-smart, weather-smart, crop-smart

JEL Classification: Q1, Q3, Q160

Introduction

Aside from oil, the primary source of employment and GDP in Nigeria is agriculture, which is mostly dependent on rainfall and is severely impacted by climate change (Ayanlade & Radeny, 2020). Due to limited adaptation capacity, human development, political will, infrastructure and technology, and insufficient resources, climate change threatens and makes agricultural livelihoods more vulnerable. As a result, both individuals and governments must take critical action (IPCC, 2021). The necessity to provide for the food demands of a fast-expanding population and shifting dietary preferences makes the issue more serious. Nigeria contributed 66.6 million tonnes of carbon (CO2) emissions, along with methane (CH4) and nitrous oxide (N20), accounting for 2% of global agricultural emissions between 2015 and 2021, according to Climate Trace (2021). Deforestation, improper fertiliser handling, and livestock management have all had an impact on greenhouse gas (GHG) emissions. The effects of climate change include declining crop and animal productivity, unpredictable

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rainfall, fluctuating temperatures, and an increase in the prevalence of pests and diseases. The periodic migration of cattle between various agroecological zones to investigate grazing supplies is another example of transhumance pastoralism, which is a cultural adaptation tactic in reaction to climate change. Drought and desertification have increased and intensified competition for scarce resources, making it more likely that farmer-herder conflicts will occur. Nigeria's agriculture cannot continue to be of a "rentier status" in terms of relying on income from natural resources through extractive activities, and such adaptation practices are necessary to mitigate the effects of climate change. Fadairo et al. (2020) and the IPCC (2021) stated that adaptation practices are crucial to reducing the impacts of climate change on food systems and agriculture. There have been a number of farmer-herder fatalities over the past ten years, with 2,000 deaths recorded in 2018.

Climate-smart agriculture (CSA) has been pushed as a key adaptation intervention by governments, non-governmental organisations, and other agencies worldwide. The FAO (2021) and the World Bank (2022) defined CSA as agriculture that enhances resilience, reduces or eliminates greenhouse gas emissions where feasible, promotes the achievement of national food security and development goals, and raises production in a sustainable manner. According to Antwi-Agyei et al. (2022) and Dougill et al. (2021), the implementation of climate-smart agriculture improved food security and livelihood, boosted farmer adaptability, reduced greenhouse gas emissions, and boosted resilience. A CSA practice that aims to achieve one CSA goal can also help achieve another goal, which has several benefits (FAO, 2021). Reduced GHG emissions, increased food production, and improved farmer resilience to climate change are all benefits of climate-smart agriculture (Barasa et al., 2021). Smart practices covering water, energy, nutrients, crops, and weather interventions are CSA practices that smallholder farmers could implement for sustainable agricultural production, according to IFPRI 2014; AGRA, 2014; Khatri-Chhetri et al., 2017; and Olorunfemi et al. (2020). Table 1 illustrates these practices.

Table 1. Categorisation of climate-smart agricultural practices

Water-smart	**Energy/carbon-smart**	**Nutrient-smart**	**Weather-smart**	**Crop-smart**
Rainwater control & use	Minimum tillage Reduced tillage Zero tillage	Green manure	Farm insurance	Drought-tolerant varieties
Land levelling	Agroforestry	Integrated nutrient use	Weather advisory services	Enterprise diversification
Efficiency-enhanced irrigation	Improved feeding techniques	Compost making	Timing of planting/harvest	Early maturing varieties
Mulching	Planting energy crops	Rotational grazing	Climate-smart housing	Crop rotation
Traversing Planting on slopes	Biochar	Intercropping		Seed banks
Cover cropping	Green energy			

Source: Authors' compilation.

According to several studies, many factors influence the adoption of climate-smart agriculture in Nigeria. In the southeastern part of the country, these factors include farming experience, education, income, ownership of livestock, credit, extension services, land ownership, land area cultivated, exposure to the media, distance to the market, water sources, leadership position, and gender (Ifeanyi-Obi et al., 2017). In the semi-arid region, non-farm activities, irrigation, various crop varieties, and soil and water conservation were adopted (Haider, 2019). In the northeastern region, the factors were the planting of improved varieties, pest-resistant varieties, weather-tolerant crop varieties, timely planting, and early maturing crop varieties (Fawole and Aderinoye-Abdulwahab, 2021). According to several authors across several studies (Kargbo et al., 2020; Muyanga et al., 2021; Tesfaye et al., 2020; Nhemachena et al., 2020), it was discovered that smallholder farmers' adoption of climate-smart agriculture practices is influenced by their access to information, credit, market information, technical assistance, and extension services.

Literature review and Literature gaps

In order to increase their resilience to climate change, agro-pastoralists combined climate-smart technologies, such as diversified farming (crop and animal production), minimum tillage, timely planting, fertiliser and manure use, agroforestry, and improved crop varieties (Nantongo et al., 2022).

In addition to using locally made pesticides, burning pastures and farm residues, early planting, indigenous medicines, indigenous crops and livestock breeds, farming and grazing along rivers and wetlands, and using tolerant or early maturing crops, Habakubaho et al. (2023) report that agro-pastoral communities also use traditional cloud/sky colour, temperature changes throughout the day, wind direction and strength, lightning, and thunder for weather forecasting.

In order to adapt to climate change, pastoralists used a variety of tactics, including restricted grazing, herd diversification, labour distribution among family members, and varied livestock product usage, according to Imana and Zenda (2023). According to Madaki et al. (2025), agro-pastoralists responded to weather fluctuations by combining knowledge about livestock with crop residue, hay conservation, irrigation, and destocking. Ndebele and Zenda (2023) report that agro-pastoral farmers can adapt to climate change by planting trees, diversifying their crop-cattle businesses, practising mixed farming, conserving soil and water, reducing the number of livestock, adjusting planting dates, adjusting irrigation, and applying fertiliser. Gudere et al. (2022) show that agro-pastoralists used various combinations of climate-smart technologies to manage diversity on the farm, manage water and water use, manage soil fertility, manage livestock, and manage pastures and conserve them. Because the majority of adaptation techniques were intended to improve household food security and livelihoods, Zampaligré and Fuchs (2019) discovered that pastoral and agro-pastoral households embraced a variety of adaptation practices rather than just one. Despite the potential for combining climate-smart agriculture to enhance natural resources and attain food security, not much research has been done on the variables influencing the adoption of multiple technologies. The adoption of collaborative climate-smart technologies has been impacted by a number of factors, including the ability of farmers to implement joint practices, adopt individual techniques, or neither. The research question that emanates from this study is: What factors influence the joint adoption of climate-smart agriculture practices among agro-pastoralists? The main objective of this study was to examine the determinants of the joint adoption of climate-smart agriculture practices by agro-pastoralists in Sokoto State, Nigeria.

Materials and Methods

Sokoto State, Nigeria (Figure 1), borders the Republic of the Niger in the arid Sahel and is encircled by isolated hills within the sandy savannah with an average annual temperature of 28.3 °C (82.9 °F). For this study, the factors that influence agro-pastoralists' joint adoption of climate-smart agriculture practices in Sokoto State were studied. Reduced agricultural output, water scarcity, widespread food insecurity, and difficulties with income security are the state's main climate change effects.

