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Typologies and drivers of the adoption of climate smart agricultural practices by smallholder farmers in rural Ghana

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ABSTRACT

This study examined the factors that determine the adoption of CSA practices in dryland farming systems. The study answers the following questions: (i) what are the typologies of CSA practices available to smallholder farmers in rural Ghana?, (ii) what is the adoption rate of CSA practices among smallholder farmers? and, (iii) what are the socioeconomic predictors of the adoption of CSA practices in rural Ghana? This paper employed mixed-method participatory approaches including surveys of 1061 households, and 15 key informant interviews supplemented with 2 regional stakeholder workshops. The study used a Principal Component Analysis (PCA) to examine the climate smart agriculture typologies adopted among the smallholder farmers. To investigate the drivers of adoption, the multinomial ordered probit model was applied. The PCA results suggested that, there were seven (7) uncorrelated dimensions involving 23 CSA practices that were generally employed – water smart practices, energy smart practices, nutrient smart practices, carbon smart practices, weather smart practices, planting smart practices, and knowledge smart practices. These 7 typologies explained 63.91% of the total variance. The PCA results indicated that smallholder farmers do not necessarily rely on a single CSA practice to cope with climate change; but utilise a combination of practices. The results of the ordered probit model suggested that the factors driving the adoption of CSA practices are mixed nuanced on the adoption typology and farmers' location and institutional factors. The paper contributes to an understanding of the different typologies for CSA practices and highlights the various socioeconomic factors driving the adoption rates of CSA practices by smallholders' farmers. This is crucial for the upscale of CSA practices in the face of climate change in Ghana and West Africa more widely.

1. Introduction

The West Africa region produces about 30% of the food requirement of the African continent and therefore it is important to enhance the resilience of food production systems within this region against climate change effects (FAO, 2015). Extreme weather events including droughts, floods, and windstorms have characterised the region (Sylla et al., 2018; Sultan and Gaetani, 2016).

With Ghana's current population estimated at 30 million, meeting the food security needs of this population requires increasing agricultural productivity. Agriculture remains the single most important sector of the Ghanaian economy, contributing significantly to the country's gross domestic product. The sector is also crucial in attaining the first and second goals of the United Nations Sustainable Development Goals (SDGs). Yet, the sector is plagued with low productivity and institutional weaknesses; resulting in market system failures, trade barriers, poor information, checkered sectoral growth, irregular income to actors, and poor infrastructural and human development. These challenges are compounded by Ghana's over-reliance on rain-fed agricultural systems; particularly in northern Ghana, where rainfall patterns are irregular and temperatures are high for most parts of the year. Ghana is projected to suffer increased temperature, rainfall variability and extreme events including droughts and floods (Asante and Amuakwa-Mensah, 2015). These will have major implications for agriculture, especially farming systems in the Sudan Savannah Zone (SSZ).

Projected increases in temperatures will lead to increased evapotranspiration that can result in significant crop yield loses. This poses significant threats to food security and household livelihood sustainability in dry regions where slight changes in rainfall patterns can lead to considerable yield and crop loses (Chemura et al., 2020).

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While these projections seem dire, a growing body of literature suggests that Climate Smart Agriculture (CSA) technologies offer prospects for smallholder farmers in dryland farming systems to maintain productivity in the face of changing rainfall patterns (Antwi-Agyei et al., 2021a; Lipper et al., 2014; Campbell et al., 2014; FAO, 2013). CSA is used to describe an agricultural system that sustainably increases productivity, enhances resilience and reduces greenhouse gases whilst facilitating the achievement of national food security (FAO, 2013). Thus, CSA revolves around three "pillars" i) sustainably increasing agricultural productivity for food and nutrition security, ii) climate change adaptation with the view of reducing exposure to short-term risks, and address long-term climate changes, iii) reducing and/or removing greenhouse gas emissions where possible (Thornton et al., 2018). By doing this, CSA practices provide a framework to enhance synergies and minimize trade-offs between adaptation and mitigation (Antwi-Agyei et al., 2023; Steenwerth et al., 2014). In this paper, an agricultural practice is defined as climate smart if it can help to achieve at least one pillar of CSA (enhancing *productivity* or building *resilience* or helping to reduce *GHG emission*). CSA practices aim to transform and reorient agricultural systems, especially for those in dryland farming systems, in support of food security within the context of climate change (Lipper et al., 2014). The adoption and mainstreaming of climate-smart agriculture (CSA) practices could create opportunities for improving food and livelihood security, mitigate emissions and enhance the resilience of the food and agricultural systems (Sain et al., 2017; Partey et al., 2018; Dougill et al., 2021).

To this end, CSA has gained considerable prominence given the adaptation and mitigation challenges confronting humanity (Kurgat et al., 2020; FAO, 2013; Lipper et al., 2014). There is a growing interest to advance the uptake of sustainable farming practices that will fortify agricultural and food systems among farmers, particularly, smallholder farmers (Abegunde et al., 2020). International and regional bodies including the Global Alliance for Climate Smart Agriculture (GACSA), the Africa Climate Smart Agriculture Alliance (ACSAA), and the West Africa Climate Smart Agriculture Alliance (WACSAA) plus a range of actors including farmers, governments, civil society organizations (CSOs), and the private sector have initiated different CSA actions (Dinesh, 2016).

A growing number of studies have also focused on the value of CSA practices in addressing the adverse impacts of climate change on livelihoods (see Lipper et al., 2014; Partey et al., 2018; Campbell et al., 2014). For example, Lipper et al. (2014) highlighted the need for urgent action from public, private and civil society stakeholders for effective implementation of CSA. Totin et al. (2018) employed a systematic literature review to explore the institutional aspects of CSA. Antwi-Agyei et al. (2021a) highlighted the motivations, barriers and enablers for the adoption of CSA practices in Ghana. Thornton et al. (2018) proposed a framework for prioritising agricultural research investments on CSA across scales. Similarly, Zougmoré et al. (2016) provided a review of climate change impacts, adaptation strategies and policy developments for the livestock, fishery and crop production sectors. In West Africa, Partey et al. (2018) reported that, CSA practices such as soil and water conservation technologies, climate information services and agroforestry provided promising options for addressing climate change threats. In Kenya, Kangogo et al. (2021) observed that farmer entrepreneurship was critical to the adoption decisions of CSA practices of smallholders.

While these studies document an impressive body of knowledge on CSA practices, there remains a dearth of scholarship on the typologies of CSA practices and the factors that predict the adoption of CSA practices by smallholder farming communities in vulnerability hotspots in dryland farming systems. Moreover, many of these studies did not consider the lived experiences of farming households and other stakeholders and how that can affect the choice of CSA practices in farming systems. Additionally, it remains unclear under what socioeconomic conditions do farming households adopt CSA practices. This critical information is lacking in the literature and hampers the design and upscaling of context relevant CSA practices to address climate risks in dryland farming systems in vulnerability hotspots. This could be attributed to the lack of appropriate typology and how this could help policy makers in making decisions on relevant local specific CSA practices. This study addresses these gaps by answering the following questions: (i) what are the typologies of CSA practices available to smallholder farmers in rural Ghana? (ii) what is the adoption rate of CSA practices among smallholder farmers? and, (iii) what are the socioeconomic predictors of adoption of CSA practices in dryland farming systems in rural Ghana? This paper contributes to the burgeoning literature on CSA practices highlighting the key socioeconomic conditions predicting the adoption of the different typologies of CSA practices. This will provide critical insights for policy makers and development practitioners in designing and upscaling appropriate CSA practices in rural Ghana.

2. Research design and methods

2.1. The study area

The study was conducted in the Upper East, Northern and the Bono East Regions of Ghana. Three local assemblies – Kintampo South district (from the Bono East Region), Savelugu district (from the Northern Region), and the Lambussie district (from the Upper West Region) were selected (Fig. 1 and Table 1), based on the levels of climate change and livelihoods vulnerability demonstrated by these study districts (Klutse et al., 2020).

The Kintampo South district lies in the transitional ecological zone of Ghana characterised by two farming seasons with majority of the people in this district employed in agriculture. There is high dependence on agro-based livelihoods on a subsistence level with only few farmers engaged in plantation and mechanized farming (Ghana Statistical Services (GSS), 2014a). The district experiences bi-modal rainfall pattern. The major raining season starts in early March and reaches its peak in June, and tapers off gradually through July.

The Savelugu municipal, on the other hand, shares boundaries with West Mamprusi to the North, Karaga to the East, Kumbungu to the West and Tamale Metropolitan Assembly to the South. It occupies an area of 1790.70 km^2. Agriculture is the predominant source of employment in this district; with an estimated 89.3% of households engaged in agriculture (GSS, 2014b). The municipality experiences a unimodal rainfall pattern. The landscape is mostly flat and gently sloping towards the North and characterised by the interior Savannah woodlands vegetation.

Carved out from the former Jirapa-Lambussie district in the Upper West region, the Lambussie district is located in the north-western corner of the Upper West Region. The rainy season lasts from June to October each year and gives way to the dry season from November to May. The district experiences a unimodal rainfall pattern and it is characterised by anthropogenic activities including bush burning, tree felling for fuel wood, sand and gravel wining, which have led to the extensive destruction of the vegetation (GSS, 2014c). Agriculture remains the main economic activity with an estimated 90% of the population engaging in agriculture largely on subsistence level.

