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USE OF CLIMATE INFORMATION AND THE ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES AMONG MAIZE-PRODUCING HOUSEHOLDS IN NORTHERN GHANA

BY

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DEDICATION

In Honour of Allah (The Almighty God) and in loving memory of my late parents, Afa Shaibu Salifu and Mma Adamu Napari, as well as my siblings and cherished nuclear family.

DECLARATION

1, Abdul-Fatawu Shaibu author of this thesis entitled "USE OF CLIMATE INFORMATION AND THE ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES AMONG MAIZEPRODUCING HOUSEHOLDS IN NORTHERN GHANA" do hereby declare that except forliterature references cited, which have been duly acknowledged, this thesis is a result of research solely conducted by me under the supervision of Professor Kwabena Asomanin Anaman, Dr Yaw Bonsu Osei-Asare and Dr. (Mrs.) Abigail Ampomah Adaku in the Department of Agricultural Economics and Agribusiness, College of Basic and Applied Sciences, University of Ghana, Legon, Accra, from August 2019 to October 2023. I wish to state further that this work has never been submitted in part or whole to this university or elsewhere for examination and award of any degree.

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ABSTRACT

Northern Ghana's agricultural systems are very vulnerable to climate variability, especially droughts, due to their overreliance on rain-fed agriculture, limited infrastructure, and weak government-supporting systems. An important feature of these agricultural systems is the limited access by farmers to enhanced weather information and services. The research study involved three regions, five districts, and seven communities in Northern Ghana that were designated as “climate communities” by active climate programmes to address the gap in knowledge and delivery of weather and climate services. The first objective assessed the utilisation of climate information at the farm level concerning the production and marketing decisions made by farmers. The second objective analysed the factors that influenced CSA adoption. The third objective was to examine how CSA practices affected crop output and net returns and the fourth determined the extent to which maize-producing households in Northern Ghana were willing to finance CSA practices. The study used a mix of simple descriptive statistics econometric modelling and qualitative measures to analyze data. Factor analysis, production function analysis, and binary and multinomial logit regression procedures were employed. The augmented production function analysis was used to assess the effect of CSA practices on the productivity of farmers, measured as crop yield per hectare. The results of the analysis indicated that State-produced daily weather forecasts seasonal climate forecasts, and Indigenous climate information had a significant role in farm-level decision-making. The study also found that factors like age, sex, farming experience, and climate exposure significantly influence the adoption of CSA practices. Improved seed varieties and enhanced soil fertility techniques positively impact maize yields and returns. The results also indicated that maize commercialization, farmer experience in agronomic practices, climate information use, farm size, and proximity to markets, had significant effects on farmers' willingness to invest in CSA practices. Male farmers were more likely to adopt CSA practices than female farmers. Overall, the study concludes that to advance the use and adoption of CSA practices, maize farmers need more access to localized climate and weather forecasts. Another key policy recommendation is to create an enabling environment through increased access of farmers to market centres based on improved infrastructural services and enhanced extension services involving regular farmer contacts with emphasis on marginalized people such as people with disabilities, women, and adherents of traditional African religions.

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ABBREVIATIONS AND ACRONYMS

ATE	-	Average Treatment Effect
CBA	-	Cost Benefit Analysis
CCAFS	-	Climate Change, Agriculture and Food Security
CGIAR	-	Consultative Group for International Agricultural Research
CIS	-	Climate Information Systems
CHIP	-	Climate Change Health Impact Profile
CSA	-	Climate-Smart Agriculture
CSIR	-	Center for Scientific and Industrial Research
ECOWAS	-	Economic Community of West African States
FAO,	-	Food and Agriculture Organisation
FBCs	-	Farmer Based Cooperatives
FBOs	-	Farmer Based Organisations
FSD	-	First Order Stochastic Dominance
GDP	-	Gross Domestic Product
GFCS	-	Global Framework for Climate Services
GHGs	-	Greenhouse Gases
GSS	-	Ghana Statistical Service
IPCC	-	Intergovernmental Panel on Climate Change
HH	–	Households
IFPRI	-	International Food Policy Research Institute
IPA	-	Innovation for Policy Action
KMO	-	Kaiser-Meyer-Olkin

KOICA	-	Korean International Cooperation Agency
MN	-	Multinomial Logit
MNP	-	Multinomial Probit
MoFA	-	Ministry of Food and Agriculture
NCCC	-	National Climate Change Committee
NCCP	-	National Climate Change Policy
NEPAD	-	New Partnership for Africa's Development
NR	-	Northern
PCA	-	Principal Component Analysis
PFJ	-	Planting for Food and Jobs
PHC	-	Population and Housing Census
SARI	-	Savannah Agricultural Research Institute
SSA	-	Sub-Saharan African
SRID	-	Statistics Research and Innovation Directorate
UE	-	Upper East
UNDP	-	United Nations Development Programme
UNFCCC	-	United Nations Framework Convention on Climate Change
UW	-	Upper West
WMO	-	World Meteorological Organisation
WTI	-	Willingness to Invest

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Due to its influence on crop yields, climate change presents significant risks to global trade, industry, and agriculture. It also represents a major challenge for farmers (Ahmad et al., 2020). The worsening climate may render farming systems, particularly in Africa, obsolete, threatening the health and happiness of many people (Ghahramani & Moore, 2016; Thornton et al., 2009).

Africa is highly vulnerable to climate change due to its reliance on natural resources and rainfed agriculture. By 2050, three percent of Africa's land could be unsuitable for maize cultivation, leading to a shift to animal farming (Jones & Thornton, 2009). Other global pressures, including demographics, urbanization, technology, and innovation, are likely to intensify the challenges faced by African countries in modernizing their economies. The continent has consistently recorded some of the highest population growth rates globally. From 2000 to 2023, for instance, Africa's population growth rate averaged between 2.5 percent and 3 percent annually, while global growth rates averaged about 1 percent (Niohuru, 2023). However, with climate-smart agriculture farmers can have opportunities for long-term and inclusive growth, enabling them to adapt to climate change and improve their livelihoods.

Climate information (CI) is structured data, analysis, and insights derived from observations, models, and research related to climate. It is used for policy development, planning, and decision-making on climate-related issues (Clark et al., 2022). Climate information services provide accessible, credible, and usable climate information for decision-makers across various industries.

(WMO, 2018). However, due to challenges such as the limited availability of accurate and timely information, tackling climate concerns in sub-Saharan Africa (SSA) and other developing nations can be extremely difficult (Nkiaka et al., 2019; Vaughan & Dessai, 2014).

Climate-smart agriculture (CSA) is a strategy to direct agricultural expansion in response to climate change. It focuses on sustainable output, increased resilience, and mitigation of greenhouse gases (Lipper et al., 2014). It aims to improve food security and development by increasing agricultural productivity and incomes without destroying the environment (FAO, 2013; Lipper et al., 2014; Sarker et al., 2019). CSA has gained worldwide interest due to its impact on agricultural output and livelihoods. In Malawi, CSA techniques have improved maize production efficiency by 63 percent the adoption of climate change management techniques has shown improvements in technical efficiency in maize production in Malawi and improved food security in the United States (Pangapanga-Phiri & Mungatana, 2021). For example, in the United States, CSA has led to improved food security and climate resilience (Lipper et al., 2018). To achieve the maximum potential of using CSA to effectively deal with climate change, considerable reforms in government policies and funding structures are needed.

