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The Influence of Climate Information Services on Climate-Smart Agricultural Investment Decisions among Smallholder Maize Farmers in Northern Ghana

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Abstract

Climate change poses significant threats to agricultural productivity in Africa particularly in regions that are dependent on rainfed agriculture. Despite the critical role of climate Information Services (CIS) in promoting adaptive practices, there is limited understanding of their impact on investment in Climate-Smart Agriculture (CSA). This study addresses this knowledge gap by examining how different sources of CIS influence smallholder maize farmers' decisions to invest in CSA practices. Using a cross-sectional survey of 566 maize-producing households across five districts in Northern Ghana, we employ descriptive statistics, the Principal Component Analysis (PCA), and a binary logit model to identify key determinants of CSA investment. The findings revealed that frequent access to daily and seasonal weather forecasts, as well as indigenous weather predictions significantly influences farmers' willingness to invest in CSA practices. Critical factors driving these decisions include maize farm size, level of commercialisation, gender, farm income and extension service visits. The results demonstrate that improving the accuracy and accessibility of CIS through traditional media, mobile platforms, and community engagement can significantly enhance investment in CSA. The key policy recommendations include promoting gender inclusivity, integrating indigenous knowledge with scientific forecasts, and expanding access to financial and advisory support. These are critical for promoting resilience and sustainability among maize-producing households in northern Ghana.

Keywords

Climate information, climate-smart agricultural practices, farm-level decisions, CSA investment, Northern Ghana.

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Introduction

Climate change, characterized by extreme weather conditions and variable precipitation patterns, is significantly reducing crop yields and agricultural productivity, making it increasingly difficult for farmers to maintain their livelihoods. The adverse effects of climate change include changes in temperature, precipitation patterns, and an increased frequency of extreme weather events such as floods and droughts. These changes pose a substantial threat to agricultural systems, particularly in Africa that rely heavily on rainfed agriculture (Serdeczny et al., 2017; Kang et al., 2009; Ahmad et al., 2020; Zeppel et al., 2014).

Africa's agricultural sector is especially vulnerable to climate change due to its dependence on natural rainfall and limited capacity for adaptation. Rainfed agriculture, which predominates in many parts of Africa, is highly sensitive to changes in precipitation and temperature. In regions like the Sahel and North-East Africa, characterised by semi-arid conditions and highly unpredictable rainfall patterns, communities frequently face extreme climate challenges, including droughts and devasting floods (Haile, 2005; Naz and Saleem, 2024). Variability in rainfall can lead to water scarcity during critical growing periods or waterlogging and soil erosion during excessive rainfall events, both of which negatively impact crop yields and food security (Serdeczny et al., 2017). Additionally, temperature increases can increase crop maturation and reduce the growing period, leading to lower yields, which can compromise food quality (Kang et al., 2009).

As a response to these challenges, Climate-Smart Agriculture (CSA) has emerged as a strategic approach designed to enhance agricultural resilience. It aims to achieve three main objectives: sustainably increasing agricultural productivity and incomes, adapting and building resilience to climate change, and reducing or removing greenhouse gas emissions wherever possible. These goals are essential for supporting national food security and development in the context of climate change (Adedeji, 2014; FAO, 2013; Lipper et al., 2014; Sarker et al., 2019).

Central to the success of CSA is the role of Climate Information Services (CIS). CIS provide timely and relevant climate-related data, forecasts, and analyses that are crucial for farmers and decision-makers. These services include weather forecasts, seasonal climate predictions, and historical climate data, which are disseminated through various channels such as radio, mobile phones, and extension services. By accessing accurate and up-to-date climate information, farmers can make informed decisions regarding crop selection, planting dates, and other important agronomic management practices, thereby reducing the risks associated with climate variability (WMO, 2018; Elazegui et al., 2017).

CIS empower agricultural stakeholders, particularly smallholder farmers, to make decisions that mitigate the impacts of climate variability and change. For instance, timely weather forecasts can help farmers optimize irrigation schedules, apply fertilizers more effectively, and take preventive measures against pests and diseases. Seasonal forecasts allow for strategic planning, such as diversifying crops or changing cropping patterns to suit anticipated climatic conditions. By integrating CIS into their decision-making processes, farmers can enhance their adaptive capacity and resilience to climate change (Elazegui et al., 2017).

Despite the recognized importance of CIS, there is a gap in understanding its impact on farmers' willingness to invest in CSA practices, particularly in Northern Ghana which is characterized by agro-ecological diversity and vulnerability to climate change (Damba et al., 2021). The region's reliance on maize farming and the varying access to climate information among farmers make it an ideal case for exploring how CIS influences agricultural investment decisions.

This study aims to fill this gap by analysing the influence of CIS on investment decisions in CSA among maize-producing households by examining how different sources and types of climate information affect farmers' investment choices. The research seeks to provide insights that can support sustainable agricultural development in the region. The findings are expected to provide recommendations that enhance the dissemination and utilization of CIS to promote investment in Climate Smart-Agriculture and improve the resilience of farming communities in Northern Ghana

Overall, this study adds to the literature by providing empirical evidence on the relationship between CIS and CSA investment decisions, offering context-specific insights for Northern Ghana, and promoting both theoretical understanding and practical applications in sustainable agriculture and climate adaptation.

Literature review

Climate Information Service (CIS) play an important role in assisting smallholder farmers in climate-smart agricultural advocacy and assisting farmers in making informed decisions related to agricultural practices. They provide farmers with critical information regarding weather patterns, forecasts and other agricultural advisory services. Farmers gain valuable knowledge that enables them to adjust their farming practices in response to changing climatic conditions by leveraging CIS, to enhance their adaptability and resilience.

Various studies have underscored the profound impact of CIS on agricultural decision-making processes among smallholder farmers. For example, through access to timely and accurate climate information, farmers are better equipped to anticipate and mitigate potential risks associated with climate variability and change (Baffour-Ata et al., 2022). Studies by Born, (2021) and Partey et al., (2018) suggest that CIS empower these farmers to implement appropriate strategies such as adjusting planting schedules, selecting appropriate crop varieties, adopting water-harvesting techniques, or implementing soil conservation measures. By integrating climate information into their decision-making processes, farmers can optimize productivity while minimising unhealthy environmental impacts. Overall, the utilization of CIS represents a significant advancement in supporting smallholder farmers' ability to cope with climate uncertainties and build resilience in their agricultural systems.

In Ghana, climate information facilitates agricultural decisions across different modes of production. However, the degree of impact and the specific decisions affected vary based on the scale of farming operations: For subsistence farming, farmers rely heavily on accurate information on the onset and cessation of rains in determining the best times for planting and harvesting (Antwi-Agyei et al., 2021), crop selection, soil and water management techniques. (Antwi-Agyei et al., 2012). For smallholder farmers, accurate climate information can help in integrated pest management, financial decisions and crop diversification. For commercial farmers the most important considerations in the use of accurate climate data are long-term forecasts, technology integration such as irrigation, precision agriculture, supply chain management and sustainable practices (Baffour-Ata et al., 2022; Yaro, 2013). These studies highlight three main cross-cutting issues, namely; capacity building through training and education of farmers across all levels about the interpretation and use of climate information to enhance their ability to make informed decisions. Secondly, there is a need to promote access to information through the appropriate dissemination channels such as radio, mobile technology, and extension services to provide timely and accurate climate information to farmers. The third and final issue is government-supportive programmes to enhance access and adaptive practices.