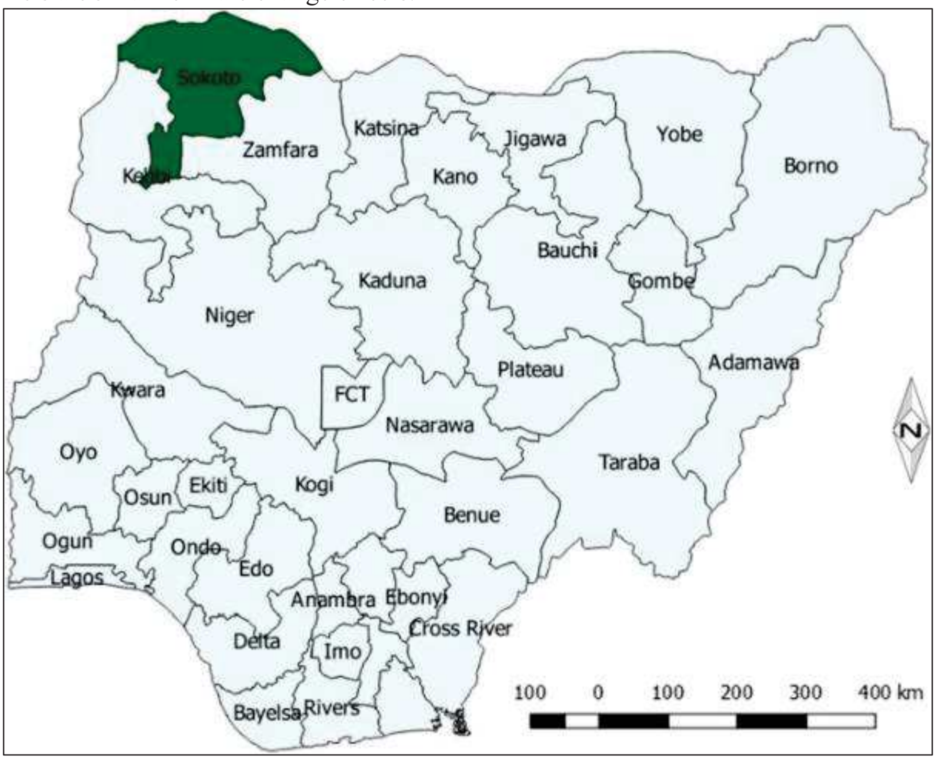

Fig. 1. Map of Nigeria showing Sokoto State

Source: Kaltungo et al. (2019).

This study focused on Sokoto State in North-West Nigeria, one of the northern states that is more severely affected by climate change (Figure 1). To get the sample, a multi-stage sampling process was employed. Twelve of the twenty-three LGAs in Sokoto State were chosen at random for the first phase. The following LGAs were selected: Shagari, Tambuwal, Tangaza, Wamakko, Wurno, Dange Shuni, Isa, Kware, Sokoto South, and Bodinga. 32 out of 307 villages were purposefully chosen for the second stage, again because of the large number of agro-pastoralists living in the villages. From the chosen communities, 428 farmers were picked at random for the third stage. Using an interview schedule based on a structured questionnaire, primary data for this study were collected from June to August 2022 during the 2022 farming season. The data included information on the socioeconomic characteristics of the farmers, their farming systems, their awareness of climate change indicators, their perception of climate change, and their adoption of various climate-smart agriculture practices under the categories of water, energy, nutrients, crops, and weather. This study is limited to the list of climate-smart agricultural practices listed in this study only and within the context of Sokoto State and its environment where the study was conducted.

The data were described using descriptive statistics, including frequency counts, percentages, and averages. The factors that influence agro-pastoralists' collaborative adoption of climate-smart agriculture techniques were determined using probit regression and multivariate probit regression analysis. According to Nagler (1994), agro-pastoralists are presumed to have two options when it comes to the probit models: they can choose to implement each of the climate-smart agriculture practices or not. Binary outcome variables, such as yes/no, were regarded as dependent variables with two possible outcomes in order to address the issues of heteroscedasticity, the model's suitability, and the satisfaction of the cumulative normal probability distribution assumptions (Gujarati, 2004).

It is assumed that Y can be specified as follows:

$Y= \beta_0+\beta_1 X_{1i} + \beta_2X_{2i}+\ldots\ldots\ldots\ldots\ldots\ldots+ \beta_{ki}X_{ki}+U_1$

And that:

$Y_i=1$ if $Y>0$

$Y_i=0$

Otherwise, where $X_1, X_2\ldots\ldots\ldots\ldots\ldots\ldots X_n$ represents vectors of random variables, β represents a vector of unknown parameters and U represents random disturbance terms (Nagler, 1994). Table 1 presents the list and level of measurements of variables in the probit model.

The factor analysis, as specified by Koutsoyiannis (1972), is presented as follows:

Given variables ($X_s\ldots$ original variables of the climate-smart practices)

$X_1\ldots X_p$ measured in 'n' farmers,

$P_1\ldots P_p$: uncorrelated linear combinations of components from the original variable,

$X_1\ldots X_p$, given as:

$$P_1 = \alpha_{11}X_1 + \alpha_{12}X_2 + \cdots + \alpha_{1p}X_p$$

$$P_2 = \alpha_{21}X_1 + \alpha_{22}X_2 + \cdots + \quad . \quad . \quad .$$

$$. \quad . \quad . \quad .$$

$$P_p = \alpha_{p1}X_1 + \alpha_{p2}X_2 + \cdots + \alpha_{1pp}X_{pz} \ldots\ldots \quad (1)$$

It is assumed that the components were not related and that the first component would account for the maximum possible proportion of the total variation in the original variables.

As a result of the interdependencies between the error terms of various techniques, farmers may choose to use a number of climate-smart agriculture methods in order to adapt to climate change. The determinants of the joint adoption of climate-smart agriculture practices were evaluated using a multivariate probit (MVP) model, whereas the individual probit model examined one practice at a time (Musafiri et al., 2022; Omodara et al., 2023).

The correlation of error terms indicates that a positive sign indicates complements and a negative sign indicates substitutes (Musafiri et al., 2020).

U_a indicates the utility of adopting the jth practice and U_n otherwise. Farmers can adopt the jth approach if $Yij = U_a\text{-}U_o > 0$. Therefore, the net utility Y*ij a farmer obtains for adopting the jth practice is a latent variable that can be predicted by the experimental factors and the multivariate normally distributed error terms (ε_i)

$$Y_{ij}^{*} = \beta_j X_i + \varepsilon_i \text{ ....(2)}$$

where X_i indicates a vector of independent variables, j climate-smart agriculture practice, $\boldsymbol{\beta}_j$ Vector coefficient, and ε_i error term. In utility maximisation theory, farmers could adopt climate-smart agriculture if the expected benefits are higher than non-adoption. This can be presented as an observable dichotomous outcome for each choice of climate-smart agriculture adopted by farmers, as shown:

$$= Y_{ij}^{*}{}^{1\ if\ Y_{ij}^{*}}_{0\ otherwise} \qquad where\ j = W, E, N, C, T\text{................ (3)}$$

where Y_{ij} indicates a binary observable variable for adopting the jth practice by the i[th] farmer. If the joint adoption of climate-smart agriculture technologies is to occur, the error terms of the equation can be described using a variance-covariance matrix as:

$$\pi = \begin{bmatrix} 1 & \delta WE & \delta WN & \delta WC & \delta WT \\ \delta EM & 1 & \delta EN & \delta EC & \delta ET \\ \delta NM & \delta NE & 1 & \delta NC & \delta NT \\ \delta CM & \delta CE & \delta CN & 1 & \delta CT \\ \delta TM & \delta TE & \delta TN & \delta TC & 1 \end{bmatrix} \text{...................................(4)}$$

where rho (δ) is a pairwise correlation between any pair of climate-smart agriculture technologies, the sign of δ between any two practices shows the relationship with a positive sign indicating complements and a negative sign showing substitutes.