Within each local assembly, three study communities were selected using non-purposive sampling based on advice from municipal and district level agricultural development officers. Hence, we selected Ayorya, Apesika and Suamire (from Kintampo South), Diare, Nakpanzoo, and Kukobila (from Savelugu Municipal), Karni, Samoa, and Kpari (from the Lambussie district). Community engagements were facilitated with the help of community gate keepers including agricultural extension officers, to introduce the research to them and solicit the involvement of the communities.

2.2. Research methodology

The data reported in this paper were collected through a fieldwork

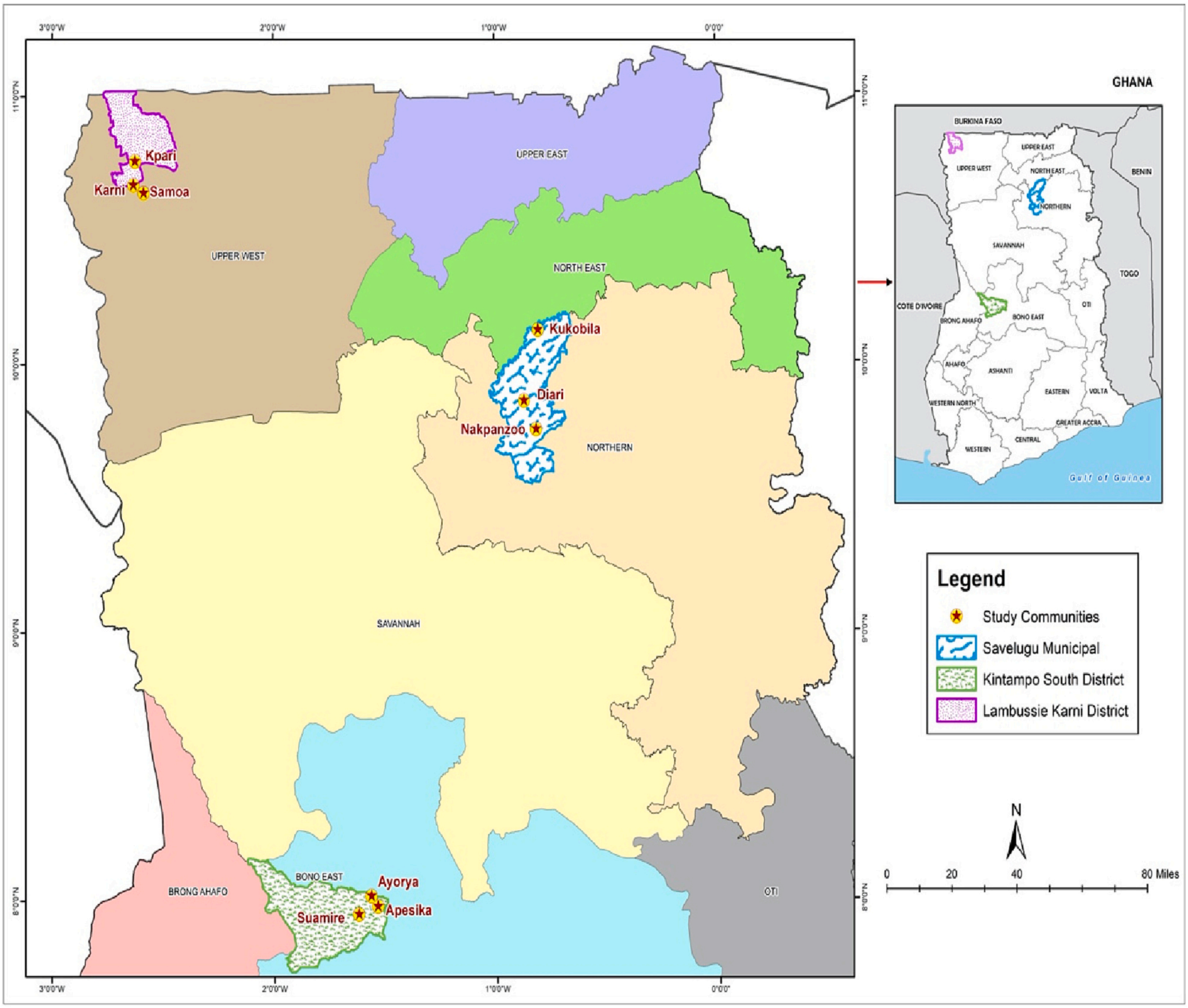

Fig. 1. Northern Ghana showing the study communities

conducted from October to December 2020 in the 9 study communities selected from the three study districts (the Kintampo South district, Savelugu municipality and Lambussie district). The fieldwork was conducted in two phases. In phase one, survey questionnaires were administered in local dialects with the assistance of local interpreters to 1061 households with the help of CSPro software (Ponnusamy, 2012). Households were randomly selected in the study communities and the head of each selected household or his representative in the absence of the head was interviewed. Survey questionnaires covered thematic areas including the general household characteristics, perception of respondents on climate change and variability, and adoption of CSA practices used by farmers. These CSA practices were identified from literature and presented to regional and district agricultural development officers for confirmation as predominant practices in the study districts. Using a 4-point Likert Scale ranging from "0" never used before to "3" used every year; the farmers were then asked to score each identified adaptation practice from 0 to 3 (see Table 2). Each questionnaire averagely took between 30 min and 1 h. Respondents to surveys questionnaires were assured of anonymity and made to understand that their participation in the research would not be compensated and that they could withdraw from the interview at any time.

Phase two involved 2 district stakeholders workshops held at Jema (in the Kintampo South district) and Lambussie (in the Lambussie district), in February 2021. The findings of the phase one were presented to stakeholders drawn across governmental departments and a cross-section of farmers to elicit response on the implications of the findings for climate change adaptation in the study districts. Additionally, 15 key informant interviews (with 5 interviews in each district) were conducted with chiefs, assembly members, chief farmers, extension officers, youth leaders and women leaders to triangulate the information obtained from the field surveys and stakeholder workshops. The key informants were selected based on their longstanding understanding of agriculture and environmental issues in the study districts. Responses from key informants were content analysed and relevant themes that emerged were identified in light of the study objectives.

2.3. Data analysis

To examine the factors that influence the choice of CSA practice, first, the Principal Component Analysis (PCA) was employed to summarize the data into a set of uncorrelated dimensions. In line with statistical practice, the appropriateness of the dataset for principal component analysis was tested using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity. The estimate of the Bartlett's test of sphericity showed that conducting a PCA on the dataset was appropriate [$\chi^2(df)$ = 8747.184 (406)***]. The confirmation of the factorability of the dataset was observed from the KMO value of 0.888 which validated the suitability of the data for PCA

Table 1
Profile of the study area districts.

	Kintampo South District	Savelugu Municipal	Lambussie District	Source
Study Area	1513.34 km^2	2022.6 km^2	811.9 km^2	(GSS, 2014a, 2014b, 2014c, 2014d)
Study Location	7° 52′ N 1° 45′ W	9° 36′ N 0° 49′ W	10° 39′ N 2° 34′ W	
Capital Town	Jema	Savelugu	Lambussie	
Agroecological Zone	Wet Semi-equatorial/ Transitional zone	Northern Savanna	Savanna	
Vegetation	Woodland Savannah Vegetation	Woodland Savannah Vegetation	Savannah Vegetation	
Total Households	15,522	138, 221	50, 896	(GSS, 2014a, 2014b, 2014c)
Population (Year)	81, 000 (2010)	139, 283 (2010)	51, 654 (2010)	(GSS, 2014a, 2014b, 2014c)
Gender (Sex Ratio)	Male (52.0%); Female (48.0%)	Male (48.5%); Female (51.5%)	Male (48.3%); Female (51.7%)	(GSS, 2014d)
Temperature	24 °C - 30 °C	16 °C - 42 °C	18 °C - 40 °C	(GSS, 2014d)
Mean Annual Rainfall	1400 mm–1800 mm	600 mm–1000 mm	900 mm-1100 mm	(GSS, 2014a, 2014b, 2014c)
Relative Humidity	41%–100%	33%	20%- 60%	(GSS, 2014d)
Major crops grown	Yam, maize, cassava, plantain, rice, cocoyam, pepper, garden eggs, groundnut, mango and cashew.	Rice, groundnut, yam, cassava, maize, cowpea and sorghum	Shea nut, groundnuts, yam, cotton, millet, rice, maize, cowpea, sorghum, bambara beans,	
Economic trees	Odum, mahogany, senya, apupuo, shea, wawa, dawadawa.	Shea trees and dawadawa	Cashew, shea, mango, baobab, kapok, dawadawa	(GSS, 2014a, 2014b, 2014c)
Ethnicity	Bono, Mo, Dagomba and Ashanti	Dagomba, Frafra, Mampurise, Ewe, Gonja	Gurunshi, Sissala, Dagaaba, Waala, Moshi, Wala, Fulani, Wangara	(GSS, 2014a, 2014b,2014c)
Key livelihood activities	Crop farming, tree planting, livestock rearing, fish farming.	Crop farming, sand winning, fishing, charcoal burning.	Crop farming, livestock rearing.	