Numerous studies have also examined the factors that influence the effective utilization of climate information services by smallholder farmers. Vaughan et al. (2019) identified factors such as trust in the information source, perceived relevance, and ease of understanding as critical determinants of CIS uptake among farmers in Senegal. Similarly, Nyadzi et al. (2019) highlighted the importance of integrating indigenous knowledge with scientific climate information to enhance the relevance and usability of CIS for smallholder farmers in Northern Ghana. However, despite the growing body of research on climate information services and agricultural decision-making, there is a need for context-specific studies to understand the unique challenges and opportunities faced by smallholder farmers in different regions. In the context of Northern Ghana, where maize production is a significant economic activity and a staple crop (Adu et al., 2014), understanding the influence of CIS on investment decisions related to climate-smart agricultural practices is crucial for promoting sustainable and resilient farming systems. This study aims to contribute to the existing literature by providing insights into the utilization of climate information services and their impact on investment in CSA among maize farmers in Northern Ghana.

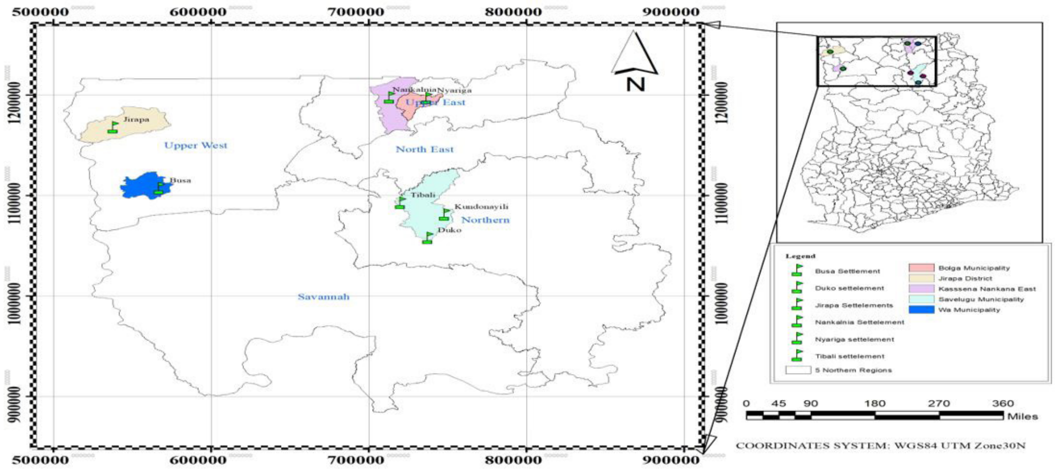
By assessing the extent to which access to climate information facilitates farm-level decisions related to land preparation, planting, harvesting, and marketing, the research will shed light on the role of CIS in supporting climate-informed agricultural practices. Additionally, by evaluating how climate information influences farmers' investment decisions in agricultural inputs and other climate-smart practices, the study will contribute to the development of strategies and policies to enhance climate resilience, productivity, and food security in Northern Ghana.

A study by Shahbaz et al., (2022) indicates that adaptation of Climate-smrt agricultural (CSA) methods is critical as climate change threatens the viability of farms run by women in Pakistan. The limited resources, cultural norms, and lack of decision-making authority faced by Pakistani women farmers hinder their ability to adjust to climate change. Women farmers with higher decisional empowerment and innovativeness positively influence the adoption of CSA practices across all resource groups, increasing adoption by 0.54 compared to low empowerment levels (Shahbaz et al., 2022). The study provides useful information, but one potential flaw is that it doesn't look at how male and female farm household members' joint decision-making influences CSA adoption.

Materials and methods

The study area

This study was carried out in the Northern, Upper East and Upper West regions of Ghana covering 5 districts and 7 communities which are identified as climate-smart villages by ongoing CSA projects involving 566 maize-producing households (Figure 1). The climatic conditions in these regions are defined by a single rainy season from May to October, with a peak in August and September, followed by an extended dry period from November to April (Bessah et al., 2022). The annual rainfall is generally low, ranging from around 800 mm to 1,100 mm, decreasing from north to south.



Source: Town and Country Planning, 2023

Figure 1: Map showing the study area.

Temperatures are consistently high throughout the year, with mean annual temperatures ranging from 27°C to 36°C, and the hottest months being March and April (Ampadu et al., 2019; Atiah et al., 2021).

The vegetation is predominantly savannah grasslands and drought-resistant, reflecting the semi-arid climate (Atiah et al., 2019). The single rainy season allows for one major growing season for crops such as millet, sorghum, maize, and groundnuts. However, irrigation is necessary for year-round agriculture due to the extended dry season. Water scarcity during the long dry season is a significant challenge in these regions, particularly in the Upper East region (Ampadu et al., 2019b). Furthermore, the study area is prone to drought conditions (Adonadaga et al., 2022), which can have severe impacts on agriculture and food security. Occasional flooding also occurs during the rainy season, especially in low-lying areas (Owusu et al., 2016).

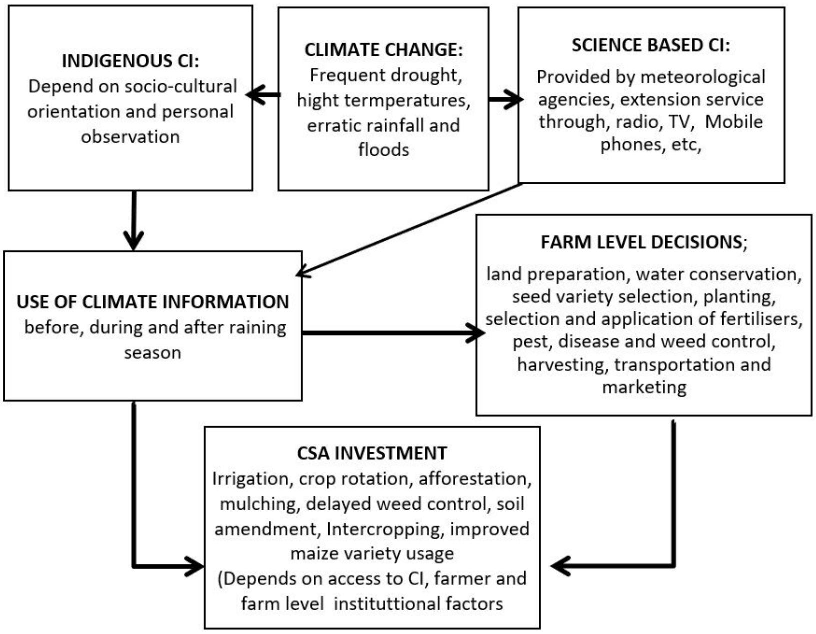
The selection of study communities was based on their climatic vulnerability and relevance to maize farming. The specific locations were chosen to capture a diverse range of farming conditions and access to CIS.

Conceptual framework

Climate change is a complex phenomenon characterized by stronger winds, hotter temperatures, more frequent droughts, unpredictable rainfall, and increased flooding. In the context of Northern Ghana, access to and utilization of climate information services are influenced by individuals' perceptions of climate change (Partey et al., 2020). Climate services play a crucial role in empowering farmers to make informed decisions regarding climate-smart agricultural (CSA) investments at the farm level, with the potential to enhance output, income, and food security (Born, 2021).

The conceptual framework (Figure 2) proposes two interconnected pathways through which access to climate information services influences farmers' CSA investment decisions. The first pathway involves the collection and analysis of scientific agro-climate data obtained from meteorological services using information and communication technology (ICT) platforms such as radio, TV, and mobile phones, as well as indigenous climate knowledge which relies upon experiences from socio-cultural perspectives and personal observation. By leveraging these resources, farmers gain a deeper understanding of climate patterns and are better equipped to make farm-level decisions regarding land preparation, water conservation, seed variety selection, planting, selection and application of fertilisers, pest, disease, weed control, harvesting, transportation, and marketing.