An ordered probit regression model was applied to determine adoption intensity and the number of climate-smart agriculture techniques adopted by the i[th] farmer because it was considered an ordinal variable. The ordered outcome could be assessed as a latent variable Y*, where Y* is the unobservable measure of farmers' adoption intensity and depicted as:

$$Y_j^{*} = X_j'\beta + u_j \text{ ....(5)}$$

For the i[th] farmer where normalisation is that the regressors x do not include an intercept, the adoption intensity increases with Y*. The probability of observing a j outcome is described as:

$$Pr[outcome\ i = j] = Pr\left[n_{j-1} < X_j'\beta + u_j \leq \alpha_j\right]\text{..........................(6)}$$

The coefficients β_1, β_2… β_{j-1} were estimated jointly with the cut points α_1, α_2, …, α_j where j is the number of the possible outcomes. U_i is assumed to be normally distributed with a standard normal cumulative distribution function. The ordered probit model is pooled and works under the assumption that the unobserved heterogeneity is uncorrelated with the independent variables.

Ethical consideration

According to the research ethics and criteria suggested by Usmanu Danfodio University's Department of Agricultural Extension and Rural Development in Sokoto, Nigeria, the study was carried out with farmers' informed consent, anonymity, and voluntary participation.

Results

Socioeconomic features, joint adoption, joint adoption substitutes and complements, joint adoption intensity, and factors analysis of the adoption variables are the categories into which the data are arranged. According to the descriptive data of agro-pastoralists shown in Table 1, the majority of respondents were married (90%), had formal education (55%) and were male (85%). The average score is 44.81 years, 22.26 years, 10.25 people, and 7.33 hectares for age, agricultural experience, and household size, respectively.

Table 2. Descriptive statistics of the sampled agro-pastoralists

Variables	Description	Mean	Std Dev
Land tenure	Dummy =1 if owned, 0 otherwise	na	na
Age	Age in years	44.81	13.55
Gender	Dummy =1 if male, 0 female	na	na
Farming experience	Farming experience in years	22.26	12.67
Marital status	Dummy =1 if married, 0 otherwise	na	na
Educational level	Dummy =1 formal education, 0 otherwise	na	na
Household size	Number of persons	10.25	7.17
Main crop farm size	Farm size in hectares	8.18	
Farm labour size	Number of farm labourers	10.02	9.04
Contact with extension services	Number of contacts with extension	1.12	2.4
Farmers' association membership	Dummy =1 if member, 0 otherwise	na	na
Credit accessed (Amount)	Amount in Naira	2.44	1.12
Sources of credit	Dummy =1 if family & friends, 0 otherwise	na	na
Total crop farm size	Farm size in hectares	7.33	5.17
Total herd size	Total livestock units	25.01	3.80
Farming systems	Dummy =1 livestock-based, 0 otherwise	na	na
Awareness	Awareness score	25.99	8.28
Perception	Perception score	39.72	17.70

na – not available.

Source: Authors' compilation.

Table 2. Determinants of the joint adoption of climate-smart agricultural practices among agro-pastoralists in Sokoto State, Nigeria

Specification	Multivariate probit estimates					Individual probit estimates				
	Water-smart Coeff. (S.E)	Nutrient-smart Coeff. (S.E)	Carbon-smart Coeff. (S.E)	Crop-smart Coeff. (S.E)	Weather-smart Coeff. (S.E)	Water-smart Coeff. (S.E)	Nutrient-smart Coeff. (S.E)	Carbon-smart Coeff. (S.E)	Crop-smart Coeff. (S.E)	Weather-smart Coeff. (S.E)
Land tenure	0.034	0.014	0.035	0.02	0.02	0.101	0.0434	0.117	0.054	0.06
	(0.012)***	(0.012)	(0.011)***	(0.013)*	(0.012)	(0.036)***	(0.0354)	(0.038)***	(0.034)	(0.04)*
Age	0.003	0	0	-0.002	0.002	0.012	0.0031	0.002	-0.003	0.01
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.0089)	(0.009)	(0.009)	(0.01)
Gender	0.19	0.298	0.193	0.216	0.031	0.626	0.0000	0.951	0.957	0.30
	(0.134)	(0.134)**	(0.124)	(0.141)*	(0.134)	(0.440)	(0.000)	(0.562)*	(0.479)*	(0.45)
Farming experience	0	0	0.002	0.001	0	-0.001	-0.0002	0.007	0.003	0.00
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.0083)	(0.009)	(0.008)	(0.01)
Educational level	-0.011	0.015	0.003	-0.001	0.02	-0.024	0.0804	0.042	0.019	0.07
	(0.023)	(0.023)	(0.021)	(0.024)	(0.023)	(0.067)	(0.0712)	(0.074)	(0.067)	(0.07)
Household size	-0.001	0	0.001	0.001	0.004	-0.004	-0.0004	0.006	0.002	0.01
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.0121)	(0.012)	(0.011)	(0.01)
Main crop farm size	0(0)	0	0	0	0	-0.001	-0.0165	-0.019	-0.001	0.00
		(0)	(0)	(0)	(0)	(0.002)	(0.0147)	(0.016)	(0.002)	(0.00)
Farm labour size	0	0.003	0	-0.001	-0.003	-0.001	0.0143	0.003	-0.004	-0.01
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.007)	(0.0094)	(0.009)	(0.007)	(0.01)
Extension contact	-0.016	-0.006	0.008	0	0	-0.044	-0.0104	0.036	-0.001	0.00
	(0.01)*	(0.009)	(0.009)	(0.01)	(0.01)	(0.027)	(0.0273)	(0.033)	(0.027)	(0.03)
Association membership	-0.004	-0.01	-0.001	0	-0.011	-0.014	-0.0315	-0.004	-0.002	-0.03
	(0.005)	(0.005)*	(0.005)	(0.005)	(0.005)**	(0.015)	(0.0164)**	(0.016)	(0.015)	(0.02)**
Credit accessed (Amount)	0	0	0	0	0	0.000	0.0000	0.000	0.000	0.00
	(0)	(0)	(0)	(0)	(0)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.00)
Sources of credit	-0.006	-0.016	0.059	0.012	-0.016	-0.017	-0.0359	0.149	0.003	-0.04
	(0.028)	(0.028)	(0.026)**	(0.03)	(0.028)	(0.081)	(0.0829)	(0.097)	(0.087)	(0.08)
Total farm size	0.006	0.004	0.003	-0.004	0.008	0.016	0.0188	0.019	-0.008	0.03
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)*	(0.013)	(0.0139)	(0.015)	(0.014)	(0.01)*
Total herd size	0.001	0.001	0.001	0.001	-0.001	0.003	0.0024	0.001	0.012	0.00
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.0041)	(0.004)	(0.021)	(0.01)
Farming systems	-0.004	-0.002	-0.001	-0.001	-0.001	-0.013	-0.0051	-0.004	-0.004	0.00
	(0.002)***	(0.002)	(0.001)	(0.002)	(0.002)	(0.005)***	(0.0046)	(0.005)	(0.005)	(0.00)
Awareness	0.013	0.017	0.015	0.02	0.009	0.039	0.0554	0.049	0.063	0.03
	(0.004)	(0.004)***	(0.003)***	(0.004)***	(0.004)**	(0.011)***	(0.0119)***	(0.012)***	(0.012)***	(0.01)**
Perception	-0.001	-0.001	0	-0.004	0.004	-0.003	-0.0033	-0.002	-0.010	0.01
	(0.002)	(0.002)	(0.002)	(0.002)**	(0.002)**	(0.005)	(0.0050)	(0.005)	(0.005)**	(0.00)**
_cons	1.034	0.859	0.934	0.905	0.992	-1530978	-144875	-2418548	-2379234	-1859196
	(0.139)***	(0.139)***	(0.129)***	(0.146)***	(0.139)***	(0.526)***	(0.4452)***	(0.713)***	(0.650)***	(0.58)***
RMSE	0.456	0.455	0.421	0.457	0.479	LR chi- 61.10	54.88	77.08	64.94	55.43
R-Sq	0.136	0.150	0.170	0.142	0.108	Pseudo R2- 0.1093	0.1008	0.1501	0.1152	0.0943
F	3.79	3.28	4.26	3.99	2.93	Log like. = -249.06	-244.731	-218.17	-249.37	-266.026
P	0.000	0.000	0.000	0.000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000