Ghana's rainfall patterns and climate challenges are well-documented, with extreme southwestern regions receiving over 2000mm per year, supporting tropical rainforests, and the northern regions receiving less than 1100mm per year. By 2100, temperatures in Ghana are projected to increase by as much as 3°C.with the northern part of the country experiencing the greatest increase (Logah et al., 2013). Predicted sea level rises in the next century will leave Ghana vulnerable, with coastal flooding and inundation expected (Abbam et al., 2018; Aryee et al., 2018a; Asamoah & Ansah-Mensah, 2020; Asare-Nuamah & Botchway, 2019; Issahaku et al., 2016).

Northern Ghana is an agro-ecological zone, that has low farm production and income, leading to widespread poverty. Climate change is expected to negatively impact cash and staple crops, particularly drought, in the region (Owusu et al., 2021; Williams et al., 2020). To address climate change and variability in northern Ghana, agriculture must become more productive and better able to withstand environmental stresses, necessitating substantial reforms in national and local government policies and funding structures.

Maize is a critical staple crop in Africa, with over 650 million people in drought-prone countries relying on it for food and income (Mulungu & Ng'ombe, 2020). Maize production accounts for about 24 percent of African agriculture and 40 percent of cereal production in Sub-Saharan Africa (Abdoulaye et al., 2011). Nigeria is the top producer in the continent, followed by South Africa, Egypt, and Ethiopia. (Kostandini et al., 2013). However, because most African maize farming is rain-fed, the continent imports 28 percent of its maize requirements (Cairns et al., 2021). In Ghana, maize is a vital crop, covering about one million hectares and accounting for 50-60 percent of the nation's grain production. The country's per capita maize consumption has been increasing, with about 75 percent of maize consumed originating from domestic production (MoFA, 2021). Maize is consumed in various ways and serves as feed for the poultry sector. The introduction of Ghana's Planting for Food and Jobs programme is reported to have led to increased maize production (MoFA, 2018). Maize production in Ghana is influenced by consumer preferences and agroecological factors, with the Savannah zone producing more than 80 percent of Ghana's maize output; this zone also has the highest per capita consumption. In the Northern, Upper East, and

Upper West regions, about 97 percent of agricultural households are engaged in maize production (MoFA, 2021).

1.2 Problem Statement

Approximately 1.23 billion people, or about 40% of the global workforce, were employed within the agrifood system in 2019 (Davis et al., 2023). As a result, any slight changes in food production patterns caused by rising global temperatures might impact millions of people who rely primarily on agricultural output for their livelihood. How sensitive or exposed farmers are to these consequences determines the extent of climate change's impact on agriculture. While climate change is projected to boost yields in high and mid-latitudes throughout the world, it is expected to decrease yields at lower latitudes, with the trend becoming more evident as time goes on. Several mechanisms could contribute to this phenomenon; for example, high temperatures during critical growth stages can severely impact crop fertility and grain formation, leading to decreased yield in staple crops (Hatfield & Prueger, 2015). Rising temperatures also increase evapotranspiration rates and crop water requirements, particularly in regions with water scarcity. At the global level, the food system may not be able to tolerate such regional variances, with output, pricing, and the danger of famine all being impacted by the added stress of climate change.

Significant drops in yield, productivity, and risk of famine are anticipated throughout Africa, with SSA losing up to 12% of its production capability. (Serdeczny et al., 2017). For example, maize farming could become unviable for up to 3 percent of the continent's agricultural land area given the occurrence of conditions related to greater or lesser emissions scenarios (Onyeaka et al., 2024). These territories, which currently sustain 35 million people, are predicted to transition from mixed-crop–livestock systems to mainly livestock-only systems (Jones & Thornton, 2009). It is further anticipated that there will be a 10 percent decline in maize output in Africa and Latin America by 2025 under various climatic scenarios, resulting in nearly 2 billion United States Dollars in yearly revenue losses (Jones & Thornton, 2009).

The agricultural sector's susceptibility to climate change and variability is widely documented in the literature (Masud et al., 2017; Panthi et al., 2016; Parker et al., 2019; Steiner et al., 2018). Because of its fundamental reliance on natural resources, the sector's production is subject to climate-related risks including extreme weather occurrences such as floods and drought. The principal challenges of agricultural output in Ghana are low soil organic matter and restricted availability of plant nutrients, all resulting from climate change.(Amfo et al., 2021; Fening et al., 2005) Total crop failure is anticipated to occur more regularly in northern Ghana, for example, once every five years as a result of delayed or diminished rainfall, severe topsoil losses from wind and water erosion are likely contributing factors to these failures (Amikuzino & Donkoh, 2012; Laube et al., 2012; Wood, 2013). Cassava and maize yields are projected to fall by 29.6% by 2080 and 7% by 2050, respectively in northern Ghana. Changes in climate will continue to exacerbate rural poverty and accelerate the process of land degradation and desertification; investment in agriculture is becoming increasingly more costly, hazardous, and less lucrative.

Ghana's agriculture sector has been an important source of livelihood for many households; it has contributed significantly to the country's GDP and export earnings since independence (Darfour & Rosentrater, 2016a; Enu, 2014; Enu & Attah-Obeng, 2013). However, Ghanaian farmers are facing numerous challenges due to erratic rainfall patterns, flooding, water erosion, crop diseases, and pest infestations (Amoateng, 2016). Farmers in the northern parts of the country are particularly vulnerable due to extreme weather conditions (Atanga & Tankpa, 2021). This vulnerability is exacerbated by the difficulty in accurately predicting weather events (Derbile et al., 2016; Kanchebe Derbile & Abudu Kasei, 2012). The country's reliance on rain-fed agriculture makes it particularly vulnerable to climate change, with only 2% of its irrigation potential being utilized (Anang et al., 2017. This vulnerability is reflected in the projected drops in production for staple crops such as cassava and maize due to temperature rises. Desertification is expected to spread at a rate of 20,000 hectares per year, and cocoa-growing regions will be impacted by poor weather conditions by 2050 (Asante & Amuakwa-Mensah, 2015). Rice, root, and tuber crops will have lower yields which can severely affect vulnerable populations, especially women and children (Klutse et al., 2021a; Tetteh et al., 2022; Wang et al., 2021).

Future climate projections (refer to the details in Table 1.1) show that projected climate changes for Ghana indicate significant warming, with temperature increases of up to 5.8°C by the late 21st century under high-emission scenarios. Rainfall patterns will become more variable, with a greater frequency of intense rainfall events alongside longer dry periods, especially in the northern regions of Ghana. Sea levels are expected to rise by up to 65 cm by 2100, posing risks to coastal areas. Additionally, soil moisture and humidity are likely to decline in the north due to increased evaporation and aridity, while evapotranspiration rates could rise by 20 percent intensifying water stress. The frequency of extreme weather, such as heatwaves and heavy rains, is anticipated to increase, highlighting the urgent need for climate adaptation strategies in agriculture, water management, and disaster preparedness.