The second pathway emphasizes the use of these climate variables which covers periods before, during, and after each rainy season for CSA investment decisions. By strengthening these linkages and supporting initiatives aimed at promoting climate resilience, the risks associated with agriculture can be reduced (Born, 2021). Overall, the conceptual framework highlights the significance of access to climate information for smallholder farmers in the face of climate



Source: Authors' elaboration from literature

Figure 2: Conceptual framework of the study.

change. By integrating climate services into their decision-making processes, farmers in Northern Ghana can make informed choices regarding CSA investments, thereby enhancing their adaptive capacity and mitigating the adverse effects of climate change.

Sampling and data collection and procedures

We employed a multi-stage stratified random sampling technique to select 566 maize-producing households, ensuring representative coverage across different agricultural regions. The first stage involved a purposive selection of five districts from the Northern, Upper East, and Upper West regions, where CSA villages were identified. The selected districts are Savelugu Municipality in the Northern Region, Bolga Municipality and Kassena Nankana District in the Upper East, Wa Municipality and Jirapa District in the Upper West Regions. In the second stage, Seven CSA communities were randomly selected from a population of ten in the five districts. The selected communities are Tibali, Duko and Kundoonayili (Savelugu Municipality), Nyariga (Bolgatanga Municipality), Nankalnia (Kassena Nankana District,), Busa (Wa Municipality) and Jirapa (Jirapa District). In the third and final stage, 566 maize farm households were randomly selected from a population of cereal crop households obtained from Ghana's Ministry of Food and Agriculture (MoFA) Facts and Figures for 2020. The sample size was determined based on the following assumptions:

1. A 95 percent confidence interval. This was to ensure that the right decisions were made about the sample for the study (Taherdoost, 2017).
2. A 5 percent level of significance. This means the probability of rejecting the null hypothesis when it is true or when it should be accepted is about 5 percent or less.
3. Since we do not have control over the research participants a 90 percent response rate was assumed.
4. The objective of the sample size determination was to look for some cases that would yield the smallest effect for the test conducted with the survey.
5. Maize-producing households were assumed to be identifiable.

To obtain the sampling frame for the three study regions, the study used the Ghana Agricultural Census data for 2018, which was obtained from MoFA (2020). Based on administrative regions and districts, the study calculated an appropriate sample of 1,113 smallholder cereal staple farmers. However, due to time and resource constraints, only 50% of the estimated sample was used for the study resulting in 566 cases chosen at random from the study regions. Some studies including Bujang et al., (2018) Burgess et al., (2016), and Taherdoost, (2016) have recognised the real-world limitations of time, money, and resources, which may force the use of smaller sample sizes than anticipated or ideal. The significance threshold was set at 0.05%, with a 95% confidence level, using the Yamane (1973) formula denoted in Equation 1:

$$n = \frac{N}{1+N(\propto^2)} \qquad (1)$$

Where; n is the sample size, N is the population or sample frame (total number of cereal crop households), and $\propto$ is the level of precision. The ideal samples for the Northern Upper East and Upper West regions of Ghana were computed by substituting N with the values obtained from MoFA Facts and Figures for 2018 (MoFA, 2021), the Ghana Agricultural census report for 2018 and the Ghana 2021 Population and Housing Census (Ghana Statistical Service, 2021, 2020). In Table 1, the specifics of the sample size determination are shown.

The study relied heavily on original data gathered through a survey. Data were collected mainly through structured questionnaires. We conducted a thorough pre-testing and validation procedure for the questionnaire to guarantee the validity and reliability of our research tool. For pre-testing, we chose 90 households in total, 30 from each of the three regions (Northern, Upper East, and Upper West). Despite not being included in the final sample, these households had traits in common with our target group. In the pre-testing, pilot interviews were conducted with selected households, observing their interpretation and answering questions. Feedback was sought on clarity, relevance, and difficulties encountered. Questionnaires were analyzed for inconsistencies and potential issues and revised accordingly.

To validate the questionnaire, we used multiple methods. First, we checked the replies for content validity by cross-referencing them with previously published studies and expert opinions. Second, we ran factor analysis on the data to make sure the constructs were legitimate. We also checked the replies for criterion validity by cross-referencing them with publicly accessible information, like official Ministry of Food and Agriculture agricultural yield records. We calculated Cronbach's alpha for each relevant question set to make sure they consistently measured the same concept and to ensure internal consistency, a subset of twenty households from the pre-test sample were re-interviewed after a two-week gap to ensure response consistency to assess test-retest reliability.

The survey period spanned August 2023 to December 2023, ensuring data collection covered both the peak growing season and the post-harvest period, allowing a comprehensive understanding of farming decisions influenced by CIS.

Analytical methods

Descriptive statistics and Principal Component Analysis (PCA) were employed to assess various CIS sources and variables considered by farmers in decision-making. A binary logit model was used to explore factors influencing farmers' willingness to invest in CSA practices. To examine the use of scientific and indigenous climate information in farm-level decision-making among maize farm households, a combination of descriptive and inferential analytical techniques was applied.

Region/Dist.	Community Name	Cereal Staple HH	Study District HH	Estimated sample	Selected Sample
Northern		86,732	4,336	366	**186**
Savelugu	Tibali				62
	Kundonayili				62
	Duko				62
Upper East		54,936	6,043[1]	375	**191**
Bolga	Nyariga				95
Kassena N	Nankalkania				96
Upper West		28,675	5,162[2]	371	189
Wa	Busa				89
Jirapa	Bompari/Jirapa				100
TOTAL				**1,112**	**566**

Note: [1] Average HH for Bolga and Kassena Nankana, [2] Average HH for Wa and Jirapa
Source: Authors' elaboration from MoFA (2021) and GSS (2021 and 2020)

Table 1: Sampling frame and sampling size determination.

Specifically, the study investigated the use of climatic information in farm-level decision-making using the Principal Component Analysis. Input variables such as the onset of rain, precipitation, temperature, wind direction/speed, sunshine, and humidity were used, while output variables such as land preparation, water conservation, seed variety selection, planting schedules, fertilizer application, pest and disease control, weed control, and harvesting were used.

The ability to get detailed insights into the elements that increase the chance that a person will be aware of, have access to, and utilize a particular climate information service is one of the main advantages of employing different methods. Given that farmers engage with climate information services in a variety of ways (Botchway et al., 2016; Vedeld et al., 2019), this approach is compatible with the complex systems concept which is the main focus of this research. As a result, multiple analytical techniques are used to show the diversity of processes and factors influencing farmer access and decision-making.

Descriptive analysis of climate information access and use

To analyse climate information access and use, we used correlation matrices and contingency tables, in addition to chi-squared tests, to gain further insight into district-specific trends observed in the study using the onset of rain, precipitation, temperature, wind direction/speed, sunshine, and humidity. The study investigated the use of climatic information in farm-level decision-making, using factor analysis. We gathered data on the several farm-level decisions that farmers usually make and the climate information that they take into account. Factor analysis is a widely used technique in social science research, including studies on agriculture, to uncover the underlying constructs or factors that influence particular behaviours or decisions and to investigate intricate interactions between numerous variables. (Abacı and Demiryürek, 2019; Mellon-Bedi et al., 2020).

Three categorised climate variables namely; daily weather forecast, seasonal weather forecast and indigenous weather projections were examined concerning farm-level decisions, such as land preparation, water conservation, seed variety selection, planting schedules, fertilizer application, pest and disease control, weed control, and harvesting. Multiple analytical techniques were utilized to showcase the diversity of processes and factors that influence farmer access to climate information and decision-making at the farm level.