Source: Authors' compilation

The elements that influenced the combined adoption of climate-smart agriculture technology were evaluated and are shown in Table 3. Multivariate probit regression analysis parameters yielded F-statistics of 2.93–4.26 and coefficients of determination (R^2) ranging from 0.108 to 0.170. This suggests that the predictor variables in the models were able to explain between 45% and 47% of the variances in the selection of climate change adaptation strategies. The use of Multivariate Probit Analysis is justified by the model's importance. The findings demonstrate the interdependence of climate-smart agriculture approaches and the biased estimates generated by the individual probit model.

Table 4 presents the results of the complements and substitutes of the joint adoption of climate-smart agriculture practices. The likelihood ratio test (Chi^2 = 485.502 Prob > Chi^2 = 0.0001.) of the error terms of different climate-smart agriculture practices equations from the multivariate probit regression model was significant at a 1% level of significance, thus indicating that the equations for adopting individual climate-smart practices were interdependent. The positive and negative correlation coefficients indicate both complements and substitutes between climate-smart agriculture practices.

Table 4. Correlation coefficients of the climate-smart agricultural practices (estimation from the multivariate probit model)

	Water-smart	Nutrient-smart	Carbon-smart	Weather-smart	Crop-smart
Water-smart	1.000				
Nutrient-smart	0.2413**	1.000			
Carbon-smart	0.344**	0.4061***	1.000		
Weather-smart	0.2279**	0.4047***	0.4847***	1.000	
Crop-smart	0.1949*	0.3646**	0.2542**	0.3260***	1.000

Likelihood ratio test of rho21 = rho31 = rho41 = rho51 = rho32 = rho42 = rho52 = rho43 = rho53= rho54 = 0: Chi2 (10) = 485.502 Prob > Chi2 = 0.0001. **p < 0.05. ***p < 0.01.

Source: Authors' compilation

In Table 5, the intensity of the joint adoption is important among agro-pastoralists to ensure their adaptation and enhance the yields of their crops and the productivity of their animals with less exposure to conflicts and other vulnerability factors. The results of the ordered probit regression show that LR Chi^2 = 144.03, Pseudo R^2 = 0.161, and Prob > Chi^2 = 0.000 to affirm that the ordered probit is reliable.

Table 5. Factors influencing the number of climate-smart agricultural practices adopted using an ordered probit model

Variables	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
Land tenure	0.019	0.032	0.610	0.543	-0.043	0.081
Age	-0.005	0.008	-0.670	0.503	-0.020	0.010
Gender	0.201	0.393	0.510	0.609	-0.569	0.972
Farming experience	-0.005	0.007	-0.610	0.542	-0.019	0.010
Educational level	-0.062	0.063	-1.000	0.319	-0.185	0.060
Household size	0.018	0.010	1.760	0.078	-0.002	0.038
Main crop farm size	0.000	0.000	0.470	0.640	-0.001	0.001
Farm labour size	0.002	0.006	0.330	0.739	-0.010	0.014
Extension contact	0.044	0.026	1.700	0.089	-0.096	0.007
Association membership	0.016	0.013	1.280	0.201	-0.009	0.041
Credit accessed (Amount)	0.000	0.000	-1.020	0.307	0.000	0.000
Sources of credit	-0.048	0.075	-0.640	0.521	-0.196	0.099
Total farm size	0.005	0.012	0.440	0.658	-0.018	0.028
Total herd size	0.001	0.002	0.510	0.609	-0.003	0.005
Farming systems	0.048	0.004	10.930	0.000	0.039	0.057
Awareness	0.012	0.010	1.190	0.233	-0.008	0.031
Perception	-0.003	0.004	-0.630	0.528	-0.011	0.006
LR Chi^2	144.03					
Pseudo R^2	0.1609					
Log likelihood	-375.699					
P	0.0000					

Source: Authors' compilation

In Table 6, an exploratory factor analysis was applied to examine the structure and dimensions of several climate-smart practices. This will help identify a set of practices usually uncorrelated from a large set of techniques, most of which are often correlated to each other.