Table 2
Criteria used to define climate smart practice adoption rates.

Likert Scale Rating	Level of preferences	Percentile
0	No adoption	0–25
1	Low adoption	26–50
2	Moderate adoption	51–75
3	High adoption	76–100

analysis (Rojas-Valverde et al., 2020).

Based on the PCA analysis all components with eigenvalues >1 were retained. The PCA was conducted using the Oblimin rotation technique. Several authors have used the PCA to categorize scientific phenomenon including climate change adaptation in the literature (Greiner and Gregg, 2011; Jeon et al., 2006; Bax et al., 2020). As displayed on Table 2, the aggregated rating scores for the identified seven common (relevant) practices were subsequently converted into percentiles and grouped according to four relevant classes (Khatri-Chhetri et al., 2017).

At the second stage of the analysis, the study used the ordered probit model to analyse the factors that influence a farmer's choice of a CSA practice. Following Khatri-Chhetri et al., 2017), the specification of the multinomial ordered probit model is given as follows:

$$\sum_{m=1}^{M} P_i(m) = F\left(X_i^{'}\beta_m : \theta\right) : m = 1, 2, 3 \dots M - 1 \tag{1}$$

$$P_i(M) = 1 - \sum_{m=1}^{M-1} P_i(m) \tag{2}$$

Where $P_i(m)$ gives the probability that a farmer, i, adopts a certain typology of climate-smart practice, m. X denotes the vector of explanatory variables affecting the probability of adoption. The explanatory variables included in this study are household and farmer-specific variables such as gender, educational level, marital status, the percentage of household members who are farmers, farming experience, climate change perception; institutional and environmental factors such as the availability of social support, access to credit, extension services, access to climate information, availability of ready markets, and government subsidies.

It was expected that differences in the farming conditions (farmer-specific and environmental factors) can also influence adoption. For instance, Deressa et al. (2009), Pomp and Burger (1995), Joshi (2005) and Bidogeza et al. (2009) suggest that conditions such as the availability of labour, availability of seeds, crop diversity, land size, and farm resource endowment can affect a farmer's motivation to implement a CSA practice. Thus, the effect of farming conditions was assessed using the landholding size, the number of crops grown (crop diversity), and the availability of extension services. Table 3 presents details of the list of explanatory variables; and Table 4 presents the descriptive statistics of variables. β_m is the set of parameters to be estimated. $F(.)$ is the probability distribution function from which the probability estimates are derived. Eq. (1) suggests that the total probability of adopting CSA practices is a function of a set of farmer-specific and environmental factors. Eq. (2) indicate that summing up the probabilities will amount to 1. The shape of the $F(.)$ is given by θ parameter. From eq. (2), the probability that a farmer will adopt a CSA practice conditioned on the set of farmer-specific and environmental characteristics can be expressed as:

$$P_i(Y_i = m|X_i) = \Phi(\beta_{0m} - \beta_m X_i) - \Phi(\beta_{0m-1} - \beta_m X_i) \tag{3}$$

Where Φ is the cumulative standard normal probability distribution function which is estimated using a maximum likelihood estimation technique. The seven (7) typologies identified in the principal component analysis were used as dependent variables in the ordered probit model, which assessed the factors that predict the probability of a farmer adopting these unique integrated strategies as suitable climate-smart agricultural technology. Thus, seven (7) models were estimated to assess the factors that predict a farmer's adoption of plant, nutrient and knowledge smart technology (PNSKT), energy, water and carbon smart technology (EWCST), knowledge smart technology (KST), energy, plant and knowledge smart technology (EPKST), knowledge and plant smart technology (KPST), weather smart technology (WST), and water, plant and carbon smart technology (WPCST). Table 5 presents a description of each technology and the practices involved. The robust standard errors clustered at the district level was applied to control for

Table 3
Description of explanatory variables.

	Descriptive
Gender	Categorical. 0 = Female; 1 = Male
Educational status	Categorical. 0 = None; 1 = Basic; 2 = SSS; 3 = Post SSS; 4 = Tertiary; 5 = Others
Marital status	Categorical. 1 = Never married; 2 = Living together; 3 = Married; 4 = Divorced; 5 = Separated; 6 = Widowed
Age	Continuous.
Extension service	Dummy; takes the value of 1 if there is access to extension services and 0 otherwise
Native	Dummy; takes the value of 1 if the farmer is a native of the village and 0 otherwise
Reliance on farm income	Dummy; takes the value of 1 if the farmer's household rely on agriculture as the only source of household income and 0 otherwise
Crop diversity index	Continuous. Defined as the number of crops grown by the farmer
Farming experience	Categorical. 1 = Below 5 years; 2 = Between 5 and 10 years; 3 = Above 10 years
Perception of changes in rainfall patterns	Dummy; takes the value of 1 if a farmer reports changes in rainfall patterns and 0 otherwise
Perception in temperature patterns	Dummy; takes the value of 1 if a farmer reports changes in temperature patterns and 0 otherwise
Access to climate information	Dummy; takes the value of 1 if a farmer has access to climate information and 0 otherwise
Information about extreme weather events	Dummy; takes the value of 1 if a farmer receives a warning on extreme weather events and 0 otherwise
Access to water	Continuous. Average time to water source in minutes
Access to social support	Dummy; takes the value of 1 if a farmer receives social support and 0 otherwise
Member of a social club outside community	Dummy; takes the value of 1 if a farmer is a member of a social club outside the community and 0 otherwise
Member of faith-based group	Dummy; takes the value of 1 if a farmer is a member of a faith-based group and 0 otherwise
Landholding size	Categorical. 1= ≤ 3ha; 2 = 3–6 ha; 3 ≥ 6 ha
Access to credit	Dummy; takes the value of 1 if a farmer has access and 0 otherwise
Regular remittances	Dummy; takes the value of 1 if a farmer receives remittances and 0 otherwise
Access to ready market	Dummy; takes the value of 1 if a farmer has access and 0 otherwise
Access to communication devices	Dummy; takes the value of 1 if a farmer has access and 0 otherwise
Housing conditions	Categorical. 1 = Owning, 2 = Renting = 2, 3 = Rent-free; 4 = Others (incl. perching, squatting)
% of household members who are farmers	Continuous. The ratio of farmers to total household size
Government subsidies	Dummy; takes the value of 1 if a farmer receives subsidies and 0 otherwise
Access of internet	Dummy; takes the value of 1 if a farmer has access and 0 otherwise

heteroscedasticity in all the empirical estimations.

3. Results and discussion

3.1. Descriptive statistics

The pooled results show that 68% of the farmers were males (Table 4). The average age of household heads was 45 years. A key footprint of climate change in agricultural communities is migration. This is generally considered a non-farm-related coping strategy, where farmers migrate from vulnerable communities to potential climate-resilient communities to undertake farming activities. According to the descriptive statistics, about 80% of the farmers were natives of the resident communities. This implies that farmers rarely migrated to neighbouring communities to farm. Social networks have been noted to improve information sharing, access to resources, and social support. Membership in associations is therefore a component of the farmers' climate adaptation mix. For instance, it was detected that about 37% of farmers were members of social clubs outside the community. There are however significant differences in club membership across the study communities. For instance, 94% of farmers in the Savelugu community belonged to a social club; compared to 78% and 56% of farmers in the Kintampo and the Lambussie communities. Notwithstanding, a total of 80% of the farmers reported belonging to faith-based institutions or associations; however, a significant percentage of such farmers were from the Lambussie community (67%). Only 18% of farmers reported being beneficiaries of social support. Again, it was identified that farmers from the Lambussie community accessed social support (56%) compared to those in Kintampo (30%) and Savelugu (28%) communities. The implication is that the average farmer in the Lambussie community is less likely to join a farmers' corporative union relative to a religious society whereas the reverse holds for their counterparts in Kintampo and Savelugu. With reference to the financial and economic capacity of the farmers, the evidence showed that access to credit is low with only 15% of farmers having access to credit. In contrast, the majority of farmers reported they have benefitted from government subsidies (71%). Access to a ready market has also been averagely high; with approximately 65% of farmers having access. Approximately, 72% of the respondents also indicated that they have access to extension services. With respect to farming conditions, Table 4 shows that on average each farmer grows four (4) types of crops on each farmland; with the average landholding size of 3–6 ha. Meanwhile, Table 4 also suggests that the perception of climate change is high and widespread among the sampled smallholder farmers.