Given that farmers engage with climate service products in various ways, employing different methods aligns with the complex systems concept.

The Determinants of Households' Willingness to Invest in CSA Practices

The drivers of maize farmers' household annual willingness to invest (WTI) in climate-smart agricultural practices were estimated using the binary logit model. WTI is conceptualized as the amount deducted from a farmer's revenue while maintaining the utility of their consumption of CSA practices. As an alternative, it is the highest amount a farmer is willing to invest in CSA to maintain utility or benefits in terms of yield and income in the face of climate variability.

Following the work of (Abugri et al., 2017) the WTI may be stated generally as a utility function:

$$V(y - WTI_{,p,q1} : Z) = V(_{y,p,q0} : Z) \quad (2)$$

Where *WTI* is the willingness of maize-producing households to invest in CSA, y is the farmer's income, V stands for the indirect utility function, q_0 and q_1 are the quality levels of CSA in terms of yield, or net return with $q_1 > q_0$ indicating that q_1 gives improved yield from a CSA practice. p is a vector reflecting the price or cost of CSA practices incurred by farm households. Individual households' socioeconomic characteristics and institutional variables are represented by Z. Using maximum bids for each CSA practice, the mean amount of *WTI* is calculated as a continuous variable from open-ended response values. The following equation was used to statistically estimate the mean *WTI* using the average of the lowest and highest bids given by the respondents;

$$meWTI = \frac{1}{n}\sum_{i=1}^{n} yi \quad (3)$$

Where *meWTI* is the mean willingness to invest in CSA practice, n is the sample size and *yi* is the reported average bid for each CSA. The farmer or farm-level characteristics and institutional elements that are likely to influence their decisions to invest (pay a minimal price) in CSA practice to improve maize yield and net returns must be identified after assessing farm household *WTI*. Such farmer/farm-level characteristics may be modelled using the binary logit model or binary probit (Daberkow and McBride, 2003; Letaa et al., 2015).

At any given time, a complex combination of socioeconomic, demographic, institutional, and biophysical factors affect farmers' decisions to adopt or reject new technologies. Therefore, it has become crucial to model farmers' reactions to agricultural innovation practices from a theoretical and empirical perspective. A mixture of qualitative and quantitative data may be used to analyse the link between adoption and its determinants. This type of study uses a binary dependent variable, where a value of 1 denotes the presence of an event and a value of 0 denotes its absence. Qualitative response models must be used for analysing such connections.

Within this context, linear probability models (LPM) are one potential strategy. A linear function of the explanatory variables is how the binary dependent variable is expressed in LPM. Although it is technically possible to estimate LPM using the conventional Ordinary Least Squares (OLS) method as a simple operation, this method has some drawbacks (Alabi et al., 2020). when using OLS regression with a binary dependent variable the results show heteroscedastic error structure and inefficient parameter estimations. As a result, confidence interval creation and hypothesis testing become unreliable and possibly deceptive (Achen, 2021; Das, 2019). Furthermore, a linear probability model might forecast values outside of the 0–1 range, which would be against the basic rules of probability. The logit and probit models are often used as qualitative response models to handle these issues and generate significant empirical results (Gujarati, 2022).

Because logit and probit models share many statistical similarities, choosing between them might be difficult. Nevertheless, within the middle range, the logistic and cumulative normal functions are very similar to one another (Stank et al., 2017). The primary distinction between the logistic and probit formulations lies in the fact that the logistic model exhibits slightly thicker tails, meaning that the logistic curve approaches the axes more slowly compared to the normal curve (Gujarati, 2022). As a result of these elements, the logistic distribution function, often known as the logit model, was selected because it closely resembles the cumulative normal distribution. Besides, it provides simplicity from a mathematical standpoint and permits a useful interpretation.

Empirical model

Following the work of Gujarati (2022), the empirical logit model is expressed as follows:

$$\text{Logit}\,(P\,(Y = 1)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon \quad (4)$$

Where P (Y=1) represents the probability that a maize-producing household is willing to invest in Climate agricultural practices. Logit (P (Y=1)) is the log odds of a maize-producing household being willing to invest, $\beta_0 \ldots \beta_n$ are the parameter estimates for the independent variables, $X_1 \ldots X_n$ the independent socioeconomic and institutional variables such as age, education, distance to the nearest market, access to climate information, and farm size; ε represents the error term.

Results and discussion

Key findings

The results indicate that the most utilized Climate Information sources among farmers were daily weather forecasts, followed by seasonal forecasts and indigenous knowledge. Additionally, farmers who frequently used CIS were more likely to invest in CSA practices, highlighting the importance of timely and accurate climate information. However, it must be noted that the variation in N in Figures 3 and 5 does not imply negligence but rather highlights the context-specific priorities and constraints of smallholder farmers. It demonstrates that farmers prioritise climate information based on its relevance to their specific farming activities and challenges, accessibility through various channels such as radio, TV, mobile phone, extension services and the ease of interpreting the data also play significant roles in determining which variables farmers actively monitor. These findings underscore the need for tailored dissemination strategies to ensure farmers can access and use relevant climate information effectively

Access to climate information

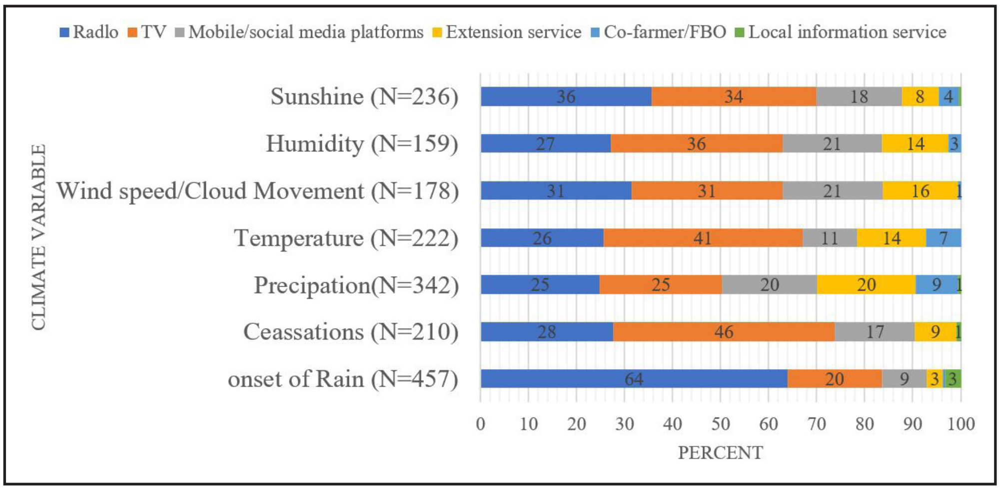
The study assesses meteorological climatic data, focusing on the sources, format, and usefulness of the information received from these sources. It also examines the indigenous climatic knowledge, evaluating the likelihood of seven different indigenous climatic indicators occurring when farmers notice these signals (Figure 3).

The study analysed the primary sources of weather and climate information across various meteorological parameters, revealing a consistent respondents' reliance on diverse media channels for dissemination of climate information.

For sunshine information, radio emerged as the leading source, accounting for 36 % of reports, followed closely by TV. In the case of humidity, TV was the dominant source at 36%, followed by radio. Wind speed and cloud movement data were evenly distributed between radio and TV, each providing 31% of the information while mobile/social media platforms contributed 21%. For temperature information TV again is the dominant channel as the primary source of receiving climate information with 41% of responses followed by radio at 26%. Precipitation data showed that the proportion respondents reliant even reliance on both radio and TV is even, each contributing to 25% of the information while mobile/social media platforms accounted for 14%. For cessation, TV was the primary source with 46% or respondents claiming to be receiving information from these sources. Finaly for the onset of rain, radio played a dominant role providing 64% of information followed by TV with 20%.