TABLE 1.1 IPCC ASSESSMENT REPORTS (AR5 AND AR6) THE CHIP 5/6 MODEL ENSEMBLES

Climate variable	Period			
	2020-2039	**2040-2050**	**2060-2079**	**2080–2099**
Annual Temperature Anomaly (°C)	+0.6 to +1.5 (+0.9 °C)	+1.2 to 2.7 (+1.7 °C)	-1.7 to +3.8 (+2.7 °C)	+2.3 to +5.3 (+3.6°C)
Annual Precipitation (mm)	-16.7 to +22.0 (+0.9mm)	-22.2 to 30.4 (+0.3 mm)	-22.9 to 38.9 (2.9 mm)	-29.7 to +45.2 (+1.6 mm)
Extreme Events	Increase in frequency of heatwaves and heavy rainfall events	More intense heatwaves, drought periods in the north	Extreme heat and rain events are more frequent	Regular, severe heatwaves, intense rainfall, and long droughts in the north
Rise in sea level (cm)	+5–10 cm	+10–20 cm	+20–35 cm	+35–65 cm
Soil Moisture (%)	Small decrease Higher evaporation in the dry season	(-2% to -5%) Drier in northern regions	(-5% to -10%) Increasing aridity	(-10% to -15%) Significant drying in dry seasons
Evapotranspiration (%)	+2 to +5% increase	+5 to +10% increase	+10 to +15% increase	+15 to +20% increase
Wind Patterns	Minor changes, a slight increase in dry-season winds	Increase in dry season winds, especially north	Higher wind variability, more dust events	Stronger dry winds, potential for more extreme wind events
Humidity	Minor increase overall	Slight rise, particularly in the rainy season	Increased in the south, more dryness in the north	Humidity increases in the south, dry north
Cloud Cover	Stable, minor increase in the rainy season	Slight increase in southern regions	Variable, with more clear skies in the dry season	Decreased cloud cover in the dry season

Source: World Bank Group (2021)

Because the rural poor in Ghana rely heavily on agricultural output, food production losses caused by climate change pose enormous obstacles in tackling food insecurity (Yaro, 2013a). These losses do not only limit the farmer's ability to reach markets due to decreased agricultural yields, but they also limit the household's opportunities for other livelihoods (Connolly-Boutin & Smit, 2016; Mihiretu et al., 2021). The savannah ecological zones are characterized by a dry climate, increasing rainfall variability, and hotter temperatures that result in decreased food output and incomes (Aniah et al., 2019). Regarding the effects of climate change and variability on livelihoods in northern Ghana, the Northern, North East, and Savannah Regions are the most vulnerable, while the Upper West and Upper East have the lowest capacity for adaptation (Etwire et al., 2013). The feedback to the social dimension is poverty among those dependent on agricultural activities. The ability to adapt to these climate stresses is complicated by non-climate stressors such as unfavourable trade policies, low technology, social norms, and degraded environment among others, that reduce the competitiveness of commercial farming. Food deficits resulting from these shortfalls in production are filled in by imports from reigns.

While the Ghanaian forest ecological zones have more favourable climates than the rest of the country, they also suffer significant variations in rainfall and temperature that could affect food and tree crop outputs and farmer incomes including those derived through international export trade (Aniah et al., 2019). Additionally, the exodus of vulnerable people from highly vulnerable regions particularly from the northern regions to the forest ecological zones creates additional pressure on environmental systems making it difficult for sustainable management of natural resources (Yaro, 2013b). As a result, northern Ghana is already exposed to harsh weather conditions (Frimpong et al., 2017). and its populations are the most vulnerable to poverty

(Zereyesus et al., 2017), this is an area where climate-smart technologies may be promoted. Since each household and individual has a different capacity for coping with and adapting to the effects of climate change, addressing vulnerability could emphasize household-specific strategies which emphasise household endowments and individual farmer risk preferences and aversion. This approach to analysing the adoption of CSA practices in Northern Ghana places households at the centre of the analysis and could allow for the identification of CSA practices which could be widely adopted by farmers.

Climate information services available to improve agricultural production as well as the barriers in accessing them by different socioeconomic groups, particularly regarding agrarian households in the Northern Region of Ghana have been less explored. Although climate science has made enormous strides in forecasting weather and climate information, local populations have yet to fully adopt the services generated by advances in climate science.

Efficient supply-side business structures that entice farmers to invest in CSA technology are lacking in most countries in sub-Sahara Africa, including Ghana (Botchway et al., 2016; Cairns et al., 2013), emphasizing the need for an analytical framework that focuses on economic evaluation of CSA practices to influence farmers' investment decisions and scale up these practices. Resource-constrained farmers are at risk of low crop yield, output, and low farm income due to scarcity of resources, including finance and credit, which may affect investment in profitable new agricultural technologies and limit the levels of inputs required to exploit the new technologies.

Climate change is threatening agriculture in northern Ghana, where a large section of the population depends on it for their livelihood. Climate-related risks such as floods and droughts, as well as rising temperatures and irregular rainfall patterns, render agriculture increasingly sensitive to food production losses. Despite the need for climate-smart agricultural practices, adoption remains low due to obstacles such as financial constraints, a lack of knowledge, and insufficient access to information and resources. To effectively address these challenges, this study investigates the role of climate information in promoting climate-smart agricultural practices in northern Ghana. It aims to understand the variables farmers use in decision-making, the effect of access to such information on adoption, and the sustainability of these practices. The study also explores households' willingness to invest in Climate-Smart Agriculture (CSA) and examines how both elites and ordinary farmers perceive climate change, climate information services, and their strategies for coping with climate-related challenges.

1.3 Research Questions

Based on the assessment of farmers' exposure to the negative impacts of climate change and variability, as well as the associated risk to agricultural output, yield, income, and livelihoods in the preceding sub-sections, the study set out to investigate the following essential questions:

Main Research Question:

How does the use of climate information affect the adoption of climate-smart agricultural practices by maize-producing households in Northern Ghana?

Specific Research Questions:

1. What types of climate information variables are used in farm-level decision-making among maize-producing households in Northern Ghana?
2. Does the access and use of climate information influence the adoption of CSA practices?
3. Does the use of CSA practices lead to improved maize crop yields and net returns?
4. Are maize-producing households willing to invest in CSA practices?
5. Do elites, such as influential farmers, climate change experts, and agricultural policy influencers, have similar or differential views about the use of climate information and its effects on CSA practices, as ordinary maize farmers?

1.4 Research Objectives

The study's main goal is to assess the association between the usage of climate information and the adoption of climate-smart agriculture (CSA) practices by maize-producing households in Northern Ghana.

Specific Objectives:

1. To evaluate the utilisation of climate information in farm level-decision among maize-producing households in Northern Ghana.
2. To examine the effect of the utilisation of climate information on the adoption of CSA practices among maize-producing households in Northern Ghana.
3. To analyse the effects of CSA adoption on maize productivity in terms of yields and net returns among maize-producing households in northern Ghana.

4. To assess maize-producing farm households' preferences and willingness to invest in CSA practices in Northern Ghana.
5. To ascertain the level of agreement between maize-producing householders and elites (influential farmers, climate change and meteorological science experts, and agricultural policy influencers) concerning the effect of climate information on the adoption of CSA practices and the impact of CSA practices on the productivity of maize farmers

1.5 Research Hypotheses

Based on the research questions and related objectives of the study, five hypotheses have been developed to allow for the establishment of conclusions which could assist in the formulation of policies to improve maize production and the well-being of maize-producing households. These hypotheses are indicated below.

Hypothesis 1:

Climate and weather information variables influence production and marketing decisions among maize-producing households.