3.2. Typologies of climate smart agricultural practices in study communities

Based on the PCA analysis all components with eigenvalues >1 were retained. All factor loadings which loaded >0.45 were selected whereas items that cross-loaded on more than one component were identified and excluded from the PCA. In the first stage, a total of 31 CSA practices were used for the PCA analysis, out of which 23 practices were identified as the key relevant adaptation options applied to address issues of climate change resilience, productivity, and environmental sustainability. Seven (7) uncorrelated dimensions (typologies) involving 23 climate-smart practices were identified; explaining 63.91% of the total variance. Subsequently, the study proceeded to define each component based on the set of CSA practices it was strongly correlated with (highlighted in bold on Tables 5 and 6). For instance, the first component which is positively correlated with the planting of drought-resistant and pest-resistant crops, planting of early maturing seeds, and cover cropping planting was described as planting, nutrient, and knowledge smart technology. Component 1 explains 25.57% of the total variance. Analysis of the factor scores shows that knowledge-smart practices dominate with planting and nutrient-smart technology used to complement efforts made through the use of knowledge-smart farming activities. Component 2, on the other hand, explains 9.76% of the total variance and positively associated with tillage by bullock, agroforestry and woodlot scheme, earth bunding, and crop-livestock integration or mixed farming. These practices are intended to ensure sustainable resource management through control of energy consumption and carbon emissions. Thus, Component 2 is defined as energy, water, and carbon smart technology. Component 3 contributes approximately 7.33% of the total variance. Component 3 is observed to be characterised by appropriate fertilizer use, early planting, timely harvesting, and appropriate land preparation. These practices can only be implemented with strong knowledge about climate change and coping strategies. Component 3 is therefore defined as knowledge smart technology.

Component 4 accounts for about 6.38% of the variance and is made up of practices such as bush fallowing, zero tillage and mixed cropping. Component 4 is therefore defined as energy, planting and knowledge

Table 4
Descriptive statistics of smallholder farmers in Ghana.

	Pooled (N = 1052)		Kintampo (N = 390)		Savelugu (N = 347)		Lambussie (N = 315)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Gender	0.68	0.47	0.48	0.50	0.88	0.32	0.71	0.46
Educational status	1.56	0.90	0.48	0.50	0.18	0.39	0.47	0.50
Marital status	3.18	0.94	0.73	0.44	0.95	0.21	0.86	0.34
Age of farmer	45.26	14.11	46.15	14.13	44.33	12.76	45.21	15.42
Extension service	0.72	0.45	0.58	0.49	0.84	0.37	0.77	0.43
Native of the town	0.80	0.40	0.50	0.50	0.97	0.16	0.99	0.11
Reliance on farm income	0.36	0.93	0.90	0.29	0.94	0.24	0.90	0.29
Crop diversity index	4.28	1.55	4.24	1.57	3.88	1.26	4.82	1.62
Farming experience	2.74	0.56	2.67	0.63	2.79	0.47	2.79	0.53
Perception of changes in rainfall	0.99	0.92	1.00	0.051	0.98	0.15	1.00	0.00
Perception in temperature patterns	0.99	0.11	0.99	0.09	0.97	0.16	1.00	0.00
Access to climate information	0.77	0.42	0.43	0.50	0.46	0.50	0.72	0.45
Info. about extreme weather events	0.62	0.49	0.62	0.49	0.86	0.34	0.34	0.47
Access to water	16.08	19.35	6.41	6.31	30.96	24.92	11.68	11.79
Access to social support	0.18	0.39	0.30	0.46	0.28	0.45	0.56	0.50
Social club membership	0.37	0.48	0.78	0.42	0.94	0.25	0.56	0.50
Member of faith-based group	0.80	0.40	0.21	0.40	0.14	0.35	0.67	0.47
Landholding size	2.27	0.78	2.40	0.83	2.05	0.38	0.21	0.41
Access to credit	0.15	0.36	0.14	0.35	0.15	0.36	2.05	0.30
Regular remittances	0.73	0.45	0.11	0.31	0.03	0.18	0.23	0.43
Access to ready market	0.65	0.48	0.94	0.24	0.52	0.50	0.45	0.50
Access to communication devices	0.85	0.35	0.78	0.41	0.97	0.17	0.81	0.40
Housing conditions	1.35	0.80	2.35	1.09	3.20	0.57	2.37	1.00
% of farmers in the household	44.04	23.79	47.91	22.76	37.14	20.34	46.87	26.78
Government subsidies	0.71	0.45	0.53	0.50	0.82	0.39	0.81	0.39
Access of internet	0.11	0.31	0.12	0.32	0.97	0.17	0.13	0.34

smart technology. Component 5 which is defined as knowledge and planting smart technology constituted 5.22% of the total variance; and comprised the use of indigenous/traditional agro-ecological knowledge and crop diversification. Component 6 accounts for 5.12% of the variance and is characterised by crop insurance scheme. Therefore, it was defined as weather smart technology. About 4.49% of the total variance could be attributed to Component 7, which was strongly correlated with sprinkler and drip irrigation, crop rotation and no burning of residues and subsequently defined as water and carbon smart technology.

A graphical representation of the PCA component loadings is presented on Fig. 2 which reveal four quadrants (I, II, III and IV) of potential technology combination. The quadrants are interpreted from northeast to southwest directions (Owusu Kwateng et al., 2020). Practices that are widely combined increases from northeast direction to the southwest. Additionally, the horizontal line from east to west shows adoption levels and climate smart practice combination typology. Specifically, quadrant 1 is characterised by water, planting, knowledge and nutrient smart practices and is christened as "general climate smart agriculture adoption". Quadrant 2 is occupied by weather smart practices. Quadrant 3 on the other hand shows zero smart technology adoption and therefore is described as "no adoption". The quadrant 4 is populated by practices that are based on knowledge smart, water smart and carbon smart technology. Again, it can be observed that the use of knowledge smart technologies dominates.

3.3. Adoption rates of climate smart agricultural practices by farmers

The results indicate that farming households in the sampled communities combined various CSA practices. A combination of energy, water, carbon, nutrient, planting, weather and knowledge smart technologies is observed among the sampled farmers. This finding corroborates the climate change literature (Sonko et al., 2020; Partey et al., 2018), suggesting that smallholder farmers in sub Saharan Africa integrate a range of adaptation practices to address climate risks. Specifically, seven typologies of CSA practices were identified.

A descriptive analysis of the climate smart adoption typologies identified among the smallholder farmers is subsequently presented on Fig. 3. Generally, the results indicate that, the level of adoption of CSA practices among the sampled farmers is averagely low; albeit the application of knowledge smart technologies is relatively widespread. Low adoption rates of CSA practices have been reported across many parts of sub-Saharan Africa (see, for example, Kurgat et al., 2020; Partey et al., 2018; Westermann et al., 2018). The low adoption could be attributed to the resource-intensive nature of some of the CSA practices including conservation agriculture (Mairura et al., 2021) and irrigation (Danson et al., 2002). Irrigation and crop rotation practices have been reported to moderate the effects of climate change and are widely used by dryland farming systems (Akinyi et al., 2021). Yet, Danson et al. (2002) noted that manual irrigation takes 38% of a farmer's time and could dissuade farmers from implementing such practice that has the potential to boost yield and build resilience to climate variability. Nonetheless, the evidence suggest that knowledge smart technologies are widely applied and integrated in the climate smart agricultural practices adopted by smallholder farmers in Ghana.

The analysis also suggests that farmers in communities in the Savelugu municipality have a lower level of adoption for all the identified technologies compared to their counterparts in other districts whereas farmers in the Kintampo district have a higher level of adoption; particularly for the integration of plant, nutrient and knowledge smart technologies; and the adoption of knowledge smart technology. They also perform relatively better in the integration of energy, water and carbon smart technologies.

3.4. Drivers of the adoption of climate smart agricultural practices by smallholder farmers

Given the categorization and subsequent characterization of the CSA practice adoption typologies, the key factors that predict the selection of CSA are presented in Table 7.

3.4.1. Plant, nutrient and knowledge smart technology (PNKST)

Plant, nutrient and knowledge smart technology describes the integration of nutrient smart, planting smart and knowledge smart technologies in crop production in an effort to adapt to the effects of climate change. The results showed that the availability of extension service increases the probability of adoption of this technology ($p < 1\%$)

Table 5
Climate smart agriculture technology matrix and adoption rate.