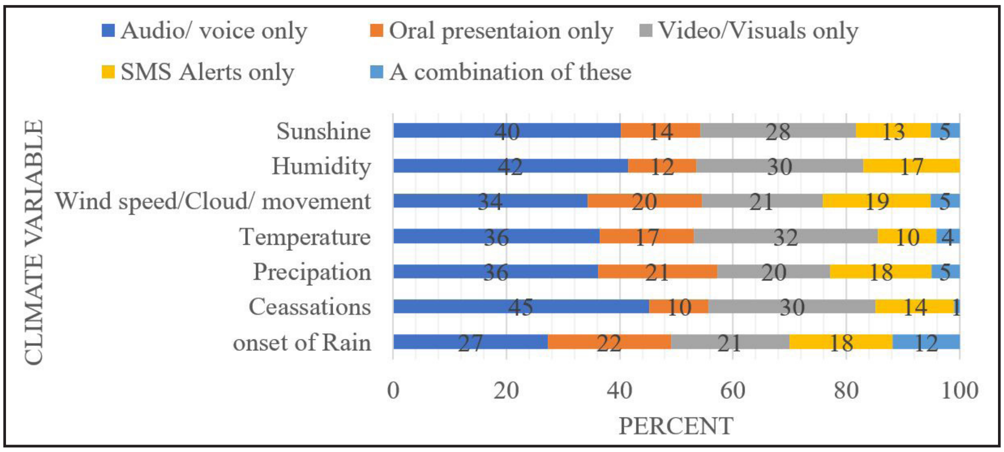
Overall, the findings suggest that radio and TV consistently serve as the most relied-upon sources of climate information across all meteorological parameters. Mobile and social media platforms, along with extension services, play secondary but significant roles as well, while information from co-farmers, Farmer-based organisations, and local information service centers have limited influence in the dissemination of weather and climate information.

The analysis of information transmission formats reveals predominant channels across various meteorological data types (Figure 4). Audio/voice consistently emerged as the primary transmission method, ranging from 27% (onset of rain) to 45% (cessations).



Source: Authors' elaboration from survey 2023

Figure 3: Main sources of climate information.



Source: Authors' elaboration from survey 2023

Figure 4: Climate information transmission.

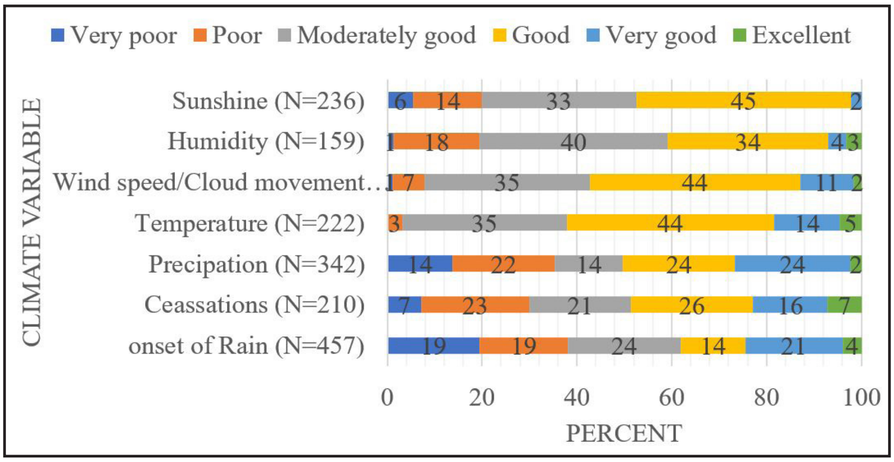
Video/visuals were the second most common channel, with percentages varying between 20% (precipitation) and 32% (temperature). Oral presentations followed, representing 10-22% of transmission methods. SMS alerts accounted for 10-19% of channels, while combined methods represented the smallest proportion, typically around 1-12% of transmissions. Each climatic information variable showed slight variations in transmission preferences, but audio/voice and video/visuals dominated across the board.

Figure 5 presents the results of the usefulness of climate information received by farmers. They were evaluated based on dependability, correctness, and general applicability using a Likert scale from 1 to 6 the following criteria to rate these variables by households (1 = very poor, 2 = poor. 3 = moderately good, 4 = good, 5 = very good, and 6 = excellent). The survey results revealed nuanced perceptions across different meteorological information types. Sunshine information received generally positive ratings, with nearly half of respondents (45%) considering it "Good" and a third (33%) rating it as "Moderately good". Humidity followed a similar pattern, with 40% rating it "Moderately good" and 34% deeming it "Good".

Wind speed and cloud movement ratings paralleled these trends, with 44% rating it "Good" and 35% selecting "Moderately good". Temperature information showed comparable results, with 44% rating it "Good" and 35% choosing "Moderately good". Precipitation data displayed more varied assessments, with equal proportions (24%) rating it "Good" and "Very good", and 22% considering it "Poor". Cessations information had a more mixed reception, with 26% rating it "Good", 23% rating it "Poor", and 21% selecting "Moderately good"

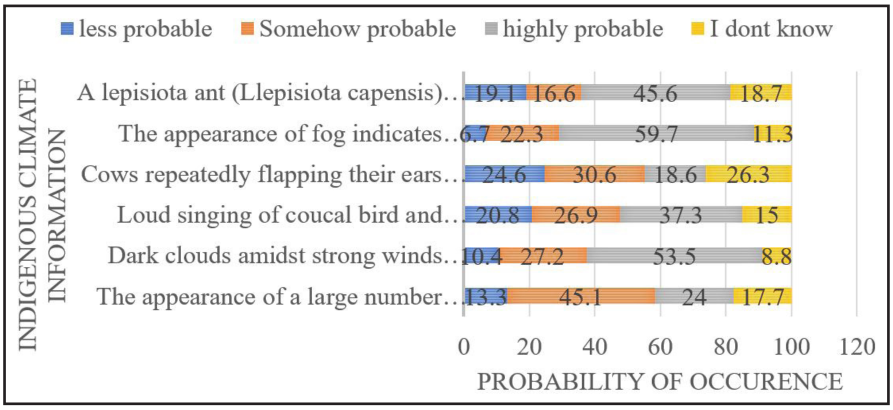
In general, most climate variables were rated positively, with "Good" and "Moderately good" being the most common ratings. Precipitation and onset of rain information demonstrated more varied usefulness ratings compared to other variables.

Assessment of the local climate knowledge in the study area is shown in Figure 6. While



Source: Authors' elaboration from survey 2023

Figure 5: Usefulness of climate information received.



Source: Authors' elaboration from survey 2023

Figure 6: Assessment of indigenous climate knowledge for all districts.

lepisiota ants move their eggs uphill during the rainy season, 45 percent of respondents said it is extremely likely that rain will fall. According to 60% of responses, the emergence of fog also indicates the impending arrival of rain. Also, according to 53% of respondents, the presence of heavy clouds and strong winds indicates a high likelihood of rainfall during the next day or a few hours. However, the majority of respondents, about 45% believe that rain can coincide with the appearance of large earthworms on a given day. Overall, any indigenous weather or climate observed slightly or strongly suggests rainfall.

Use of climate information in farm-level decisions

Factor analysis was utilized to discern the key dimensions or factors relevant to incorporating climate information into farm-level decisions. In particular, Principal Component Analysis (PCA) was applied, employing a Varimax rotation approach. This method plays a crucial role in revealing the underlying components within the data, shedding light on its structural patterns. Within the rotated component matrix, the loadings of individual variables on three extracted components are revealed.