Some studies lend credence to the idea that farmers rely on reliable sources of climate information when making decisions in the face of rising climate uncertainty (Guido et al., 2021; Smith et al., 2021; Warner et al., 2022). The information offered about the climate is sometimes incomplete for farmers to make the best-informed decisions about climate change. Decisions made at the farm level may be impacted by this lack of access to essential climatic information. According to Cairns et al. (2013), climatic variability and change may have an impact on crop management and production options, and they emphasize the importance of adjusting climate-smart agriculture to local conditions.

According to Asfaw et al., (2012), farmers' perceptions of risk and crop choices may be influenced by the availability of climatic information factors, leading to varied farm-level decisions. In Tanzania, the accuracy of weather forecasts was increased by integrating traditional and modern methods allowing farmers to manage their crops more successfully (Balehegn et al., 2019; Radeny et al., 2019). These findings suggest that while meteorological data is important, the combination of modern and traditional weather forecasting methods can lead to better decisions about crop management. Farmers make complex decisions in production and marketing, each requiring distinct types of information. Production decisions rely on technical data such as soil quality, weather forecasts, and resource availability, and financial data on costs, credit, and historical yields (Finger et al., 2019; Guido et al., 2021; Shah & Wu, 2019). For marketing, farmers use market intelligence and pricing data to time sales and choose profitable channels, considering logistics like transportation, storage, and proximity to markets (Dimitri & Gardner, 2019; Tripathi et al., 2023). Production information is generally scientific and technical, while marketing information is more speculative and requires verification. Farm characteristics, such as size, production system, and market focus, shape how information is used. Recognizing these differences helps farmers manage their operations effectively.

Hypothesis 2:

Maize farmers' adoption of climate-smart agricultural (CSA) practices is influenced by their socioeconomic backgrounds, the institutional factors and challenges they encounter, and their access to climate information.

Several studies have found positive correlations between farmer and farm-level characteristics, as well as institutional factors, and CSA adoption in developing countries (Glemarec, 2017a; Lunduka et al., 2019; Martey et al., 2020; Venkatramanan & Shah, 2019). The adoption of drought-tolerant maize in northern Ghana, for example, is primarily driven by seed availability, extension service, labour availability, and farm household location (Martey et al., 2020). Indigenous weather and climate forecasting have been proven to be an effective information source for agricultural decision-making, especially considering climate change. Similarly in other Sub-Saharan African countries farmers' adoption of CSA techniques is highly impacted by their access to extension services, education, financing, and membership in farmer-based organisations (Mujeyi et al., 2020a; Rubiano et al., 2018).

Hypothesis 3:

CSA practices improve maize yield and net return of smallholder farmers.

There is evidence to support the hypothesis that varying CSA practices result in varying maize yields and net returns. In Zimbabwe, using CSA techniques including intercropping and mulching resulted in better maize yields than using traditional techniques (Mujeyi et al., 2020b). The implementation of conservation agricultural methods, such as crop residue preservation and low tillage, led to greater maize yields and net returns in Pakistan (Somasundaram et al., 2020). In some developing countries, including Ghana, joint adoption of CSA, including drought-tolerant seed varieties and insurance, has increased maize yield (Martey et al., 2020; Zhang et al., 2019). In Ethiopia using better maize varieties, intercropping, organic and inorganic fertilisers, and crop rotation increased maize yields and net returns (Bedeke et al., 2019).

Hypothesis 4

The willingness of maize-producing households to invest resources in the adoption of CSA practices is influenced by their socioeconomic characteristics and farm-level and institutional factors.

There is evidence that socioeconomic, farm-level, and institutional variables affect the preferences and willingness of maize-producing households to invest in CSA practices. Rural farmers in India, for example, prefer CSA methods because they are less risky and improve soil quality (Khatri-Chhetri et al., 2017). In Nigeria, farmers are most willing to pay for knowledge-smart, water-smart, nutrient and weather-smart strategies (Anugwa et al., 2022).

Farmers' preferences for certain CSA techniques were shown to be influenced in Malawi by land tenure, access to climate knowledge, and market possibilities, and increasing willingness to invest in CSA was linked to projected threats from climate change or farm exposure to climate risk. The adoption of CSA practices in Kenya, Uganda, and Tanzania was shown to be influenced by household wealth, loan availability, weather information, and social capital (Wang et al., 2018). In Ghana, household income, education level, and access to credit influenced farmers' willingness to adopt CSA practices, and farmers who perceived the benefits of CSA practices to be higher than the costs were more willing to invest in them (Mensah et al., 2021).

Hypothesis 5

Climate information has a significant impact on the adoption and productivity of climate-smart agricultural practices among maize farmers, a consensus shared by both ordinary farmers and experts in the fields of climate change and meteorological science.

The adoption and use of inputs in farm production require information about the nature of the inputs and their effects on farmer productivity and income. This information largely flows from elites and experts to ordinary farmers. Even in traditional agriculture, the widespread adoption of inputs and crop varieties has been contingent on the flow of reliable and accurate information about these practices from sources, often elites, to ordinary farmers. As such, the sustainable and extensive use of CSA practices in maize production in Northern Ghana would depend on the symmetric information flowing from elites to ordinary maize farmers. One can then hypothesize that ordinary farmers and elites have an agreement on the positive effect of climate information on the choice of CSA practices and the influential impact of CSA practices on maize production.

1.6 Relevance of the study

According to some analysts such as Aryee et al. (2018b), the rising poverty rates in most parts of Northern Ghana are due to exceptionally large household sizes and bad climatic conditions, both of which have a significant negative influence on agricultural and rural livelihoods. However, over the previous 30 years, poverty rates and overall Gini coefficients have decreased significantly in Nigeria and Senegal, both of which have similar climatic endowments to Ghana (Cairns et al., 2013; Lipper & Zilberman, 2018; Tambo, 2016; World Bank, 2021). However, in Ghana, the national income inequality, as measured by the Gini coefficient, has steadily increased over the last 30 years with average poverty rates increasing for most tribes in Northern Ghana (World Bank, 2021). This would suggest that other factors beyond climatic variability could be influencing the worsening poverty rates in Northern Ghana. In Northern Ghana, no matter where a household is located, the household head's post-basic education has a significant impact on whether the household is likely to reduce its poverty level. Further, households with more dependent women are more likely to reduce their poverty levels, and access to productive assets is essential to combating rural poverty (Jatoe & Al-Hassan, 2019).

A more comprehensive understanding of the factors influencing the use of climate information and the adoption of CSA practices among maize-producing households is needed to inform targeted interventions and support mechanisms. The existing literature on this topic offers several important contributions. Djido et al., (2021) examined the extent to which weather and climate information services drive the adoption of CSA practices in Ghana, focusing on the northern region and maize production. While informative, the study could be expanded to other maize-producing regions and incorporate a broader range of crops or agricultural systems. Damba et al., (2021) presented a comprehensive assessment of CSA and climate information services (CIS) prioritization in Ghana, covering multiple regions and stakeholder groups. However, the study lacks a specific focus on maize-producing households. Tepa-Yotto et al., (2022) and Yeboah et al., (2022) provided valuable insights into the capacity-building efforts and stakeholder engagement related to CSA and CIS in Ghana but did not delve deeply into the experiences and challenges faced by maize-producing households.