	Pooled		Kintampo		Savelugu		Lambussie		Description
Practices	Mean	SD	Mean	SD	Mean	SD	Mean	SD	
Water Smart Practices									**Activities geared towards improving water efficiency**
- Sprinkler and drip irrigation	0.27	0.64	0.21	0.55	0.29	0.55	0.31	0.80	*Minimizes water loss*
- Water management and water harvesting	1.16	1.02	0.81	0.94	1.43	1.03	1.30	0.96	*Creative ways to store rainwater and reducing water loss*
- Cover crop method	1.42	1.03	1.68	0.91	0.78	0.82	1.81	1.04	*Growing cover crops to maintain soil moisture*
Energy Smart Practices									**Activities towards ensuring energy efficiency**
- Zero tillage/Minimum tillage	1.26	1.06	1.77	0.87	0.44	0.64	1.53	1.12	*Reduces energy use in land preparation*
- Tillage by bullock	0.23	0.63	0.04	0.23	0.18	0.39	0.52	0.98	*Using bullock for tillage practice*
- Conservation agriculture	1.23	0.86	1.28	0.77	0.81	0.74	1.62	0.89	*Using appropriate methods to ensure sustainability*
- Earth bunding	0.34	0.63	0.11	0.42	0.50	0.61	0.45	0.78	*Ridge of compacted earth constructed to control soil erosion*
- Stone bunding	0.13	0.40	0.07	0.29	0.17	0.40	0.17	0.50	*Stone bunds form a barrier to slow down water runoff.*
Nutrient Smart practices									**Practices geared towards nutrient use efficiency**
- Inter cropping with legumes	1.52	1.04	1.58	1.00	0.86	0.82	2.18	0.84	*Planting of legumes among crops to raise nitrogen supply*
- Composting	0.47	0.74	0.39	0.65	0.38	0.57	0.68	0.94	*Using decomposed plant materials as soil amendments*
- Crop residue mulching	1.27	1.10	1.67	0.97	0.65	0.79	1.45	1.25	*Covering the soil to make it favourable for plant growth*
- Crop-livestock integration	0.90	0.98	0.64	0.86	0.52	0.73	1.65	0.95	*Mixed farming to ensure supply of biomass and feed*
- Bush fallowing	1.38	1.05	2.06	0.85	0.60	0.68	1.41	1.03	*Land use efficiency to allow soil nutrient recovery*
Carbon Smart									**Practices geared towards reducing pollution in all forms**
- Agro forestry and woodlot schemes	0.51	0.77	0.34	0.68	0.40	0.56	0.84	0.95	*Interaction of agriculture and trees*
- Appropriate and timely weed and pest control	1.99	0.83	1.93	0.85	1.71	0.79	2.36	0.71	*Good pest management practice to lower use of chemicals*
- No burning of residues biomass on farms	1.31	0.96	1.24	0.79	1.10	1.00	1.63	1.03	*Reduce pollution*
Weather Smart									**Practices geared towards ensuring earning security**
- Crop insurance schemes	0.29	0.57	0.28	0.59	0.29	0.51	0.29	0.62	*Purchase of crop insurance to reduce income risk*
- Use of climate information services	1.20	0.83	1.14	0.80	1.41	0.73	1.06	0.91	*Use of reports to guide planting and harvesting activities*
Knowledge Smart									**Use of science and experience to reduce risk of loss**
- Use drought tolerant crop varieties	1.24	0.97	1.28	0.96	0.94	0.87	1.53	0.99	*Planting of crops that can withstand long droughts*
- Use pest resistant plant varieties	1.21	0.76	1.25	1.02	0.74	0.76	1.70	1.01	*Planting of crops that can withstand pest attacks*
- Planting early maturing varieties of crop	1.63	0.96	1.57	0.98	1.29	0.95	2.08	0.76	*Planting of crop varieties that grow early in the season*
- Appropriate fertilizer use	1.86	0.89	1.70	0.90	1.81	0.80	2.13	0.91	*To reduce chemical use*
- Seed and fodder banks	2.05	0.92	2.16	0.89	1.51	0.87	2.50	0.66	*Storing of seeds for next season*
- Early planting	1.87	0.84	1.96	0.77	1.68	0.76	1.97	0.97	*Planting early to avoid loss due to short season*
- Appropriate land preparation devoid of slash and burn	1.41	0.94	1.21	0.79	1.26	0.93	1.84	0.98	*Land preparation practices that sustain soil quality*
- Use of indigenous agro ecological knowledge	1.46	0.96	1.70	0.94	1.27	0.89	1.40	1.00	*Use of local knowledge for adaptation purposes*
- Timely harvesting of produce and storage	2.08	0.76	2.20	0.67	1.76	0.81	2.27	0.71	*Proper harvesting and storage practices*
Planting Smart									**Practices that maximize yield and quality produce**
- Appropriate planting method (spacing)	1.82	0.80	1.82	0.77	1.49	0.76	2.18	0.74	*Good spacing methods for crops*
- Crop rotation	2.02	0.91	2.10	0.65	1.60	1.06	2.39	0.82	*Alternating planting to maximize soil nutrient use*
- Crop diversification	1.25	0.86	1.61	0.78	1.04	0.78	1.20	0.90	*Planting different varieties of crops*
- Mixed cropping	1.62	1.01	2.00	0.77	0.80	0.83	2.04	0.90	*Plants different types of crops together*

Means signify adoption Levels: 0 = No adoption; 1 = Low adoption; 2 = Moderate adoption; 3 = High adoption.

(Table 7). Analysis also portrayed that gender is a significant factor that influences the use of PNKST ($p < 1\%$). Specifically, male farmers are less likely to adopt this strategy compared to their female counterparts. According to literature, there is a correlation between perceived climate risk and climate change technology adoption. Several indicators have been advanced in the literature to proxy perceived climate risk including perception of rainfall and temperature changes, access to climate information and warnings of extreme weather events. However, the results revealed that while the effect of perceived temperature changes on the adoption of PNKST is statistically not different from zero; farmers who perceive significant changes in rainfall pattern have a strong probability of adopting plant, nutrient and knowledge smart technology ($p < 1\%$). On the other hand, while access to climate information reduces the probability of adopting PNKST ($p < 1\%$), farmers who are likely to receive information about extreme weather events are more likely to adopt the PNKST technology than their counterparts who do not ($p < 1\%$). This is instructive, since the analysis also portray that access to the internet ($p < 1\%$) and communication devices ($p < 1\%$) increases the probability of adopting the PNKST technology. According to Bezgrebelna et al. (2021) and Natarajan et al. (2019) climate adaptation strategy may come at a huge cost which the smallholder farmer may not have the capacity to invest. The availability and access to finance is therefore an important element that can influence the adoption of climate smart practice. Focusing on access to credit, remittances, government subsidy, and ready market; the ordered probit regression results suggest that averagely, financial capacity influences the adoption of PNSK ($p < 1\%$). However, access to government subsidy is likely to increase PNSK adoption whereas access to credit, remittances and ready market significantly reduce the probability of PNSK adoption among farmers in the study communities. In terms of farm-related factors, the results suggest that the probability of PNSK adoption increases with land size ($p < 1\%$), famer's experience and among households whose prime occupation is farming ($p < 1\%$).

3.4.2. Energy, water and carbon smart technology (EWCST)

This technology describes the integration of activities considered as identities of energy smart, water smart, and carbon smart technology by farmers. While the rate of adoption is relatively low (0.73%), Table 7 suggests that its level of adoption is influenced, to a large extent, by the farmer's financial capacity. Among the existing typologies, EWCST adoption may require a relatively large investment; therefore, access to financial resources play a critical role in its application. For instance, the results showed that reliance on agricultural income increases the probability of EWCST adoption ($p < 1\%$). The results suggest that there is a limited number of farming-related factors influencing the adoption of EWCST including access to extension services ($p < 1\%$) and land size (p

Table 6
Principal Component Analysis of climate smart agricultural practices.

	1	2	3	4	5	6	7
. Using Drought Tolerant Crop Varieties	**0.806**	−0.023	0.086	−0.061	0.012	−0.078	0.063
Use Pest Resistant Plant Varieties	**0.802**	0.040	0.153	0.082	−0.219	−0.027	−0.142
Planting Early Maturing Varieties of Crop	**0.797**	−0.049	0.010	−0.112	0.171	−0.011	0.068
Cover Cropping Planting Cover Crops to Maintain Soil Moisture	**0.625**	−0.072	0.086	0.229	0.115	−0.014	0.084
Planting Legumes Among Crops	**0.583**	0.163	−0.007	0.239	0.163	−0.003	0.099
Tillage by Bullock	0.037	**0.694**	−0.048	0.012	0.187	−0.025	0.046
Agroforestry and Woodlot Schemes	0.094	**0.673**	−0.117	0.081	−0.209	0.378	−0.184
Crop Livestock Integration Mixed Farming	0.350	**0.642**	−0.107	0.091	−0.012	0.129	−0.002
Earth Bunding	−0.320	**0.618**	0.074	−0.042	0.237	−0.259	0.063
Water Management and Water Harvesting	−0.146	**0.562**	0.170	−0.057	−0.119	−0.161	−0.017
. Appropriate Fertilizer Use Right Quantity and Right Time	0.102	−0.116	**0.774**	0.100	0.032	0.093	−0.099
. Early Planting	0.085	0.067	**0.733**	−0.133	0.135	0.026	0.036
Timely Harvesting of Produce and Storage	0.006	−0.031	**0.685**	0.316	−0.107	0.192	0.054
Appropriate Land Preparation Devoid of Slash and Burn	0.223	0.214	**0.494**	−0.081	−0.132	−0.200	0.352
Bush Fallowing	0.104	0.035	−0.181	**0.784**	−0.077	0.106	0.037
. Zero Tillage / Minimum Tillage	−0.020	−0.008	0.239	**0.731**	0.182	−0.001	−0.081
. Mixed Cropping: Planting Different Type of Crops Together	0.132	0.012	−0.218	**0.612**	−0.113	0.165	−0.113
. Use of indigenous/traditional agro-ecological knowledge	−0.093	−0.018	−0.006	0.081	**0.779**	−0.166	0.186
Crop Diversification	0.034	0.012	0.116	0.054	**0.765**	−0.076	−0.234
Crop Insurance Schemes	0.191	0.064	0.041	0.158	0.162	**−0.861**	0.012
Sprinkler and Drip Irrigation	0.152	0.207	0.194	−0.040	0.145	−0.258	**0.623**
Crop Rotation	0.229	0.086	0.231	−0.019	0.118	−0.124	**0.585**
No Burning of Residues Biomass on Farms	0.239	0.069	0.054	0.285	0.043	0.188	**0.477**
Total extraction	5.88	2.25	1.69	1.47	1.20	1.19	1.03
Percentage of variance	25.57	9.76	7.33	6.38	5.22	5.16	4.49
Cumulative percentage	25.57	35.33	42.66	49.04	54.26	59.42	63.91

KMO = 0.888; Bartlett's test of sphericity (df) = 8747.184 (406) ***.
1 = Knowledge, water and nutrient smart technology; 2 = energy, water and carbon smart technology; 3 = knowledge smart technology; 4 = energy, planting and knowledge smart technology; 5 = knowledge and planting smart technology; 6 = weather smart technology; 7 = water, planting and carbon smart technology.