Table 6. Exploratory factor analysis of climate-smart agriculture technologies

Factors	Eigenvalue	Difference	Proportion	Cumulative	Uniqueness
Water conservation	9.069	6.809	0.603	0.603	0.421
Water harvesting	2.259	0.442	0.150	0.754	0.413
Drip irrigation	1.817	0.998	0.121	0.874	0.368
Furrow-irrigated beds for planting	0.819	0.179	0.055	0.929	0.573
Land levelling	0.640	0.072	0.043	0.971	0.598
Mulching	0.568	0.154	0.038	1.009	0.507
Drainage management	0.414	0.074	0.028	1.037	0.517
Planting of cover crops	0.340	0.060	0.023	1.059	0.755
Nutrient-smart	0.280	0.076	0.019	1.078	0.292
Integrated soil fertility management	0.204	0.029	0.014	1.092	0.460
Green manuring	0.175	0.069	0.012	1.103	0.611
Use of organic fertilisers	0.107	0.026	0.007	1.110	0.630
Energy/carbon-smart	0.081	0.023	0.005	1.116	0.304
Agroforestry	0.058	0.027	0.004	1.120	0.432
Biochar application	0.032	0.020	0.002	1.122	0.366
Minimum tillage	0.012	0.021	0.001	1.123	0.737
Integrated pest management	-0.009	0.007	-0.001	1.122	0.510
Weather-smart	-0.015	0.019	-0.001	1.121	0.264
Livestock climate-smart housing	-0.034	0.009	-0.002	1.119	0.531
Weather agro-advisory services	-0.044	0.016	-0.003	1.116	0.470
Farm insurance	-0.059	0.014	-0.004	1.112	0.386
Crop-smart	-0.074	0.005	-0.005	1.107	0.407
Planting improved crop varieties	-0.078	0.049	-0.005	1.102	0.547
Contingency crop planning	-0.128	0.017	-0.009	1.093	0.480
Planting of early-maturing varieties	-0.145	0.009	-0.010	1.084	0.566
Crop rotation	-0.154	0.041	-0.010	1.073	0.527
Total crop farm size	-0.195	0.006	-0.013	1.060	0.584
Total herd size (TLU)	-0.201	0.009	-0.013	1.047	0.032
Farming system	-0.210	0.017	-0.014	1.033	0.328
Awareness of climate change incidence	-0.226	0.045	-0.015	1.018	0.481
Perception of climate change	-0.271	.	-0.018	1.000	0.031

Source: Authors' compilation

Discussion

The sampled agro-pastoralists are in their prime working years and would be open to innovations that would improve their standard of living and ensure sustainability, according to the trend of socioeconomic parameters in Table 2. These findings are consistent with those of other authors who found that agro-pastoralists had a mean herd size of 20 cows, were mostly male, under 35, married, untrained, unable to obtain credit, and not affiliated with cooperative societies (Yakubu et al., 2016; Abdulkarim et al., 2022).

Joint adoption of climate-smart agriculture technologies

In Table 3, the adoption of climate-smart agriculture techniques, socioeconomic factors, extension services, awareness, and perception of the technologies are shown. The adoption of water-smart practices was influenced by land tenure ($\beta = 0.034$, $p < 0.01$), extension contact ($\beta = -0.016$, $p < 0.01$), awareness ($\beta = 0.009$, $p < 0.01$), and farming systems $\beta = -0.004$, $p < 0.01$) with extension contact and the farming system being inversely related. The adoption of climate-smart agriculture practices has been found to be influenced by a number of factors, including age, gender, and education level (Kosoe and Ahmed, 2022); agroecological zones, land tenure systems, and religion (Mamun et al., 2021); marital status, income, access to credit, and extension services (Myeni and Moeletsi, 2020); the source of information (Olorunfemi et al., 2020); and education, household size, income, perceptions of climate change, and farmland size (Kassa and Abdi, 2022).

The determinants of carbon-smart adoption are land tenure ($\beta = 0.035$, $p < 0.05$), sources of credit $\beta = 0.059$, $p < 0.05$), and awareness ($\beta = 0.015$, $p < 0.01$). Telephone-mediated agricultural guidance, according to Gupta, Ponticelli, and Tesei (2021), would boost agricultural output and modernisation. Crop-smart techniques were significantly and positively influenced by land tenure $\beta = 0.02$, $p < 0.05$), gender ($\beta = 0.216$, $p < 0.10$), awareness ($\beta = 0.02$, $p < 0.001$) and perception ($\beta = -0.004$, $p < 0.05$). Male and female farmers have varying access to climate-smart farming information and inputs (Gebre et al., 2019; Oduniyi and Tekana, 2021). The adoption of nutrient-smart practices was significantly influenced by gender ($\beta = 0.298$, $p < 0.05$), association membership ($\beta = -0.01$, $p < 0.10$) and awareness ($\beta = 0.017$, $p < 0.001$). According to Otitoju and Enete (2016), farmers' deep understanding of climate change influences their adoption of smart practices and association membership ($\beta = -0.011$, $p < 0.05$), total farm size ($\beta = 0.008$, $p < 0.10$), perception ($\beta = 0.004$, $p < 0.005$) and statistically significantly influenced the adoption of weather-smart practices. Climate and ecological zoning, access to extension services, and the diversity of agricultural systems influence adoption (Nyang'au et al., 2021; García-Jiménez, 2022; Dhehibi, 2022). Several authors have identified a number of factors that influence farmers' adoption of climate-smart agriculture techniques, including agroecological zones, input accessibility and availability (Mulema et al., 2020), market product demand, knowledge, awareness, as well as skills in farming systems, policy and institutional support, household size and educational attainment, information access (Kassie et al., 2021; Mofya et al., 2021), access to finance and other productive resources (Saidu et al., 2020), and land tenure systems (Amare et al., 2020). Omodara et al. (2023) discovered that these characteristics corroborated the authors previously mentioned, whereas Musafiri et al. (2022) revealed similar parameters as predictors of the joint adoption of climate-smart agriculture techniques in Kenya.

Complements and substitutes of the joint adoption of climate-smart agriculture practices

Table 4 illustrates the recognised complements between weather-smart, crop-smart, carbon-smart, nutrient-smart, and water-smart activities. According to Musafiri et al. (2022) and Omodara et al. (2023), farmers in Kenya and Nigeria, respectively, reported complements and substitutes. The use of common resources and the fact that one company's byproducts are used as inputs by another can be used to explain technology complementarity. Similarly, cooperative use of resources can raise income, adjust to climate change, and improve agricultural productivity. The phrases "carbon-smart and crop-smart", "weather-smart and crop-smart", and "nutrient-smart and crop-smart" can be substituted by agro-pastoralists. Replacements frequently result from improvising the application of certain approaches for a variety of early maturation and weather adaptation goals.

The intensity of the joint adoption of climate-smart agriculture practices

In Table 5, only three variables were significantly influencing the intensity of the joint adoption of climate-smart agriculture, namely, household size ($\beta = 0.018$, $p < 0.10$), extension contact ($\beta = 0.044$, $p < 0.10$) and farming systems ($\beta = 0.048$, $p < 0.001$). A favourable correlation was found between the degree of collaborative adoption of climate-smart agriculture technology and the involvement of extension agents. According to this, agro-pastoralists who interacted with extension services more frequently were more likely to simultaneously implement climate-smart practices than those who did not. Serote et al. (2023) claim that engaging with extension services removes barriers to the implementation of climate-smart agriculture. For Kelil et al. (2020), extension services improve the use and accessibility of climate-smart agriculture knowledge. Elia (2017) asserts that extension services in central semi-arid Tanzania enhanced farmers' understanding of climate change and variability, hence fostering climate change adaptation. Extension services are an important way to communicate with farmers, and according to Colussi et al. (2022), communication affects how technology is used.

Household size had a positive correlation with the extent to which households implemented climate-smart agriculture practices together. The findings indicated that large families were more likely to embrace climate-smart practices cooperatively. To meet their immediate labour demands, many farm families rely on their own family members because implementing climate-smart practices may require more man-days than traditional farming methods. The combined use of climate-smart agricultural practices may lead to a higher demand for labour, which could be the result of a more intense adoption. Farming systems predicted the degree of collaborative adoption of climate-smart agriculture solutions favourably. As a result, the demand for agricultural systems practices will determine the quantity and diversity of climate-smart methods used by agro-pastoralists. Collaborative adoption of innovations may also be facilitated by the resources that farming systems make available to other agricultural enterprises. Ricart et al. (2022) stress that farming systems have an impact on the adoption of climate-smart agriculture approaches. Akano et al. (2022) assert that farming practices influence the adoption of climate-smart agriculture practices.