From the above, further research is needed to expand the understanding of climate change adaptation (CSA) practices in maize-producing regions in Ghana. This could involve geographical expansion and the experiences and decision-making processes of maize-producing households which could provide deeper insights. This knowledge can inform the development of more effective interventions to support sustainable agricultural practices and climate resilience in northern Ghana.

1.7 The Scope and Limitations of the Study

The study focuses on maize-producing households in Northern Ghana, investigating their utilization of climate information and the adoption of climate-smart practices. It employs utility maximization theory as a theoretical framework to analyze the decision-making process of farmers. Additionally, multinomial logit and binary probit models are used to examine adoption and investment decisions related to climate-smart agricultural practices.

The study recognizes that the sample size of 566 respondents has limits in terms of generalizability. Despite efforts to assure representativeness, the results may not accurately reflect the variety of households in Northern Ghana that grow maize. Financial limitations hindered the use of rigorous qualitative methodologies, such as Focus Group Discussions, which might have offered consensus-based insightful analysis of social dynamics and contextual factors connected to the adoption of climate-smart activities and the use of climate information. The findings of the study are specific to the northern regions of Ghana and may not be directly applicable to other regions or countries. Agro-climatic conditions, socioeconomic contexts, and cultural factors in different settings can impact the adoption of climate-smart agricultural practices differently. Potential limitations, such as measurement errors, should be considered when interpreting the results.

1.8 Organization of the Thesis Report

This report is organized into seven chapters. In chapter 1 the thesis report starts by giving a background and context on the study topic. It describes the goals of the study and emphasizes the relevance of the research topic. Key ideas, hypotheses, and pertinent prior research are compiled in the literature review part of Chapter 2. It highlights the key arguments and conclusions made in the literature and points out any gaps that the thesis needs to address. Chapter 3 focuses on the methodology, describing the research design, data collection methods, and data analysis techniques utilized in the study. Moving on to Chapter 4, the findings related to factors analysis and econometric modelling related to research objectives 1 and 4 respectively are presented and discussed. Chapter 5 then presents the discussion of findings related to research objectives 2 and 3. The study includes a qualitative investigation of the elites' viewpoints on climate change and climate information in Chapter 6 using in-depth interviews to gain insightful knowledge about these dynamics in Northern Ghana. Finally. Chapter 7 centres on providing summaries, drawing conclusions, and presenting policy recommendations based on the research outcomes.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive overview of the existing body of literature concerning the relationship between climate knowledge and information and their impact on the adoption and outcomes of Climate-Smart Agriculture (CSA) practices, specifically their effects on maize productivity. Drawing upon a wide array of research publications accessible through diverse databases, this review delves into the accessibility and availability of climate information, the adoption of climate-smart practices, and the factors that impact their utilization. The chapter starts with an examination of climate change and its global repercussions, with a particular emphasis on its implications for agriculture, particularly in the context of Ghana. Subsequently, the chapter presents a succinct summary of multiple empirical studies on this subject. These studies serve as a basis for identifying knowledge gaps within the existing literature, for which attempts are made to address in this study.

2.2 Discussion of Key Concepts Relevant to the Research Problem

2.2.1 Climate Change Adaption, Mitigation and Resilience

Adaptation

Adaptation refers to the methods through which human beings improve their ability to cope with an uncertain future. The phrase ‘climate change adaption’ refers to a combination of actions, methods, procedures, and policies designed to mitigate the effects of existing or anticipated climate change on individuals, communities, and the economy (Ayers & Dodman, 2010; Franks &

Hoffmann, 2012). Adapting to climate change means taking steps to directly reduce the negative consequences of climate change or to capitalize on the beneficial aspects of climate change by making the necessary modifications and changes or adjustments to human systems to minimize the negative effects of climate change.

Mitigation

Climate change mitigation refers to actions that reduce the potentially harmful effects of global warming by reducing the atmospheric concentration of GHGs. It means controlling greenhouse gases to stabilize climate change at an acceptable limit (Yaro, 2013).

Resilience

Resilience entails making a conscious effort to embrace strategies that safeguard vulnerable individuals to diversify revenue sources and preserve current livelihood systems.

2.2.2 Adaptation and Mitigation Options in Ghana

The degree of vulnerability of the agricultural sector to climate change is contingent on a wide range of local environmental and management factors. Ghana's agricultural sector has the potential to contribute to global efforts to reduce GHG emissions and sequester atmospheric carbon while at the same time increasing the sustainability of agricultural production. Tables 2.1 and 2.2 summarize adaptation and mitigation options available to Ghanaian farmers. The review presented in the earlier section indicates that integrating climate change adaptation and mitigation into the development agenda is important for addressing the impact of climate change on agricultural production and food security. To achieve this, stakeholders need to be engaged in employing a holistic approach to address the effects of climate change. A priority is to strengthen the resilience of rural communities and help them to cope with this additional threat to food security. Adaptation and mitigation measures could be implemented together.

TABLE 2. 1 ADAPTATION OPTIONS AVAILABLE TO GHANAIAN FARMERS

Adaptation Options	
Option 1 Dealing with risk and uncertainties	
Short-term measures	***Mid-to-long term measures***
Information services and early warning	Climate modelling, impact and vulnerability assessment
Crop insurance	
Awareness and access to information	R&D on improved seeds and technologies
Participatory planning	Strengthening seed systems
Flood control	
Option 2 Farming practices and technologies	
Short-term measures	***Mid-to-long term measures***
Indigenous knowledge	
Drought/flood-resistant varieties	Improved crop practices and production technology
Crop diversification and specialization	Changing plot locations
Pest and disease control	Irrigation
Water management and moisture control	
Fertilisation	

Source: World Bank Group, (2021)

TABLE 2. 2 MITIGATION OPTIONS AVAILABLE TO GHANAIAN FARMERS

Mitigation options	**Resilience options**
Appropriate use of fertilisers	Irrigation infrastructure
Use of improved crop varieties	Access to reliable water for agriculture
Crop rotations with legume crops	
Use of agroforestry	
Adoption of no-tillage or reduced tillage	
Use of crop residues for mulch	
Improved water management for irrigated crops	

Source: World Bank Group, (2021)

2.3 Climate Information Services

Climate information includes long-term projections that take into account decadal, multi-decadal, and centennial time scales as well as short-term estimates that cover daily weather forecasts, and monthly, and seasonal forecasts (D. M. Smith et al., 2019; Tommasi et al., 2017). Climate services provide user-driven enhanced climate data and information that allow for risk-efficient management choices to be made. A climate information service helps people and organizations in society make better ex-ante decisions (Paterson et al., 2022). To produce timely advice that end users can comprehend, assist their decision-making, and enable early action and readiness, a climate service needs to be properly and iteratively involved. Users must be responsive to their demands and effortlessly obtain climate services.

Services that provide access to climate information are crucial tools for assisting Sub-Saharan African smallholder farmers in adapting to climate change (Cacho et al., 2020). Therefore, additional information on crop selection, market accessibility, plant protection, and climate-smart agricultural practices should be offered alongside climatic information to increase adaption to climate change (Muema, 2018.; Webber et al., 2014). This is because farmers' decisions are impacted by ambiguous climate information unless they are translated and supported by advisory services that are tailored to meet their needs. When climatic data is combined with agronomic counselling, the term "climate information services" is employed.