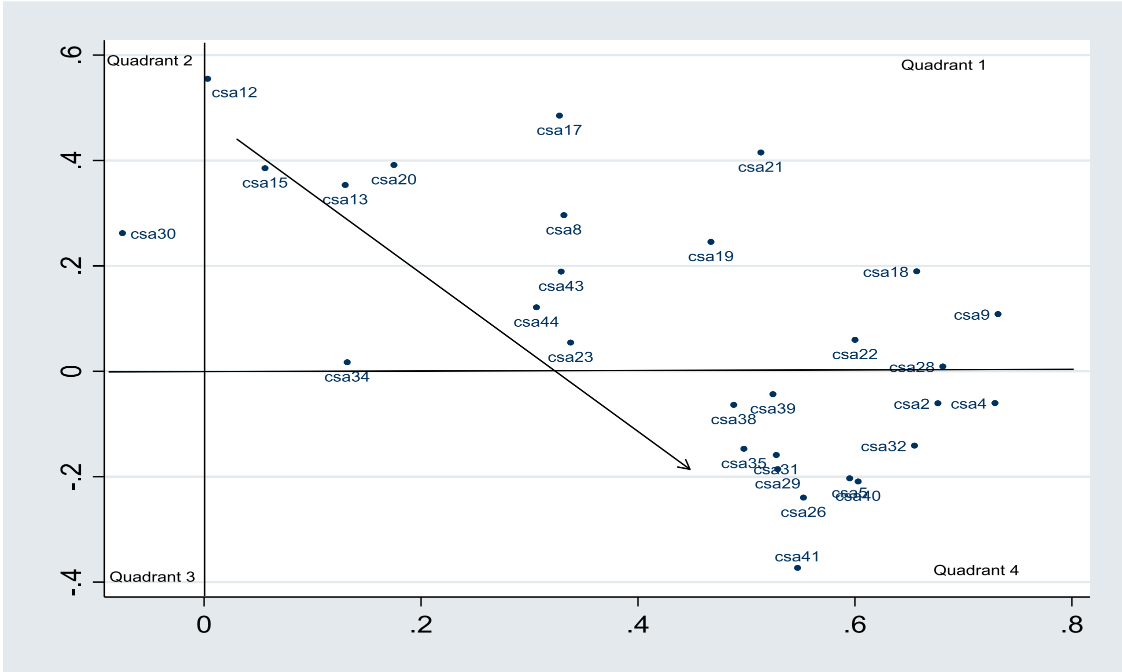

Fig. 2. PCA plot of climate smart practices identified.

< 1%) which positively affects the probability of adoption. Again, the evidence suggests that access to regular remittances ($p < 1\%$), government subsidies ($p < 1\%$) and credit facilities ($p < 1\%$) increase the likelihood of a farmer adopting this technology. Access to credit is critical for farming households in dryland farming systems in northern Ghana where poverty levels are relatively high (Ghana Statistical Services, 2021), making it difficult for farmers to implement CSA practices. Again, it is also difficult for farming households to obtain credit facilities from the banking institutions because of the high perceived risk of rain-fed agricultural systems predominant in these study areas. Access to extension services is crucial in dryland farming systems where access to climate information can help farming

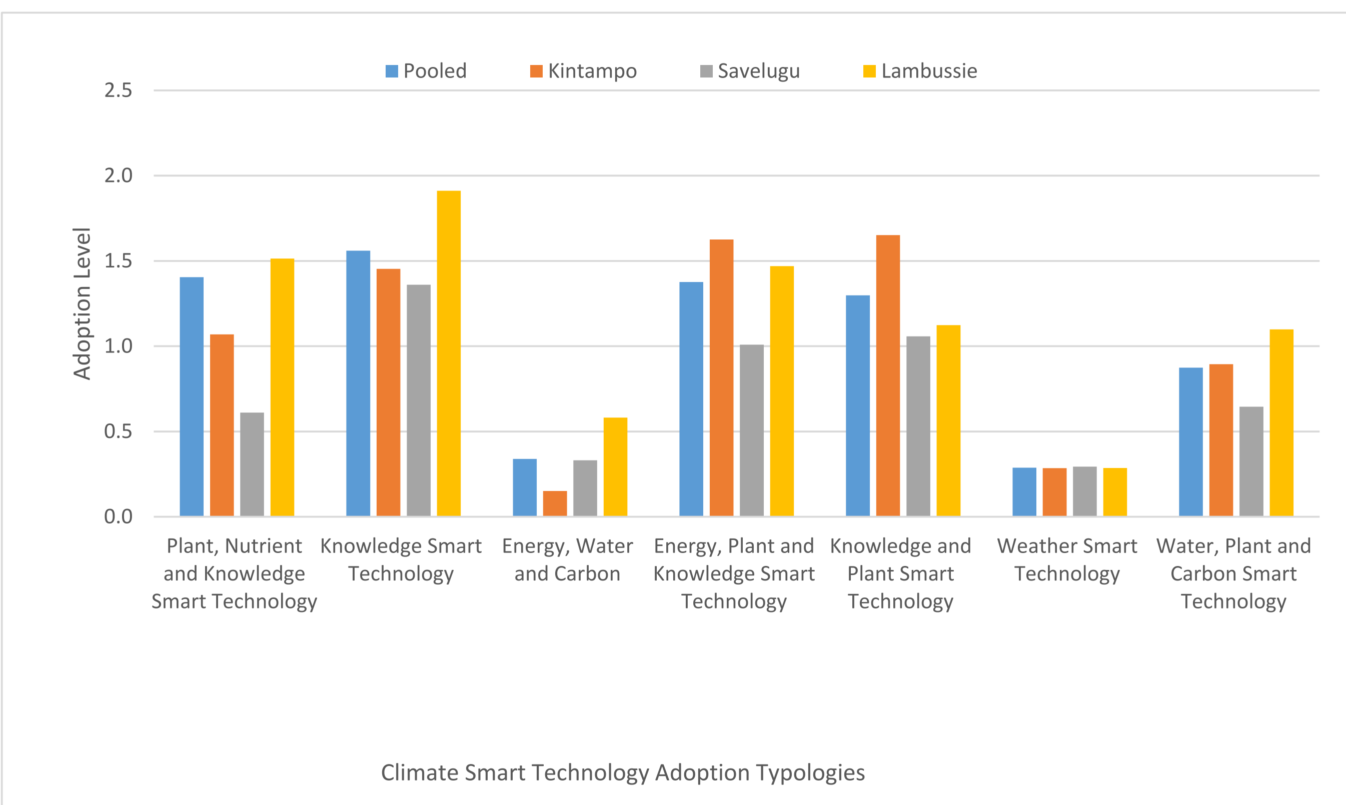

Fig. 3. Climate smart adoption levels by smallholder farmers.

Table 7
Ordered probit regression estimate of determinants of climate smart adoption.