Firstly, the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests are used to determine if the data was acceptable for factor analysis. While the KMO assesses sampling adequacy and data suitability, Bartlett's test of sphericity examines the null hypothesis that the correlation matrix is an identity matrix, indicating that the variables are uncorrelated. The results of the test presented in Table 2 suggest that the data is reasonably acceptable for factor analysis, based on the KMO value of 0.649. The estimated chi-square value of 638.854 with 36 degrees of freedom and a significance level of 0.000 from Bartlett's test indicates that the null hypothesis is rejected, showing that the data is appropriate and the correlation between variables is strong enough to uncover underlying elements.

Factor 1 is characterized by substantial factor loadings associated with variables related to daily weather forecasts, with particular emphasis on "Climate information that offers immediate decisions at the farm level" (0.744), "Climate information which is precise" (0.647), and "Climate information that allows effective crop management" (0.621). This underscores the pivotal role that accurate and timely daily weather forecasts play in farm-level decision-making and the successful management of crops. Farmers utilize daily weather forecasts to optimize their agricultural practices. This information enables them to plan irrigation schedules, apply fertilizers and pesticides at optimal times, and schedule harvesting activities to coincide with favourable weather conditions (Obert et al., 2016). Additionally, forecasts help farmers anticipate and mitigate risks associated with unexpected weather events, thereby safeguarding crop yields and ensuring the sustainability of their farming operations (Klemm and McPherson, 2017).

Factor 2 has significant factor loadings for the statements "Climate information allows for long-term planning" (0.793) and "Climate information allows mitigation planning" (0.704), which are variables related to seasonal weather forecasts. This demonstrates the significance of seasonal weather forecasts for long-term agricultural planning and risk reduction. Farmers can benefit from seasonal forecasts in many ways, including crop selection, irrigation management, pest and disease control, crop rotation and land use, infrastructure investments, and preparedness for drought and floods. They support farmers with resource allocation, irrigation schedule planning, and planting and harvesting schedule adjustments. Long-term weather patterns can also be used to optimise yields, cut down on waste, and allocate resources more wisely. In addition to directing infrastructure investments in areas vulnerable to extreme weather, such as irrigation systems and climate-resilient storage facilities, long-term forecasts also aid in the creation of preparedness plans.

Factor 3 is defined by a high factor loading for the statement "CI allows for trust in local knowledge" (0.828). This finding highlights the value of local indigenous knowledge of the weather and implies that it plays a vital role in farm-level decision-making such as land preparation, fertiliser application, seed selection, weed and pest control, and harvesting. Indeed, some studies report that indigenous climate knowledge is rooted in local cultures and traditions, making it highly relevant to farmers. however, it is specific to a region's ecosystem and weather patterns, enabling farmers to make decisions tailored to their region (Ajani et al., 2013; Balehegn et al., 2019). Additionally, there is a connection between indigenous climate calendars and sustainable farming practices which lies in the seamless integration of traditional ecological knowledge into farmers' decision-making processes. For example, from the perspectives of Balehegn et al., (2019), indigenous climate information can provide insights into potential risks and uncertainties associated with weather patterns, enabling farmers to develop strategies for mitigating them. Thus, community collaboration and trust in indigenous climate information increase the likelihood of farmers relying on it for decision-making.

The results of the factor analysis indicate that the studied climatic variables can be categorized into two main constructs. Factor 1 focuses on factors providing immediate and precise information for farm-level decisions, effective crop management, and timely crop harvest. This is likely associated with daily weather forecasts from meteorological agencies and similar institutions. Factor 2, however, is centered around climate information conducive to long-term planning, mitigation against climate hazards, and water conservation, suggesting a distinct construct related to seasonal weather forecasts. Factor 3, comprising climate information that builds trust in local knowledge, is easily accessible and cost-effective, providing supplementary information related to indigenous weather predictions. In summary, the study underscores the importance of considering various climatic variables in analyzing their impact on farm-level decisions, emphasizing the relevance of daily, seasonal, and indigenous weather projections and predictions for such analyses.

Determinants of household willingness to invest in CSA

A binary logistic regression model was used to analyze the impact of socioeconomic and institutional factors on maize-producing households' decisions to invest in climate-smart agricultural practices. Eleven variables were included in this investigation, and eight of them were statistically significant at levels between 5% and 1%. Table 3 summarizes the results.

Model diagnostics

The diagnostic test in the logit model demonstrates model performance and goodness-of-fit. The degree to which the model fits the data is gauged by the log-likelihood. Maximising the likelihood function is the objective of logistic regression. The lower value for the model's deviation, of 274.424, indicates a better fit for the model. A pseudo-R-squared statistic called Cox and Snell R-squared shows how much of the variation in the dependent variable is explained by the logistic regression model. A result of 0.465 indicates that 46.5% of the variation in the dependent variable is explained by the model. Unlike R-squared in linear regression, it doesn't have a clear explanation,

Items/Factor/Climate information	Mean	Factor loadings	Percentage of variance explained
Factor 1: Daily Weather Forecast	Â	Â	16.1
CI offers immediate decisions at the farm level	1.3834	0.744	
CI is precise	2.136	0.647	
CI allows effective crop management	2.0848	0.621	
CI allows for a timely harvest	2.5512	0.421	
CI required for pest and disease control	2.765	0.114	
Factor 2: Seasonal Weather Forecast	Â	Â	13.96
CI allows for long-term planning	1.7756	0.793	
CI allows mitigation planning	2.6678	0.704	
CI allows for water conservation plans	2.2544	0.49	
Factor 3; Indigenous Weather predictions	Â	Â	12.89
CI allows for trust in local knowledge	2.636	0.828	
CI is easily accessible and less costly	2.6078	0.21	
CI provides supplementary information	2.4806	0.208	
KMO Measure of Sampling Adequacy			0.649
Bartlett's Test of Sphericity	Approx. Chi-Square		638.854
	df		36
	Sign		0

Source: Authors' elaboration from survey 2023

Table 2: Principal Component Analysis (Varima Rotation Method).

although it does give some indication of the model's goodness of fit. Therefore, it should be considered a rough indicator of the goodness of fit or evaluated with other models. Another pseudo-R-squared metric is the Nagelkerke R-squared, which is a modified version of the Cox & Snell R-squared. It is 0.694, meaning that 69.4% of the variation in the dependent variable is explained by independent variables. The performance of the logistic regression model is assessed by comparing it to a null model, which has no predictors. The logistic regression model surpasses the null model in this comparison, according to the chi-square statistic, which produces a significant result of 354.333 with a p-value of 0.000 and 1 degree of freedom. Thus, a strong indication of the explanatory power of the model.

Sex of respondents

The categorical variable used to quantify sex is gender (1=Male, 0=Female). The "sex" variable's coefficient is 2.100. For a one-unit change in the "sex" variable, while holding all other factors constant, this indicates the log-odds change in the probability that farmers will spend money on climate-smart farming practices. A positive coefficient suggests that being classified as "Male" is thought to be connected with a greater log-odds of farmers' readiness to invest than being classified as "female" When all other factors are held constant the "sex" variable has a statistically significant impact on farmers' desire to invest in climate-smart farming practices at 1 percent. For example, women may have less access to credit or land, making it harder for them to invest in these practices. However, in the decision-making process for land use, Glemarec (2017b) revealed apparent inequalities in gendered knowledge, preferences, risk-taking, and access to innovation that affect t the adoption of agroforestry techniques and other investment possibilities by men and women which reflects different exposure to and perceptions of risk. This is the case in northern where women do not play leading roles in household decisions due to socio-cultural and economic factors. For example, there are still differences in how much each gender contributes to cultivation choices and how they spend their agricultural income in Northern Ghana (Yokying & Lambrecht, 2020). Nonetheless, CSA investment risks are more likely to affect female farmers than male farmers (Glemarec, 2017).