Factors analysis of the adoption factors on climate-smart agriculture

Factor loadings are the weights and correlations between each variable and adoption in Table 6. The greater the load, the more significant it is in determining the dimensionality of the component. A negative value indicates an inverse influence on the factor. The factors that have the opposite effects include climate-smart livestock housing, weather-advisory services, farm insurance, crop-smart, planting improved crop varieties, planting early-maturing varieties, crop rotation, total crop farm size, total herd size (TLU), farming system, and awareness of the incidence of climate change. The activities are not particularly popular, and either fewer people are using them or people don't think much of them. Farmers' decisions and willingness to pay for the adoption of climate-smart agriculture are influenced by the cost of technology implementation, according to Khatri-Chhetri et al. (2017). The eigenvalues are the total variance accounted for by each factor. The Kaiser criterion suggests retaining those factors with eigenvalues equal to or higher than 1. The results depict that the first five factors explained 97% of the variance, with factors 1 to 5 contributing 60.3%, 15.0%, 12.1%, 5.5%, and 4.3%, respectively. Factor 1 demonstrated the highest eigenvalue with 9.06, followed by Factor 2 with 2.25, Factor 3 with 1.18, Factor 4 with 0.82, and Factor 5 with 0.64. The difference between one eigenvalue and the next depicts some form of magnitude between sequential eigenvalues. The proportion indicates the relative weight of each factor in the total variance. The first factor explains 60.3% of the total variance, while the cumulative shows the amount of variance explained by successive factors. For example, Factor 1 and Factor 2 account for 67.54% of the total variance. The uniqueness is the variance that is 'unique' to the variable and not shared with other variables. It is equal to 1 – communality (variance that is shared with other variables). The overall factor model shows that water conservation accounts for about 42 percent of the variance. With 29.2% and 26.4% of the variance not explained by other variables, respectively, nutrition-smart and weather-smart exhibit low variance. Significantly, the more "uniqueness" a variable has, the less relevant it is in the factor model. The highest coefficients of uniqueness are found in minimum tillage and cover crop planting, with respective values of 0.73 and 0.75. This suggests that these methods have been widely used and adopted in the research region. In Nigeria, conservation agriculture practices include minimum tillage and using cover crops (Kolapo and Kolapo, 2023). To lessen the long-term effects of climate change, farmers in northern Nigeria use legumes and cover crops, compost, and practise minimal tillage (Fawole and Aderinoye-Abdulwahab, 2020).

Conclusions and policy implications

Although the parameters had conflicting effects that impacted the joint use of climate-smart techniques, the study found that agro-pastoralists used various climate-smart agriculture practices. Association membership, gender, perception, farming systems, land tenure, extension contact, awareness of climate incidents, and sources of credit all had a big impact on the collective adoption of climate-smart agricultural practices. Variations in the socioeconomic characteristics of agro-pastoralists have diverse effects on the degree and intensity of the adoption of climate-smart practices. The climate-smart activities' positive and negative correlation coefficients show that they complement and replace one another. In order to effectively spread and embrace climate-smart practices among agro-pastoralists, which curbs the practice of transhumance and its associated conflicts, the significant variables serve as indicators of important issues that must be thoroughly studied.

The study's findings have several policy implications, including the necessity of improving end users' access to various streams of climate adaptation solutions due to the accompanying services that each of the innovations in the package of climate-smart agricultural practices requires. Similar to this, implementing several climate-smart agricultural practices (CSAPs) has important policy ramifications, such as improved food security, heightened climate change resilience, and decreased greenhouse gas emissions, all of which eventually support sustainable agricultural development and the accomplishment of more general sustainable development objectives.

Declaration of competing interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abdulkarim, A., Aljameel, K.M., Maigandi, S A., Na-Allah, Y. (2022). Diagnostic survey on utilization of Kanwa by ruminant livestock farmers in Sokoto state, Nigeria. *Nig. J. Anim. Prod.*, 49(3), 285-293. https://doi.org/10.51791/njap.v49i3.3560.

Akano, O., Modirwa, S., Oluwasemire, K., Oladele O. (2022). Awareness and Perception of climate change by smallholder farmers in two agroecological zones of Oyo state Southwest Nigeria. *GeoJournal*. https://doi.org/10.1007/s10708-22-10590-y.

Alliance for a Green Revolution in Africa (AGRA). (2014). Africa agriculture status report: Climate change and smallholder agriculture in sub-Saharan Africa. Nairobi, Kenya.

Amare, D., Wondie, M., Mekuria, W., Darr, D. (2020). Agroforestry of Smallholder Farmers in Ethiopia: Practices and Benefits. *Small Scale Forestry,* 18, 39-56.

Amare, T., Zegeye, A., Yitaferu, B., Steenhuis, T., Hurni, H., Zeleke, G. (2014). Combined effect of soil bund with biological soil and water conservation measures in the Northwestern Ethiopian Highlands. *Ecohydrology and Hydrobiology,* 14(3), 192-199, doi:10.1016/ j.ecohyd.2014.07.002.

Antwi-Agyei, P., Abalo, E.M., Dougill, A.J., Baffour-Ata, F. (2021). Motivations, enablers and barriers to the adoption of climate-smart agricultural practices by smallholder farmers: Evidence from the transitional and savannah agroecological zones of Ghana. *Regional Sustainability*, 2(4), 375-386.

Antwi-Agyei, P., Atta-Aidoo, J., Asare-Nuamah, P., Stringer, L.C., Antwi, K. (2023). Trade-offs, synergies and acceptability of climate smart agricultural practices by smallholder farmers in rural Ghana. International Journal of Agricultural Sustainability, 21(1), 2193439.

Ayanlade, A., Radeny, M. (2020). COVID-19 and food security in Sub-Saharan Africa: implications of lockdown during agricultural planting seasons. *npj Science of Food*, 4(1), 13.

Barasa, P.M., Botai, C.M., Botai, J.O., Mabhaudhi, T. (2021). A review of climate-smart agriculture research and applications in Africa. *Agronomy*, 11(6), 1255.

Climate Trace (2021). Nigeria Emitted 4.9% of Global Agricultural Emissions in 2021. https://www.climatescorecard.org/2023/03/nigeria-emitted-4-9-of-global-agricultural-emissions-in-2021/.

Colussi, J.; Morgan, E.L.; Schnitkey, G.D.; Padula, A.D. (2022). How communication affects the adoption of digital technologies in soybean production: A survey in Brazil. *Agriculture*, 12, 611.

Dhehibi, B., Dhraief, M.Z., Ruediger, U., Frija, A., Werner, J., Straussberger, L., Rischkowsky B. (2022). Impact of improved agricultural extension approaches on technology adoption: Evidence from a randomised controlled trial in rural Tunisia. *Experimental Agriculture*. https://doi.org/10.1017/S0014479722000084.