Various categories of climate information-related goods and services have been developed over time; Personalized information for farmers (Archer, 2003), daily weather forecasts, decadal agro-meteorological bulletins, and monthly and seasonal climate outlooks (Masesi, 2019) are some of the climate products and services. A service that provides meteorological and seasonal climate forecast information has been running for some time in Ghana. However, many farmers do not find the data helpful for making decisions at the farm level (Sarku et al., 2022). Farmers' use of weather and climate information is frequently stated to be limited by forecast accuracy, timeliness, and mismatches between forecast information and needs (Asare-Nuamah & Botchway, 2019). To forecast weather and seasonal climatic trends, the bulk of farmers rely on their innate ecological knowledge. However, due to the one-directional premise that underlies its creation, Ghana's present meteorological and seasonal climate forecast information systems are severely constrained in their usage where users have little to no input; science is the only source of fresh knowledge that is made available to them (Mkuhlani et al., 2022).

2.3.1 Indigenous Climate Information and Forecasting

Smallholder farmers in northern Ghana have long relied on indigenous knowledge and practices to navigate the region's variable climate and make informed decisions about their agricultural activities. These indigenous climate information systems often incorporate observations of environmental indicators and traditional forecasting techniques that have been developed and refined over generations. Understanding the role and reliability of these indigenous approaches is crucial for enhancing climate resilience and supporting the adoption of climate-smart agricultural (CSA) practices among maize-producing households.

A study by Nyadzi et al., (2021), explores indigenous techniques for weather and seasonal climate forecasting in northern Ghana. Key indigenous indicators include observation of natural phenomena, traditional divination practices, and interpretation of environmental cues. Farmers also transfer knowledge from elders to younger generations, relying on their community's wisdom. The study found that indigenous forecasting is reliable and credible due to its relevance to local conditions, temporal and spatial accuracy, compatibility with traditional practices, and long-term experience. However, there is a need to integrate indigenous climate information systems with scientific meteorological data and forecasting methods. By combining indigenous and scientific knowledge, farmers can access more comprehensive and reliable climate information, supporting their agricultural decision-making and adoption of climate change adaptation practices. Future research should focus on bridging the gap between indigenous and scientific climate information through collaborative data collection, joint interpretation of climate patterns, and tailored forecasting tools.

2.3.2 Modern Climate Information

Smallholder farmers rely heavily on climate information services (CIS) to manage climate-related hazards and adapt to climate change (Ngigi & Muange, 2022). The two main ways to combat the effects of climate change are the adoption of climate-smart agricultural practices and the dissemination of climate knowledge (Gomez-Zavaglia et al., 2020).

The generation, translation, transfer, and use of climate knowledge and information in climate-informed decision-making and climate-smart policy and planning is generally referred to as Climate information services (CIS) (Vaughan et al., 2018). CIS aims to promote climate-smart agriculture and support adaptation to climate variability and change in agriculture. By influencing farmers and institutional decision-making, it aims to produce local climate knowledge and support efforts to build resilience and manage climate risk (Born, 2021).

There are two main channels through which climate services can enhance the adoption of CSA: Improving farmers' capacity to embrace CSA and strengthening the supportive environment for CSA upscaling. However, because climate information is often improperly disseminated to farmers (Waaswa et al., 2021), the majority of farmers continue to rely on farming practices that do not fully combat the effects of climate change.

Access to services that provide climatic information is a key issue in the sustained use of this type of information for farmer development. The most vulnerable farmers in rural areas have limited access to climate services despite their greater need for them (Buckland & Campbell, 2021; Tall et al., 2014). Factors including appropriateness, timing, dependability, ease of understanding, language, and infrastructural development limit access to climate data (Edwards, 2010). Additionally, socioeconomic factors such as age, gender, education, ownership of communication devices, and access to climatic data also have an impact on the sustainable use of climate information.

The purpose of this study is to analyse how smallholder maize-producing households make decisions concerning their access to various sources of climate information. Ways that could be explored to enhance the use of climate information and maximize the advantages of CSA adoption are evaluated. This is done through the investigation of the link between climate information and the adoption of CSA practices. The use of climatic data to impact mitigation decisions is still sporadic despite increasing research into climate variability and its implications on African agriculture (Ncoyini et al., 2022). For communities in north-eastern Ghana, where vulnerable farmers and land users must modify their practices to ensure their livelihoods, changes in rainfall patterns are especially worrying (Kanchebe Derbile & Abudu Kasei, 2012). Having a better understanding of how climate information affects smallholder decision-making can lead to more successful adaptation plans and better agricultural outcomes.

2.4 Climate-Smart Agriculture as a Farming Practice or Technology

CSA is not a completely new production method, but rather a production philosophy that relies on the already existing tools and devices of conventional agriculture, as well as on new and novel technologies. CSA is a method that includes several aspects entrenched in local settings rather than a collection of procedures that can be used everywhere.

CSA includes investments, institutions, regulations, and technology that are used both on and off the farm. It is narrowly interpreted as either precision agriculture or smart agriculture and the difference lies in their approaches. On the other hand, precision agriculture is a management approach that ultimately aims at input optimization, smart agriculture aims to optimize the entire farming system. Moreover, smart farming relies on farm-level data and other data sources particularly, weather and climate information, which makes it possible for comparison.

CSA can be envisioned as a strategy for reforming and refocusing agricultural growth in light of emerging climate change realities (Lipper et al., 2018). It's all about agricultural techniques that sustainably raise production, improve resilience (adaptation), reduce Green House Gases (GHGs) (mitigation) as much as possible, and help meet national food security and development goals (FAO, 2013; Lipper et al., 2014; Sarker et al., 2019). As a result, the primary purpose of CSA is to improve food security and development, with productivity, adaptation, and mitigation defined as the three interconnected pillars' (FAO, 2013) required to accomplish this purpose.

The first pillar of CSA, which focuses on productivity, entails a long-term rise in agricultural productivity and earnings from both crops and livestock while maintaining environmental quality. The adaptation pillar primarily focuses on CSA, which decreases farmers' short-term risk and strengthens their resilience by increasing their ability to adjust and sustain their livelihoods in the event of long-term climate change stress. The focus here is on preserving the ecosystem services offered to farmers and other living things, whereas mitigation is concerned with CSA activities that should assist in always reducing GHG emissions at all times.

In effect, the key characteristics of CSA that are required to go through these processes and achieve the overriding goal include practices that maintain the ecosystem services (Rubiano et al., 2018), have multiple entry points at different levels context-specific (Mwongera et al., 2017; Shelhamer & Zee, 2003) and CSAs that engages women and marginalized groups (Dhenge et al., 2016; Shilomboleni, 2020)

The ideas above offer various components of a climate-smart agriculture system; the management of farms, crops, and livestock, including aquaculture, to improve food security and livelihoods (Zougmoré et al., 2016), the management of ecosystems and landscapes for conservation purposes(Fenta et al., 2019), farmer services to manage climate risks or impacts (Antwi-Agyei & Stringer, 2021a; Mittal & Hariharan, 2018), and adjustments to the food system that increase benefits of CSA (Zougmoré et al., 2021) are key components of a viable CSA system.