Age of respondents

The "Age" variable, which is expressed in years, has a statistically significant influence on farmers' desire to invest in climate-smart agricultural practices, with a statistical significance l evel of 1 percent. Holding other factors constant, the positive coefficient (0.158) and the corresponding odds ratio (1.171) indicate that an increase in age is linked to a greater likelihood of desire to invest in climate-smart agriculture practices. In contrast to younger farmers, elderly farmers are more likely to be prepared to invest in such practices in practical terms. This finding is in line with several previous research, such as Jahan et al., (2022;) and Ojo et al., (2021). found that farmers' age may affect their capacity to access financial resources since older farmers may have more established credit and financial stability, which may alter investment choices Investment choices can also be influenced by government initiatives and incentives aimed at particular farmer age groups. However, other research suggests that older farmers may be less risk-averse, leading them to make conservative investment decisions (Hannus & Sauer, 2020; He et al., 2019) while others may make decisions that are in line with their retirement plans, such as investments meant to provide income in retirement, (Kirkpatrick, 2016; May et al., 2019) which could lead to less investment in CSA practices.

Farm size

The "Farm Size" variable, which is measured in hectors, has a statistically significant influence on farmers' willingness to invest in climate-smart agricultural practices with a p-value = 0.001). Holding other variables constant, the positive coefficient (0.717) and the corresponding odds ratio (2.047) indicate that larger farm size is related to a higher probability of maize-producing households' willingness to invest in CSA practices. Is reported that larger-scale farmers are more inclined to implement new technologies, invest more time and resources in learning about farming techniques, and place greater emphasis on using productive rather than processing technology (Hu et al., 2022).

The evidence suggests that larger farms may have greater financial resources and access to credit, which can make it easier to invest in new technologies and practices that promote climate resilience (Idrisa et al., 2012; Lalou et al., 2019) Additionally, larger farms may have more diversified production systems and greater market opportunities, which can provide incentives for investing in climate-smart practices that improve productivity (Pascual et al., 2017). This finding suggests that opportunities for specialised interventions and capacity-building initiatives are presented by the larger farm owners' willingness to invest in CSA practices in Northern Ghana. These interventions must be created to take into account the particular requirements of farms of various sizes, fostering inclusive and sustainable agricultural growth in these regions.

Years of earming experience

This is a continuous variable measured as the number of years a farmer has spent in farming activities. Years of farming experience" is a statistically significant predictor, and it is estimated that for every additional year of farming experience, the likelihood of being willing to invest in climate-smart agricultural practices decreases by a factor of about 0.900, assuming that all other variables in the model remain constant. This implies that more seasoned farmers are more unlikely to be prepared to invest in climate-smart farming.

The association between farmers' experience and their readiness to invest in cutting-edge agricultural technology that is adaptable to climate change has been studied in some developing nations. While some studies observed positive correlations between these elements some others have reported negative correlations It has been shown, for example, that in Nigeria, farmers with a lot of experience are frequently more inclined to make irrigation infrastructure investments and choose drought-resistant crop varieties in areas prone to drought (Igberi et al., 2022). Also in South Africa, seasoned farmers could be more inclined to spend money on precision farming tools like GPS-guided tractors and sensors since they are aware of the potential advantages in terms of making the best use of resources, using less inputs, and adjusting to changing weather conditions. These stem from their familiarity with local weather and farming conditions.

On the other hand, the ability or inclination of a farmer to invest in resilient farming techniques can often be negatively impacted by their wealth of expertise, even if farming experience normally helps farmers make better decisions. Such circumstances are context-specific and, hence should not be applied in all situations. For example, farmers with a lot of experience could be quite committed to conventional farming practices (Krzywoszynska, 2019; Vitari & Whittingham, 2018). They may be accustomed to their current farming practices and may perceive new methods as unnecessary or too costly. The relationship between traditional farming practices and technology adoption is complex and content-specific but there is some evidence to suggest traditional farmers may be less likely to invest in new agricultural technology. For example, in India, farmers who had more experience with modern agricultural practices were more likely to adopt new technologies, while those who relied heavily on traditional practices were less likely to do so (Jain, 2017). This is still a problem, even in some European countries, because local farmers still place a high value on their experience, which is not being utilized to its full potential as countries move towards more sustainably-friendly agronomic practices (Šūmane et al., 2018).

Extension visits

This variable is measured as the number of extension visits received by the farmer in each farming season. The variable is statistically significant at 1 percent and it is estimated that for every additional visit of extension officers to farmers, the likelihood of being willing to invest in climate-smart agricultural practices increases by a factor of about 2.169, assuming that all other variables in the model remain constant. This implies that farmers who receive more extension visits in a season are more likely to invest in climate-smart farming. The adoption of soil conservation techniques, which are crucial for CSA, by farmers in Uganda increased dramatically as a result of increased access to extension services (Turyasingura & Chavula, 2022). According to a report by Khalid and Sherzad (2019), effective extension services offer individualized advice based on regional circumstances, which can increase the applicability of CSA techniques. Farmers are more willing to invest in techniques that are suited to their particular needs when they receive tailored guidance (Khalid and Sherzad, 2019).

Distance to the nearest market

This is a continuous variable measured in kilometres. The negative coefficient shows that a lower desire to invest in CSA practices is correlated with a longer distance of the farmer to the market. The probability of being willing to invest in climate-smart agricultural practices decreases by a factor of approximately 1.298 as the distance to the nearest market increases when all other variables in the model remain constant. The variable is statistically significant at 1%. The market here could be a maize output market or a market for CSA inputs. Farmers who are near a market may have easier access and a larger consumer base, which might result in a greater rate of turnover than farmers who must travel far to reach the market and incur related transportation expenses whether in the input or the output market.

There is a growing body of empirical evidence that suggests that distance to input and output markets is an important factor influencing farmers' decisions to invest in agricultural technologies. Such evidence is even popular among developing countries (Gollin et al., 2014; Suri and Udry, 2022). For example, in Kenya, Malawi Tanzania and some other African countries, farmers who lived closer to markets were more likely to adopt hybrid maize varieties while those who were closer to inputs markets such as improved seeds, fertilisers and other agricultural inputs were positively associated with adoption of improved agricultural technologies (Arslan et al., 2017; Fisher et al., 2015; Makate et al., 2023). According to Altieri et al., (2015), farmers in remote areas may have less access to information regarding climate-resilient farming practices and strategies and may be less exposed to agricultural innovations. This knowledge gap may have an impact on their awareness and investment inclination.

Overall, the evidence suggests that access to input and output markets is an important factor influencing farmers' decisions to invest in agricultural technologies. Therefore increased investment in new technology and improved agricultural production may result from expanding market access through policies and actions that lower transportation costs, enhance market information systems, and construct infrastructure. For farmers in Northern Ghana, where inadequate infrastructure already prevents them from accessing markets, this is essential.

Level of maize commercialisation

The variable "whether farming is mainly commercial" is treated as a binary predictor variable, and is typically coded between 0 and 1. If farming is mostly commercial, it takes on a value of 1, and 0 otherwise. The likelihood of being willing to invest in climate-smart agricultural practices is approximately 1.536 times higher when farming is primarily commercial as compared to when it is not. This predictor is statistically significant at the 5 percent significance level. Maize commercialisation and CSA investment have a complicated relationship. Some commercialization may emphasize immediate profits over long-term sustainability, which could result in resource misuse or a disregard for conservation measures. Additionally, the effects of commercialization can differ between various farming techniques and geographical areas. According to some studies such as Abdoulaye et al., (2011) and Martey et al., (2020b), higher commercialization of maize production may give farmers extra revenue they can use to finance CSA techniques. Farmers that earn greater revenue might be able to pay the initial costs of implementing climate-resilient practices and technologies (Karanja Ng’ang’a et al., 2017). Commercialized maize farmers may also have easier access to funding, market information, and agricultural extension services, all of which are necessary for implementing CSA techniques. Investment choices might benefit from having access to resources and information.