	Model 1: PNKST	Model 2: EWCST	Model 3: KST	Model 4: EPKST	Model 5: KPST	Model 6: WST	Model 7: WPCST
Age	0.002 [0.003]	−0.005 [0.004]	0.006 [0.003]*	−0.011 [0.004]***	−0.003 [0.003]	0.006 [0.003]*	0.002 [0.003]
Gender	−0.185 [0.084]**	0.074 [0.114]	−0.149 [0.083]*	−0.148 [0.102]	0.241 [0.083]***	0.107 [0.118]	0.102 [0.085]
Educational status	−0.030 [0.085]	0.065 [0.109]	0.010 [0.085]	−0.170 [0.104]	0.066 [0.081]	0.095 [0.110]	0.036 [0.088]
Native	0.255 [0.119]**	0.236 [0.182]	0.060 [0.116]	−0.074 [0.137]	0.082 [0.104]	0.461 [0.158]***	0.091 [0.117]
Reliance on Agric Income	0.031 [0.120]	0.377 [0.173]**	−0.255 [0.114]**	−0.182 [0.151]	−0.139 [0.122]	−0.154 [0.138]	−0.153 [0.147]
Extension service	0.267 [0.094]***	−0.388 [0.112]***	0.193 [0.095]**	−0.021 [0.110]	−0.142 [0.077]*	−0.529 [0.103]***	0.178 [0.093]*
Crop diversity index	0.039 [0.026]	0.095 [0.034]***	−0.048 [0.025]*	0.011 [0.030]	0.102 [0.024]***	−0.062 [0.032]*	0.057 [0.026]**
Farming experience [Base Category: Below 5 years]							
1. Between 5 and 10 years	0.136 [0.185]	0.296 [0.281]	−0.024 [0.173]	0.563 [0.226]**	0.024 [0.167]	−0.253 [0.202]	0.097 [0.180]
2. Above 10 years	0.307 [0.170]*	0.313 [0.259]	0.081 [0.164]	0.571 [0.213]***	0.194 [0.156]	−0.415 [0.187]**	0.088 [0.160]
Climate change perception [Rainfall]	1.198 [0.534]**	−0.303 [0.377]	0.317 [0.523]	−0.123 [0.393]	0.746 [0.380]**	−0.661 [0.308]**	0.998 [0.524]*
Climate change perception [Temperature]	0.411 [0.343]	0.319 [0.443]	−0.554 [0.502]	−0.744 [0.358]*	0.483 [0.250]*	−0.348 [0.284]	0.537 [0.341]
Access to climate information	−0.439 [0.129]***	0.149 [0.155]	−0.379 [0.122]***	0.050 [0.141]	0.295 [0.119]**	−0.001 [0.176]	−0.193 [0.123]
Receiving warning about extreme weather events	0.546 [0.110]***	0.043 [0.133]	0.298 [0.104]***	0.313 [0.130]**	−0.312 [0.104]***	0.478 [0.143]***	−0.153 [0.115]
Member of a social club outside community	0.230 [0.098]**	−0.097 [0.117]	0.013 [0.091]	−0.330 [0.119]***	0.022 [0.100]	0.231 [0.120]*	0.172 [0.097]*
Member of faith-based group	0.117 [0.098]	−0.114 [0.118]	0.355 [0.094]***	0.025 [0.113]	0.727 [0.094]***	0.154 [0.146]	0.150 [0.099]
Social support	0.158 [0.104]	0.513 [0.127]***	0.059 [0.099]	0.306 [0.124]**	−0.113 [0.105]	−0.170 [0.143]	−0.074 [0.108]
Land size [Base category: Below 3 ha]							
1. Between 3 and 6 ha	0.282 [0.107]***	0.409 [0.150]***	0.189 [0.104]*	−0.012 [0.121]	0.102 [0.097]	−0.048 [0.130]	−0.160 [0.108]
2. Above 6 ha	0.402 [0.111]***	0.622 [0.159]***	0.193 [0.112]*	0.182 [0.133]	0.101 [0.104]	−0.095 [0.140]	−0.320 [0.117]***
Access to credit	−0.483 [0.110]***	0.368 [0.126]***	−0.406 [0.114]***	0.006 [0.142]	0.083 [0.103]	0.374 [0.126]***	−0.237 [0.113]**
Regular remittances	−0.275 [0.098]**	0.435 [0.151]***	−0.339 [0.118]***	−0.052 [0.132]	−0.166 [0.120]	−0.150 [0.172]	−0.222 [0.125]*
Government subsidies	0.782 [0.105]***	−0.111 [0.117]	0.483 [0.100]***	−0.143 [0.110]	0.132 [0.092]	−0.322 [0.105]***	0.427 [0.097]***
Access to ready markets	−0.158 [0.099]	0.121 [0.112]	−0.290 [0.094]***	0.231 [0.131]*	−0.017 [0.095]	0.755 [0.131]***	−0.180 [0.103]*
Communication devices	0.335 [0.115]***	−0.037 [0.148]	0.584 [0.110]***	0.283 [0.130]**	0.108 [0.107]	−0.042 [0.149]	0.433 [0.106]***
Access to internet	0.468 [0.126]***	0.292 [0.169]*	0.313 [0.122]***	−0.106 [0.151]	−0.028 [0.118]	0.131 [0.153]	0.352 [0.131]***
Housing conditions [Base category: Owning]							
1. Renting	0.138 [0.215]	−0.316 [0.329]	0.008 [0.182]	−0.002 [0.224]	−0.211 [0.117]*	0.619 [0.265]**	−0.211 [0.184]
2. Rent-free	0.160 [0.122]	−1.610 [0.257]***	−1.323 [0.161]***	−0.093 [0.234]	−0.405 [0.115]***	0.116 [0.149]	−0.421 [0.158]***
3. Others [Squatting, Perching and so on]	−1.299 [0.272]***	−5.357 [0.160]***	−1.322 [0.183]***	−4.838 [0.364]***	−1.494 [0.280]***	−1.086 [0.389]***	−0.414 [0.204]**
Percentage of farmers in HH	0.717 [0.173]***	−0.599 [0.201]***	0.432 [0.186]**	0.180 [0.185]	0.180 [0.185]***	−0.027 [0.177]	0.259 [0.163]
Community [Reference category: Apesika]							
1. Suamire	−0.226 [0.154]	−0.148 [0.231]	−0.302 [0.129]**	−0.385 [0.161]**	−0.385 [0.161]***	0.271 [0.198]	0.052 [0.139]
2. Ayorya	0.282 [0.143]**	−0.353 [0.231]	−0.074 [0.166]	0.070 [0.166]	0.070 [0.166]***	0.346 [0.191]**	0.076 [0.146]
3. Diara	−1.106 [0.174]***	0.631 [0.240]***	−0.306 [0.175]*	−3.112 [0.431]***	−3.112 [0.431]***	0.551 [0.199]***	−0.469 [0.184]**
4. Kukuobila	−1.610 [0.211]***	1.372 [0.273]***	−0.219 [0.217]	−2.222 [0.373]***	−2.222 [0.373]***	0.744 [0.233]***	−0.466 [0.229]**
5. Nakpanzoo	−1.352 [0.200]***	0.219 [0.289]	−0.974 [0.205]***	−5.727 [0.194]***	−5.727 [0.194]***	−0.056 [0.282]	−1.041 [0.204]***
6. Kami	0.007 [0.179]	1.542 [0.259]***	0.008 [0.186]	−0.039 [0.204]	−0.039 [0.204]***	−0.031 [0.267]	−0.120 [0.188]
7. Kpare	0.937 [0.186]***	0.790 [0.243]***	0.826 [0.182]***	−0.033 [0.214]	−0.033 [0.214]***	1.183 [0.222]***	0.369 [0.184]**
8. Samao	0.081 [0.174]	0.719 [0.241]***	−0.083 [0.180]	−0.209 [0.228]	−0.209 [0.228]***	0.705 [0.219]***	−0.141 [0.177]
Observations	1052	1052	1052	1052	1052	1052	1052
Adoption Percentage	16.65	0.73	26.07	25.68	20.82	2.48	7.56
Wald Test of robustness (*p* -value)	509.9 (0.000)	4365.2 (0.000)	365.29 (0.000)	7720.96 (0.000)	501.95 (0.000)	210.17 (0.000)	217.43 (0.000)
Log Pseudolikelihood	−970.251	−523.193	−1060.14	−547.709	−1156.96	−608.840	−837.909
Pseudo R-square	0.228	0.274	0.163	0.294	0.137	0.149	0.122

Standard errors in parentheses have been corrected for heteroscedasticity. $^{*}p = 0.1$, $^{**}p = 0.05$, $^{***}p = 0.001$ (statistically significant).
PNKST = Plant, Nutrient and Knowledge Smart Technology; EWCST = Energy, Water and Carbon Smart Technology; KST = Knowledge Smart Technology; EPKST = Energy, Planting and Knowledge Smart Technology; KPST = Knowledge and Planting Smart Technology; WST = Weather Smart Technology; WPCST = Water, Planting and Carbon Smart Technology.

households in important crop and farm management decisions.

The analysis further suggest that the percentage of household members who are farmers ($p < 1\%$) and the crop diversity index ($p < 1\%$) reduces the likelihood of adopting EWCST. Meanwhile, farmers who occupy rent-free houses or either perching or squatting are less likely to adopt this strategy compared to those who live in their own houses ($p < 1\%$). In terms of external effects, the ordered probit regression results indicate that access to social support ($p < 1\%$), and the location of the farmer ($p < 1\%$) are the institutional and locational factors predicting the adoption of energy, water and carbon smart agriculture typology among farmers. For instance, farmers in communities within Savelugu municipality (Kami, Kpare and Samao) and Lambussie district (Diara, Kukuobila and Nakpanzoo) demonstrate a higher probability of adopting this smart technology compared to their counterparts in communities within the Kintampo district.

3.4.3. *Knowledge smart technology (KST)*

The evidence shows that there is a large number of farmers who prefer the use of knowledge-smart technology (26.07%). Farmer-specific and household characteristics that predict the adoption of this technology include the farmer's age, farmer's gender, reliance on agricultural income, receipt of regular remittances, percentage of farmers in the household as well as housing residency characteristics. For example, older farmers have a strong probability of adopting this technology compared to young farmers. There is also an indication that female farmers are more likely to adopt this technology than male farmers. Meanwhile, the higher the percentage of farmers in a household, the higher the probability of adoption. It is also evident that farmers who own their houses have a higher probability of choosing this technology than those who live in rent-free houses or squat.

Focusing on the effect of location and institutional factors, it is observed that membership in a faith-based institution, access to information on extreme weather events, and availability of government subsidies positively influence the probability of adopting this technology. On the other hand, the farmer's accessibility to credit, ready markets, and climate information system have a negative effect on the probability of KST adoption. With reference to farming conditions, Table 7 indicates that the probability of adopting knowledge smart technology is significantly predicted by the crop diversity, availability of extension services, and land size. Results further show that land size and crop diversity have a positive effect on the probability of adopting knowledge smart technology.