2.5 Climate Change Policy in Ghana

According to the World Bank, if immediate climate action is not taken in Ghana, at least one million additional people could become poor because of climatic shocks. By 2050, income for households in poverty could decrease by up to 40% (World Bank, 2022) as a result of climate change. Ghanaian farmers face challenges such as unpredictable rainfall, rising temperatures, droughts, desertification, pests, diseases, and soil salinization due to sea level rise and tidal flooding (Awuni et al., 2023) To achieve food security and poverty reduction objectives amid climate change, CSA is being included in subregional and national development plans in Africa, which is a project under NEPAD's climate change agenda (Mrabet & Moussadek, 2022).

As one of Ghana's initiatives to combat climate change, agriculture and food security, contributed 27% of the national budget between 2015 and 2020 as a strategy to mitigate climate change impact. (Republic of Ghana, 2021). In addition, various projects have been launched. First, a National Climate Change Committee (NCCC) was created in 2010, and since then, four national climate change documents have been created: the National Climate Change Policy Framework and National Climate Change Adaptation Strategy in 2010, the National Climate Change Policy (NCCP) in 2014, and the National Climate Change Policy Action Programme for Implementation in 2015 (Essegbey et al., 2015; Republic of Ghana, 2013).

The NCCP outlines the vision and objectives, particularly concerning successful adaptation, social development, and mitigation. The policy sought to develop the required human resources as well as structures for climate-resilient agriculture and food security. In 2015, the Consultative Group for International Agricultural Research (CGIAR) released the National Climate-Smart Agriculture and Food Security Action Plan of Ghana (2016-2020) in partnership with the Government of Ghana (Essegbey et al., 2015). This was followed by an Investment Framework for Resource Mobilization into Climate Smart Agriculture (CSA) (FAO & MoFA, 2018) and the Climate Smart Agriculture Investment Plan for Ghana (World Bank & MoFA, 2020). As different agroecological zones and the multilevel nature of implementing these plans in Ghana's decentralized local government system are considered, all of these initiatives aim to provide policy direction for CSA and its integration into agriculture.

Various CSA players, technologies, practices, and investments have been profiled for different agroecological zones in Ghana so far, but CSA mainstreaming remains a challenge, particularly in the savannah ecological zones, despite widespread knowledge of climate change impact on agriculture (Ng'ang'a et al., 2021). The plans lacked relevant data on local climate change trends and impact, resulting in disparities between CSA mainstreaming, development goals, and objectives, generating critical issues regarding ownership and localization, especially in the savannah ecological zones. In addition, there is little mention of climate finance potential to support CSA initiatives in the plans.

2.6 Maize Production System and Yield Indicators

In Ghana, maize is a major cereal staple cultivated for many years mostly by smallholder farmers with little resources and in rain-fed environments (Darfour & Rosentrater, 2016b). Maize accounts for 50% of the total cereal production in Ghana, with reported postharvest losses between 5% and 70%. However, the country will increase overall cereal production until 2080, if the expansion of agricultural land and farmers' practices to climate change are implemented (Fisher et al., 2015a).

The four primary agro-ecological zones for maize agriculture in Ghana are the coastal savannah zone, the forest zone, the transition zone, and the Guinea savannah zone, which covers most of the lands in northern Ghana. The agro-ecological zones' features determine the maize farming system.

It is estimated that about 10 percent of losses in maize yield will occur in 2050 without intervention; an intervention will sufficiently compensate for the degree of losses (Jones & Thornton, 2009). There have been initiatives to double the productivity of maize to enhance livelihood opportunities from sustainable maize-based systems. Scientists at CGIAR have released over 650 superior, high-yielding maize varieties that are stacked with characteristics that are pest and disease-resistant, nutrition-enhancing, and climate-adaptable (Krishna et al., 2023).

Despite some modest progress in the development of maize-based agricultural systems in Ghana, several obstacles still exist in the cultivation, harvest, shelling, transportation, storage, and processing of maize. Poor management techniques, such as low plant populations, improper planting times, inadequate weed control, limited use of inputs particularly fertilizer and improved seeds, improper timing of application of sufficient quantity of fertilizers, improper drying and storage facilities resulting in high post-harvest losses, and limited market access are additional constraints on maize production (Wongnaa et al., 2021). Despite attempts to increase maize production, fall armyworm infestation and extremely heavy rains have recently reduced maize productivity. For instance, a severe El Nino weather phenomenon in 2015/2016 caused a marginal decline in maize output from 1.9 metric tons per hectare in 2015 to 1.7 metric tons per hectare in 2026 (MoFA, 2021; Owusu et al., 2019). Ghana also experienced a severe maize grain crisis between late 2020 and the middle of 2021 as a result of the minor season crop failure in 2020

The northern part of Ghana is characterized by smallholder agriculture in which 80% of the population engages in subsistence farming that is dominated by low farm productivity and farm incomes (MoFA, 2021). The low level of production is caused, among other things, by the insufficient use of improved seed variety, insufficient soil amendments, and restricted access to financing. Barely 20% of farmers utilize enhanced seeds (IPA, n.d.).

Although there has been a steady growth in maize yield in Ghana over the last 30 this trend is not widespread. For example, except Upper West Region, maize yield in the northern regions of Ghana is below the national average. Based on the 2017/2018 agricultural census data, none of the 40 districts of the five northern regions was among the top 10 in maize production (MoFA, 2021). The middle belt regions namely Ashanti, Eastern, and the two Bono regions had relatively higher maize yields in 2020. This trend is consistent with previous data from 2013 to 2016 (see Table 2.3 in the appendix section).

2.7 Review of Choice models

Choice models are the most often used techniques for analyzing the adoption of technology in agriculture. As used by researchers, choice modelling involves efforts to simulate an individual's or a group's decision-making process, based on preferences. Typically, the approach is linked to the employment of discrete options, for example, the choice of X strategy over Y strategy. This choice is associated with the concept of utility maximization. The primary types of choice modelling, probit and logit models, have been used frequently to assess the adoption of CSA practices (Andati et al., 2022; Kifle et al., 2022; Negera et al., 2022). In general, since CSA involves some practices, farmers may choose from, count models or regression models are frequently used to examine the likelihood and extent of technology adoption (Gebru et al., 2021).

The analysis of farmers' adoption decisions regarding climate-smart agricultural (CSA) practices in northern Ghana presents a complex decision-making scenario that necessitates robust econometric modelling. This study argues that both the Binary Logit and Multinomial Logit (MNL) models provide appropriate analytical frameworks for understanding these adoption patterns, considering the unique socio-economic context of northern Ghana and the multifaceted nature of CSA practices. The binary logit model is particularly suitable for analyzing the initial adoption decision of specific CSA practices. Its appropriateness can be justified through several key considerations including the discrete nature of adoption decisions (Feder et al., 1985). utility maximization behaviour (McFadden, 2001) and non-linear probability relationships (Speers et al., 2003). The multinomial logit on the other hand is essential when analysing choices of CSA practices from a set of alternatives including crop diversification, soil conservation, water management, and agroforestry (Greene & Hensher, 2003).

In the context of northern Ghana, the IIA assumption is often reasonable as farmers typically view different CSA practices as independent alternatives, each evaluated on its own merits. The model can incorporate various practice-specific attributes and farmer characteristics that influence adoption decisions (Train, 2009). Therefore, the typical data collected in northern Ghana agricultural surveys naturally align with these models; binary outcomes deal with information on whether specific practices are adopted (yes/no), multiple categories that deal with data on different types of adopted practices, and independent variables that deal with socio-economic characteristics, farm attributes, and institutional factors.