Access to climate information

This variable was treated as a dummy with a value of 1 representing a farmer having access to climate information and 0 otherwise. Access here is defined in terms of possession or access to the various communication channels through which climate information can be disseminated such as TV, radio, mobile phone and the internet and through extension. The threshold for having access to climate information is a farmer having at least a TV or radio which are the common media for disseminating climate information. The positive coefficient means that when farmers have access to climate information, their log odds of being willing to invest in climate-smart agricultural techniques rise by 1.748, all other things being equal. When farmers have access to climate information, their likelihood of being willing to invest in climate-smart agriculture is about 5.741 times higher than when they do not. For example, climate information such as daily and seasonal weather or rain forecasts has increased farmers' awareness of climate risks and helped them to make more informed decisions regarding management practices (Antwi-Agyei, Dougill, and Abaidoo, 2021; Djido et al., 2021; Ngigi and Muange, 2022).

This finding suggests the need for improved dissemination of climate information to farmers. Governments, NGOs, and other organizations should work to provide accessible and relevant climate information to farmers to help them make informed decisions about climate-smart practices. Additionally, efforts should be made to improve the capacity of extension services to provide information on climate-smart agriculture and support farmers in adopting these practices.

It is important to emphasise that, the analysis reveals that age positively influences the likelihood of investing in Climate-Smart Agriculture (CSA) practices, while years of farming experience exhibit a negative relationship. This discrepancy can be explained by the fact that older farmers may have greater financial resources, decision-making authority, and a broader knowledge base (Rose et al., 2018), which facilitates investments in innovative practices like CSA. Conversely, extensive farming experience may foster a preference for traditional methods (Šūmane et al., 2018), leading to resistance against adopting new practices. Additionally, more experienced farmers may perceive CSA as a complex or risky investment, further diminishing their willingness to invest (Musyoki et al., 2022; Ngoma et al., 2019; Tong et al., 2019).

The negative constant reflects the baseline tendency of households not to invest in CSA practices without considering other factors. Its statistical significance reinforces the model predictors significantly in influencing CSA investment decisions beyond the baseline. Thus, the negative constant emphasises that CSA investment does not occur spontaneously but requires interventions. This aligns with the study's objective to identify key drivers of CSA investment and suggests actionable areas such as improving access to climate information and extension services for policy. The theoretical basis for the significance of a negative constant term can be found in studies such as Jiri et al., (2016), Klemm and McPherson (2017), and Munteanu et al., 2018).

The findings underscore the dominance of radio for rainfall-related information and the role of television in providing updates on temperature, sunshine, humidity, cessation dates, wind speed, and cloud movement. These findings can be valuable for policymakers and climate service providers in understanding the preferred channels for disseminating climate information to the local population and improving the effectiveness of information delivery. The results also suggest that the Ghana Meteorological Services have been relatively successful in delivering accurate and reliable climate information related to sunlight, humidity, wind speed, and temperature. Respondents perceive the information on these variables obtained from all sources (including the Ghana Meteorological Services) to be of satisfactory quality.

The results also highlight the indigenous climatic knowledge of respondents regarding specific indicators of rainfall. It reveals that there

Variables	Coeff.	S.E.	p-value	Odd ratio
FBO Membership	-0.466	0.366	0.203	0.628
Sex	2.100	0.358	0.000***	8.163
Age	0.158	0.025	0.000***	1.171
Religion (Muslim dummy variable)	-0.343	0.316	0.278	0.710
Marital Status	0.493	0.364	0.175	1.638
Farm Size	0.717	0.216	0.001***	2.047
Years of Farming Experience	-0.106	0.021	0.000***	0.900
Extension Visits	0.774	0.168	0.000***	2.169
Distance to the nearest market	-0.261	0.066	0.000***	1.298
Level of Commercialisation	0.429	0.218	0.049**	1.536
Access to Climate information	1.748	0.330	0.000***	5.741
Constant	-9.466	1.218	0.000***	0.000
Observations				566
-2 Log likelihood				274.4
Cox & Snell R Square				0.465
Nagelkerke R Square				0.694
Chi-square				354.333
p-value				0.000

Source: authors' elaboration from survey 2023

Table 3: Determinants of households willing to invest in csa practices.

is a widespread belief among respondents in the correlation between earthworm activity and rainfall, as well as the reliability of dark clouds amidst strong winds as a signal of imminent rainfall. However, the perception regarding the significance of singing birds and flying insects as rainfall indicators varies across the study districts. These findings provide insights into the local community's understanding of climate patterns and their reliance on traditional indicators. This knowledge can be valuable for improving climate communication and developing effective adaptation strategies in Northern Ghana.

Conclusion

The study highlights the role of Climate Information Services (CIS) in driving Climate-Smart Agriculture (CSA) investments among maize farmers in Northern Ghana. It integrates scientific and indigenous climate knowledge, providing a unique perspective on farmers' adaptation to climate variability. Radio and television are the primary sources of climate information for maize farmers in Northern Ghana, providing reasonably good quality data on key climatic factors. However, perceptions of service quality vary. The study emphasizes the value of indigenous knowledge in complementing formal climate services, Therefore, tailoring climate information to the specific needs of the local community is essential for improving their understanding of weather patterns.

The PCA analysis highlights the significance of different aspects of weather information for farm-level decision-making. The study identifies two underlying constructs of climatic variables: Factor 1 focuses on immediate farm-level decisions, involving daily weather forecasts, and Factor 2 on long-term planning and mitigation against climate hazards. It also highlights the importance of incorporating indigenous knowledge in agricultural decision-making. Thus, emphasising the need for a comprehensive approach to understanding the impact of multiple climatic variables on agricultural practices.

The results additionally underscore the multitude of factors impacting farmers' inclination to allocate resources towards climate-smart agricultural practices. Farmers' decisions are significantly influenced by gender, age, farm size, farming experience, extension visits, market access, commercialisation, and availability of climate data. However, its limitations include limited generalisability, lack of detailed cost-benefit analysis, and self-reported data.

Policymakers can use these insights to enhance CIS accessibility, address gender disparities, and provide financial support. Investing in visual and auditory communication tools can also enhance the transmission of climate information to smallholder farmers. Quality improvement in specific climate information services can be achieved by enhancing the accuracy and reliability of precipitation forecasts, onset of rains, and cessation dates.

Incorporating indigenous knowledge into formal services can enrich the content and foster cultural relevance. Tailoring climate information services to local needs and perceptions is crucial. Capacity-building programs can enhance farmers' understanding of climate information, while regular community feedback mechanisms can assess the effectiveness of climate services. Promoting multi-stakeholder collaboration between meteorological services, local authorities, non-governmental organisations, and community leaders can create a holistic approach to climate information dissemination.

Strategies to promote investment in climate-smart agriculture and access to climate information are critical. These include promoting gender equality in access to resources, tailoring support programs for older farmers, improving market access, encouraging commercialization while focusing on sustainability, enhancing rural communication infrastructure, and providing training programs on climate-smart practices, risk management, and technology adoption. These strategies aim to improve farmers' access to resources, reduce risks, and promote sustainable agricultural practices.

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