Dougill, A.J., Hermans, T.D., Eze, S., Antwi-Agyei, P., Sallu, S.M. (2021). Evaluating Climate-Smart Agriculture as Route to Building Climate Resilience in African Food Systems. *Sustainability,* 13(17), 9909.

Elia, E. (2017). Farmers' awareness and understanding of climate change and variability in central semi-arid Tanzania. *University of Dar es Salaam Library Journal*, 12(2), 124-138.

Fadairo, O., Olajuyigbe, S., Adelakun, O., Osayomi, T. (2023). Drivers of vulnerability to climate change and adaptive responses of forest-edge farming households in major agro-ecological zones of Nigeria. *GeoJournal*, 88(2), 2153-2170.

FAO (2021). Climate-smart agriculture case studies 2021 – Projects from around the world. Rome. https://doi.org/10.4060/cb5359en

Fawole, B.E., Aderinoye-Abdulwahab, S.A. (2021). Farmers' adoption of climate smart practices for increased productivity in Nigeria. In African Handbook of Climate Change Adaptation (pp. 495-508). Cham: Springer International Publishing.

García-Jiménez, C.I., Velandia, M., Lambert, D.M., Mishra, A.K. (2022). Information sources impact on the adoption of precision technology by cotton producers in the United States. *Agrociencia* https://doi.org/10.47163/ agrociencia.v56i1.2688 .

Gebre, G.G., Isodab, H., Rahut, D.B., Amekawa, Y., Nomura H. (2019). Gender differences in the adoption of agricultural technology: the case of improved maize varieties in southern Ethiopia. *Women's Studies International Forum,* 76, 102264.

George, J., Adelaja, A., Awokuse, T., Vaughan, O. (2021). Terrorist attacks, land resource competition and violent farmer-herder conflicts. *Land Use Policy*, 102, 105241. https://doi.org/10.1016/j. landusepol.2020.105241.

George, J., Adelaja, A. Vaughan, O., Awokuse, T. (2022). Explaining transhumance-related violence: Fulani Ethnic Militia in rural Nigeria. *Journal of Rural Studies,* 89, 275-286.

Gudere, A., Wemali, E., Ndunda, E. (2022). Adaptation of Climate-Smart Technologies among Agro-Pastoralists of Marsabit County, Kenya. *East African Agricultural and Forestry Journal*, 86(1-2), 9-9.

Gujarati, D. (2004). Basic Econometrics, 4th edn, McGraw-Hill, Maidenhead

Habakubaho, T., Mhache, E.P., Saria, J. (2023). Investigating indigenous knowledge developed by agro-pastoralists to cope with climate change and variability in the agro-pastoralism region of Rwanda. *Ghana Journal of Geography*, 15(3), 48-91.

Haider, H. (2019). Climate change in Nigeria: Impacts and responses. K4D Helpdesk Report 675. Brighton, UK: Institute of Development Studies.

IFAD (2018). Ensuring environmental sustainability and building resilience to climate change. https://www.ifad.org/de-DE/web/guest/climate-and-environment

Ifeanyi-Obi, C.C., Issa, F.O., Aderinoye-Abdulwahab, S.O. Ayinde, A.F., Umeh, O.J., Tologbonse, E.B. (2022). Promoting uptake and integration of climate smart agriculture technologies, innovations and management practices into policy and practice in Nigeria. *International Journal of climate change strategies and management*, 14(4), 354-374.

Iiyama, M., Neufeldt, H., Dobie, P., Njenda, M., Ndegwa, G., Jamnadass, R. (2014). The potential of agroforestry in the provision of sustainable woodfuel in sub-Saharan Africa. *Current Opinion in Environmental Sustainability*, 6, 138-147. https://doi.org/10.1016/j.cosust.2013.12.003.

Imana, C., Zenda, M. (2023). Impact of Climate Change on Sustainable Pastoral Livelihoods in Loima Sub-County, Turkana County, Kenya. *South African Journal of Agricultural Extension (SAJAE)*, 51(1), 13-33. https://doi.org/10.17159/2413-3221/2023/v51n1a11367.

International Food Policy Research Institute (IFPRI) (2014). Farmers Preference for Climate Smart Agriculture: An Assessment in the Indo-Gangetic Plain. Discussion paper. IFPRI, New Delhi.

IPCC (2021). Special report on climate change and land, Chapter 5 Food Security. https://www.ipcc.ch/site/assets/uploads/sites/4/2022/11/SRCCL_Full_Report.pdf.

Kaltungo, B.Y., Saidu, S.N.A., Kudi, C.A., Isma'il, M., Jacob, R.J., Salisu, U., Baba, Y.A., Buhari, H.U. (2019). Geo-Spatial Distribution of Brucella melitensis Infection in Selected Local Government Areas of Katsina and Sokoto States, Nigeria. *Nigerian Veterinary Journal*, 40(2) 95-103. https://dx.doi.org/10.4314/nvj.v40i2.1.

Kargbo, A., Jawo, E., Amoutchi, A. I., Ndow, M., Bojang, A., Zainabou, D., ... Kuye, R. (2023). Perceptions and impacts of climate variability on livestock farming in The Gambia. *Journal of Applied Animal Research*, 51(1), 366-374.

Kassa, B.A., Abdi, A.T. (2022). Factors Influencing the Adoption of Climate-Smart Agricultural Practice by Small-Scale Farming Households in Wondo Genet, Southern Ethiopia. *SAGE Open*, 12(3). https://doi.org/10.1177/21582440221121604.

Kassa, B.A., Abdi, A.T. (2021). Factors Influencing the Adoption of Climate-Smart Agricultural Practice by Small-Scale Farming Households in Wondo Genet, Southern Ethiopia. *SAGE Open,* 12(3), 1-13 DOI: 10.1177/21582440221121604

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. *Land Use Policy,* 42, 400-411.

Kelil, A., Girma, Y., Hiruy, M. (2020) Access and use of agricultural Information in Africa: A conceptual review. *Information and Knowledge Management*, 10, 1-5.

Khatri-Chhetri, A., Aggarwal, P.K., Joshi, P.K., Vyas, S. (2017). Farmers' prioritization of climate-smart agriculture (CSA) technologies. *Agricultural Systems*, 151, 184-191, https://doi.org/10.1016/j.agsy.2016.10.005.

Kolapo, A., Kolapo, A.J. (2023). Implementation of conservation agricultural practices as an effective response to mitigate climate change impact and boost crop productivity in Nigeria. *Journal of Agriculture and Food Research*, 12, https://doi.org/10.1016/j.jafr.2023.100557.

Kosoe, E.A., Ahmed, A. (2022). Climate change adaptation strategies of cocoa farmers in the Wassa East District: Implications for climate services in Ghana. *Climate Services,* 26, 100289.

Koutsoyiannis, A. (1972). Theory of Econometrics: An Introductory Exposition of Econometric Methods. Second Edition. New York: Barnes &; Noble Books.

Kpadonou, R.A.B., Owiyo, T., Barbier, B., Denton, F., Rutabingwa, F., Kiema, A. (2017). Advancing climate-smart-agriculture in developing drylands: Joint analysis of the adoption of multiple on-farm soil and water conservation technologies in West African Sahel. *Land Use Policy*, 61, 196-207.