3.4.4. *Energy, planting and knowledge smart technology (EPKST)*

This technology describes the integration of energy-smart, planting smart and knowledge-smart technologies by farmers. Table 7 shows that farmers in the Kintampo and Lambussie districts mostly adopt this smart technology. The results show that adoption level is also influenced by household factors such as the age of the farmer, farming experience, and access to communication devices. For instance, the probability of adoption is found to be higher for young farmers, farmers with more experience, and those who have access to communication devices. Other factors which influence decisions to adopt this technology include perception of temperature patterns, access to information on extreme weather events, membership of a social group outside the community, and access to social support. Group membership provides safety nets and informal social support systems to farmers. It also greatly influences farmer-to-farmer peer learning through the sharing of information on good farming practices. Farmer's decisions to adopt certain CSA practices is greatly influenced by the social and behavioural interactions and engagements within the social groups (Atta-Aidoo et al., 2022). Studies elsewhere have suggested that group membership is critical for the adoption of CSA practices (Mango et al., 2017; Diouf et al., 2019; Macharia et al., 2020). In Nepal, Dhakal and Rai (2020) observed that the adoption of agroforestry practice was greatly influenced by membership of groups.

3.4.5. *Knowledge and planting smart technology (KPST)*

It is also evident that there is a proportion of farmers who combine knowledge-smart with planting-smart technology. Analysis shows that approximately 20.82% of sampled farmers practice this technology. Findings suggest that adoption is influenced by predominantly farming conditions and some household factors (Table 7). The key factors that influence adoption are the perception of climate change, access to climate information and weather reports, and the level of crop diversity. For example, we observed a positive relationship between the perception of rainfall and temperature changes and KPST adoption level. This is important as farmers will only initiate climate change adaptation actions if they can perceive significant changes in climatic variables that influence farm management decisions (see Mairura et al., 2021). In Ghana, previous studies suggest that smallholder pineapple farmers who had a strong perception of the changing weather patterns were more likely to adopt climate change adaptation measures (Antwi-Agyei et al., 2021b). The implication is that farmers who have a strong perception of climate variations in rainfall and temperature patterns have a greater probability of adopting this technology. Moreover, increased access to climate information systems was revealed to have a positive correlation with farmers' choice for this technology. Results further showed that farmers who live in their own residences have a higher probability of adopting this technology than those living in rented or rent-free residences. Education was found to be a key determinant of CSA practices particularly those related to knowledge and planting smart technology (Table 7). Farmers with a higher level of education have a stronger probability of KPST adoption. This is related to the fact that better-educated farmers are able to access information that may be relevant for climate change adaptation. This is consistent with previous studies (see Mwinkom et al., 2021; Antwi-Agyei et al., 2021c) indicating that household heads with more education are more likely to adopt CSA practices including the planting of drought-resistant varieties.

In addition, the availability of extension services has a significant effect on the probability of adopting knowledge and planting smart technology. Access to climate information through extension services plays a critical role in the probability of adoption for smallholder farmers in dryland farming systems. For instance, in Ghana and Kenya, Antwi-Agyei et al. (2021c) and Muema et al. (2018), respectively, reported that access to climate information enabled farmers to make key farm management decisions.

3.4.6. *Weather smart technology (WST)*

The evidence suggests that the level of adoption of weather smart technology through the patronage of crop insurance schemes is low among the farmers. Analysis shows that roughly 2.48% of sampled farmers use weather-smart technology. Nonetheless, household factors such as gender, reliance on farm income, and being a member of a social group outside the community influenced the probability of adoption of weather-smart technology. The ordered probit model results show that the probability of adoption is lower for women than men. Again, the higher the reliance on agriculture income, the higher the probability of the adoption of weather-smart technology. Again, the probability of adoption of weather-smart technology is also found to be influenced by locational factors. Results suggest that less experienced farmers are more likely to adopt weather-smart technology compared with more experienced farmers [above 10 years]. This is plausible due to the fact that farmers with greater experiential capital may expect to rely on their experiences to resolve any shortfalls in income or agriculture output; but the less experienced farmers may see the opportunity to transfer risk, as a result of the insurance scheme, as a better alternative than relying on their low experience. Older farmers tend to rely more on the traditional indigenous knowledge acquired over several years of farming. This finding compares favourably with other studies suggesting that older farmers are less likely to adopt new agricultural interventions (Antwi-Agyei et al., 2020; Muema et al., 2018).

3.4.7. Water, planting and carbon smart technology (WPCST)

Results in Table 7 indicate that water, planting, and carbon smart technology is predicted by mainly institutional factors and household factors such as access to credit, ownership of communication devices, and access to the internet. The evidence also suggests that access to government subsidies, receipt of regular remittance, and access to ready market are also significant predictors of the adoption of water, planting and carbon smart technology. The landholding size of the farm was also found to be a significant predictor of the adoption of water, planting, and carbon-smart technology. Our findings are in sync with evidence by Amadu et al. (2020), suggesting that various farm and farmer characteristics have been found to influence the adoption of CSA by farmers. Land and crop management farm decision are made by male farmers and this often constrain the ability of female farmers to initiate CSA practices. This is consistent with the findings of Ferdous and Mallick (2019); suggesting that female and migrant farmers are constrained by insecure tenure systems that compromise their overall resilience to climate risks in dryland farming systems. Patriarchal norms in most of these societies often preclude female farmers from land ownership, limiting their adaptation options. CSA, however, could play a significant role in reducing the gender gap in labour burden for women in agriculture (Khatri-Chhetri et al., 2017). Developing gender-responsive targeted approaches that focus on the particular needs, priorities, and realities of men and women in the design and application of CSA could foster an equal alignment of the differentiated needs of both genders (Lipper et al., 2014; Huyer et al., 2015; Khatri-Chhetri et al., 2017).

4. Conclusion

The paper examined the typologies and key factors driving the adoption of climate-smart agriculture practices in rural Ghana; with a particular focus on farmers in the Savelugu municipality, Kintampo South and Lambussie districts. Results revealed that seven (7) uncorrelated typologies involving twenty-three (23) CSA practices were generally employed by smallholder farmers in the study districts. These typologies include: water-smart practices, energy-smart practices, nutrient-smart practices, carbon-smart practices, weather-smart practice, planting-smart practices, and knowledge-smart practices. Such typologies have value for policy in the design and implementation of appropriate policy options for the adoption of CSA practices. Policymakers often develop one-size fit all climate change adaptation policies; hence, an understanding of these typologies provide opportunity for policy makers to design locally relevant and context-specific adaptation policies. This will invariably improve the upscaling of CSA adoption in dryland farming systems in Ghana and West Africa more widely.

Findings further showed that the smallholder farmer combines a multiplicity of CSA practices; albeit the level of adoption of climate-smart agriculture is low. Among the mix of technologies, the results suggested that only knowledge-smart technology and weather-smart technology are implemented singularly. However, while it is also common to combine knowledge-smart technology with other smart technologies, weather-smart technology is strictly used exclusively. Thus, farmers who use weather-smart technology are not likely to adopt other technologies to complement the gains obtained in the use of the technology.

A key result of this research is that the decision to adopt a CSA practice (whether an integrated technology or a single technology) is motivated by several factors including education, access to climate information, the supply of credit facilities, access to information on extreme weather events, membership of a social group outside the community and access to government subsidies, group membership. The multiple adoption of CSA practices is explained by institutional and farming factors that pertain within the locality. However, the results suggested a contingency approach in policy efforts addressing the use of CSA practices in the district. For example, whilst the adoption of knowledge smart technologies will be widespread, the findings suggest that combinations with some planting, energy, and nutrient-smart technologies will be widely accepted. However, farmers with greater access to institutional resources such as access to climate information, extension services, and government subsidies may be more engaging.

The findings also highlighted the relevance of social support systems, perception of climate change and to ready markets. However, smallholder farmers with more access to climate information may be more reluctant in choosing a set of practices that place emphasis on planting, nutrient, and knowledge-smart technology or just knowledge-smart technology. Access to extreme weather information, credit, and membership of social groups increases the adoption of weather-smart technologies; plausibly because these indicators or factors highlight impending threats and the farmer being aware may have been considering alternative extant remedies or coping strategies. The availability of a crop insurance scheme may be considered an optimal strategy to transfer risks. It might also not be wrong to assume that the predictors may fall in line with a risk-averse farmer. Similarly, it was observed that farmers who have limited access to credit, remittances, and government subsidies have a superior likelihood of adopting integrated water, planting, energy, and carbon-smart technologies. These context-specific local factors driving the adoption of CSA practices should be clearly considered in efforts at promoting the adoption and upscale of CSA practices in northern Ghana.

Our results underscore the need for policymakers and development practitioners to consider context-specific factors in the design and implementation of CSA practices aimed at addressing climate risks. Our analysis suggests that CSA practices that are more likely to need substantially greater capital inputs are less likely to be used in rural Ghana, underscoring the stark discrepancy between the use of knowledge-smart and weather-smart technologies. Future studies should consider simulating what kinds of CSA practices might be employed by farming households and the possible outcomes associated with such interventions.

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Declaration of Competing Interest

The authors have no relevant financial or non-financial interests to disclose.

Data availability

Data will be made available on request.

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