Madaki, M.Y., Barnabas, B., Shehu, A., Ullah, A., Bavorova, M. (2025). Institutional services towards climate action: A case of climate change adaptation of agro-pastoralists in the drylands of Nigeria. *Climate Policy*, 1-15.

Mairura, F.S., Musafiri, C.M., Kiboi, M.N., Macharia, J.M., Ng'etich, O.K., Shisanya, C. A., ... Ngetich, F.K. (2022). Farm factors influencing soil fertility management patterns in Upper Eastern Kenya. *Environmental Challenges,* 6, 100409.

Mamun, A.A., Roy, S., Islam, A.R.M.T., Alam, G.M.M., Alam, E., Chandra Pal, S., Sattar, M.A., Mallick, J. (2021). Smallholder Farmers' Perceived Climate-Related Risk, Impact, and Their Choices of Sustainable Adaptation Strategies. *Sustainability*,13(21), 11922. https://doi.org/10.3390/su132111922.

Mofya-Mukuka, R., Hichaambwa, M. (2018). Livelihood effects of crop diversification: a panel data analysis of rural farm households in Zambia. *Food Security*, 10(6), 1449-1462.

Mulema, J., Mugambi, I., Kansiime, M., Chan, H.T., Chimalizeni, M., Pham, T.X., Oduor, G. (2021). Barriers and opportunities for the youth engagement in agribusiness: empirical evidence from Zambia and Vietnam. *Development in Practice*, 31(5), 690-706.

Musafiri, C.M., Macharia, J.M., Ng'etich, O.K., Kiboi, M.N.. Okeyo, J., Shisanya, C.A., Okwuosa, E.A., Mugendi, D.N., Ngetich, F.K. (2020). Farming systems' typologies analysis to inform agricultural greenhouse gas emissions potential from smallholder rain-fed farms in Kenya. *Scientific African*, 8, e00458.

Muyanga, M., Aromolaran, A.B., Jayne, TS., Liverpool-Tasie, L.S.O., A., Titus, Adelaja, A., Obayelu, E., Issa, FO., Lifeyo, Y. (2022). Changing Farm Structure and Agricultural Commercialisation: Implications for Livelihood Improvements Among Small-Scale Farmers in Nigeria. APRA Working Paper 93. Brighton: Future Agricultures Consortium.

Myeni, L., Moeletsi, M.E. (2020). Factors Determining the Adoption of Strategies Used by Smallholder Farmers to Cope with Climate Variability in the Eastern Free State, South Africa. *Agriculture*, 10(9), 410. doi.org/10.3390/agriculture10090410.

Nagler, J. (1994). Scobit: An Alternative Estimator to Logit and Probit. *American Journal of Political Science,* 38(1), 230-255.

Nantongo, B., Ssekandi, J., Ngom, A., Dieng, B., Diouf, N., Diouf, J., Noba, K. (2022). Predicting the adoption of multiple climate-smart agriculture technologies in Tambacounda and Kolda, Senegal. *Journal of Agricultural Extension and Rural Development*, 14(4), 163-172.

Ndebele, Z., Zenda, M. (2023). Climate Change Impact and Adaptation of Agro-Pastoral Farmers in Awerial County, Lakes State of South Sudan. *South African Journal of Agricultural Extension*, 51(3), 135-160. https://doi.org/10.17159/2413-3221/2023/v51n3a14086.

Nhemachena, C., Nhamo, L., Matchaya, G., Nhemachena, C.R., Muchara, B., Karuaihe, S.T., Mpandeli, S. (2020). Climate Change Impacts on Water and Agriculture Sectors in Southern Africa: Threats and Opportunities for Sustainable Development. *Water*, 12(10), 2673. https://doi.org/10.3390/w12102673.

Nyang'au, J.O., Mohamed, J.H., Mango, N., Makate, C., Wangeci, A.N. (2021). Smallholder farmers' perception of climate change and adoption of climate-smart agriculture practices in Masaba South Sub-county, Kisii, Kenya. *Heliyon*, 21, 7(4):e06789. doi:10.1016/j.heliyon.2021.e06789.

Oduniyi, O.S., Tekana, S.S. (2021). Does Information Acquisition Influence the Adoption of Sustainable Land Management Practices? Evidence from Mpumalanga Province South Africa. *Frontiers in Sustainable Food Systems*, 5:769094. doi: 10.3389/fsufs.2021.769094.

Olorunfemi, T.O., Olorunfemi, O.D., Oladele, O.I. (2020). Borich needs model analysis of extension agents' competence on climate smart agricultural initiatives in South West Nigeria. *The Journal of Agricultural Education and Extension*, 26:1, 59-73, DOI: 10.1080/1389224X.2019.1693406.

Omodara, O.D., Ige, O.A., Oluwasola, O., Oyebanji, A.T., Afape, O.O. (2023). Factors influencing cassava farmers' choice of climate change adaption practices and its effect on cassava productivity in Nigeria. *Heliyon*, 9(3).

Otitoju M.A., Enete, A.A. (2016). Climate change adaptation: Uncovering constraints to the use of adaptation strategies among food crop farmers in South-west, Nigeria using principal component analysis (PCA). *Cogent Food & Agriculture*, 2: 1178692.

Ricart, S., Castelletti, A., Gandolfi, C. (2022). On farmers' perceptions of climate change and its nexus with climate data and adaptive capacity. A comprehensive review. *Environmental Research Letters*, 17 083002.

Saidu, A.I., Yeom, C. (2020). Success Criteria Evaluation for a Sustainable and Affordable Housing Model: A Case for Improving Household Welfare in Nigeria Cities. *Sustainability*, 12(2), 656. https://doi.org/10.3390/su12020656.

Serote, B., Mokgehle, S., Senyolo, G., du Plooy, C., Hlophe-Ginindza, S., Mpandeli, S., Nhamo, L., Araya, H. (2023). Exploring the Barriers to the Adoption of Climate-Smart Irrigation Technologies for Sustainable Crop Productivity by Smallholder Farmers: Evidence from South Africa. *Agriculture*, 13, 246. https://doi.org/10.3390/ agriculture13020246.

Tesfaye, H., Baye, B., Eyob, B., Kaleb, K., Daniel, H., Fitsum, D. (2018). Impact of improved wheat variety on productivity in Oromia Regional State, Ethiopia. *Greener Journal of Agricultural Sciences,* 8(4), 74-81, doi:10.15580/GJAS.2018.4.092117135.

World Bank (2022). Climate -Smart Agriculture. https://www.worldbank.org/en/topic/climate-smart-agriculture.

Yakubu, D.H., John, B., Yekinni, O.T., Muhammad, M.B., Abdullahi, M.K., Adisa, R.S. (2016). Agricultural information channels used by livestock farmers in Wurno local government area of Sokoto State, Nigeria, *Nigerian Journal of Rural Sociology*, 16(4). DOI: 10.22004/ag.econ.287482.

Zampaligré, N., Fuchs, L.E. (2019). Determinants of Adoption of Multiple Climate-Smart Adaptation Practices in Sudano-Sahelian Pastoral and Agro-Pastoral Production Systems. *Sustainability,* 11(18), 4831. https://doi.org/10.3390/su11184831.

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