The binary logit model has some advantages such as easy conversion of coefficients for easy interpretability, and less sensitivity to violations of normality assumptions compared to linear probability models (Harrell, 2015; Tillmanns & Krafft, 2022). It also provides clear measures of model fit through pseudo-R^2 statistic (O'Connell, 2006). On the other hand, the MNL's key advantages include the fact that it can incorporate both alternative and individual-specific variables, but its main limitation is that it requires an adequate sample size (Newman & Bierlaire, 2009). With a sample of 566 households, the MNL is therefore adequate for analysis.

The combined use of binary and multinomial logit models provides a robust analytical framework for understanding CSA adoption in northern Ghana. The Binary Logit model effectively analyzes individual practice adoption decisions, while the MNL model captures the complexity of multiple practice choices. Their theoretical foundations, empirical track record, and methodological advantages make them well-suited for this analysis, despite some limitations that can be addressed through appropriate testing and specification procedures. Some studies such as Mulwa et al., (2017) and Ndamani & Watanabe, (2016) support the use of these models in similar contexts.

2.7 Review of Empirical Studies

2.7.1 Climate Information Service Access and Use

Access to and use of climate information services in northern Ghana are significantly impacted by perceptions of climate change (Partey et al., 2020). Born (2021) claims that climate services offer two crucial channels for encouraging the adoption of CSA practices. First, they give farmers the ability to invest in CSA practices at the farm and make climate-informed decisions that may increase their output, income, or food security. Farmers who receive training in using digital tools and analyzing agroclimatic data are better able to understand and implement climate-smart agriculture (CSA) strategies. These efforts help increase the farmers' climate resilience. The second approach is to create a supportive environment. This involves extension policy and helping build the capacity of community and state institutions involved in agricultural development. The goal is to promote initiatives that enhance climate resilience and reduce risks associated with agriculture (Born, 2021).

The importance of access to climate information by smallholder farmers amid devastating climate change can therefore not be over-emphasized. Several empirical studies have analysed the determinants of access to climate information services in northern Ghana; for example, access to climate information and adoption of CSA practices (Alidu et al., 2022; Djido et al., 2021; Zakaria et al., 2020); opportunities and barriers to the uptake of climate information (Antwi-Agyei et. al., 2021) and prioritisation of climate-smart agriculture and climate information services (Damba et al., 2021).

However, despite the vast amount of information available on climate change, there are still difficulties in recognizing the many climate information products and services that suit the demands of smallholder farmers, particularly when it comes to making decisions about response to climate variability at the farm level. For example, poor coordination among government entities responsible for the creation and transmission of useful climate information results in obstacles to getting accurate, timely, and tailored climate information (Antwi-Agyei et al., 2021). Additionally, efforts to mainstream climate services through sectoral policy initiatives to increase the adaptability of stakeholder institutions are frequently overlooked (Naab et al., 2019).

In Ghana, inadequate accurate meteorological and climate data and services, required to facilitate the use of climate-resilient farming techniques, make smallholder farmers more vulnerable (Alidu et al., 2022; Antwi-Agyei et al, 2021). According to available literature, farming decisions, such as land preparation and planting schedules, the kind of seed variety to use, and other tactical decisions to handle the risks of severe weather, are not supported by meteorological and climate information (Asare-Nuamah & Botchway, 2019; Dakurah, 2021).

What connection exists between locally derived climatic information and that based on the modern science of meteorology? Does the farmer comprehend the science-based knowledge and data on climate and weather if he/she has access to them? Is it advantageous to the farmer to use local climate information or non-instrument weather forecasting[1] when making climate decisions at the farm level? Although local weather forecasting is well established in many African communities, including Ghana, comprehensive investigation and documentation of such practices including their accuracy and dependability is mostly missing (Graham et al., 2022; Leal Filho et al., 2022; Osumba, 2022). A complete understanding of how smallholder maize-producing households in northern Ghana acquire and use climatic information in their adaptation to climate change through the use of CSA practices is therefore imperative.

The delivery of agrometeorological products to farmers creates a platform for the on-farm establishment of several diverse adaptation techniques for various farming systems in Ghana, which is also an essential factor to consider. Accessing climate information services involves using and adopting a variety of analytical techniques. Many studies analyze farmers' awareness, access,

[1] When instruments and reports are unavailable, non-instrumental weather forecasting techniques can be employed to corroborate weather reports or make weather predictions.

and use of distributed climate services as well as their decision-making processes concerning weather and climate information products using qualitative methods (Baffour-Ata et al., 2022; Buckland & Campbell, 2021; Gadgil et al., 2002). Therefore, to evaluate maize farm household climate knowledge and its impact on farm-level operation with climate-smart agriculture in northern Ghana, a focus on analytical methodologies that are mostly qualitative and descriptive is imperative.

2.7.2 Determinants of CSA Adoption

CSA is a method of production that makes use of traditional agriculture tools and equipment as well as cutting-edge innovations that can eventually permeate all of agriculture over a long period. It is generally linked to the concept of improving the usage of farm inputs partly through the integration of various agronomic and farming methods and systems. CSA could be seen as a long-term investment as its successful integration into production and socio-economic systems depends on different stakeholders, such as researchers and development partners, responsible governance structures, and supporting agricultural policy (Girvetz et al., 2017). In contrast to the standard, business-as-usual strategy, the site-specific qualities (innovativeness and flexibility) of the CSA may improve resilience and lower food security threats. Inevitably, the use and acceptance of these innovative approaches have drawn considerable attention, particularly in developing nations where the productivity of their agriculture is seriously challenged by climate change and variability.

Due to differences in meteorological conditions, geographic systems, and agricultural production systems, the factors influencing CSA adoption vary significantly among the different regions of the world. Extension services, expertise and skills, and education are prioritized throughout East

Asia and the Pacific (Acevedo et al., 2020). Education is the primary element driving CSA adoption in Latin America, the Caribbean, the Middle East, and North Africa (Mizik, 2021). The primary variables in South Asia are the usage of farm inputs, like seeds and fertilizers, the social status of households, and education. In SSA, extension services, farm inputs, social status, experience, and skills of households are the key determinants of its adoption (Barasa et al., 2021).

The drivers of adoption or non-adoption could also be influenced by ecological conditions and the different types of CSA practices. For instance, farmers' expertise or skills, access to knowledge, high costs-access to financing, input accessibility, and labour intensity all have a significant impact on the adoption and usage of water management strategies such as irrigation, and improved varieties (Mango et al., 2018). Access to climate information services, which is a component of CSA practices, is also impacted by inadequate internet, inadequate knowledge, and bad perceptions of climate change (R. B. Zougmoré et al., 2021). Crop rotation and the use of organic manure were found to be the most popular CSA practices in South Africa based on judgments of compatibility with technical, economic, and environmental factors (Abegunde et al., 2020).

The adoption of CSA in Ghana is influenced by a variety of variables that are dependent on ecological zones. In cocoa-growing regions, for instance, factors such as land tenure, farmer age, farm location, and access to extension services are important factors influencing adoption; whereas in other regions, such as the savannah ecological zones, factors like farmer participation in training programs, attitudes (such as benefit evaluation or risk aversion), and availability of credit or financing are important determinants of CSA adoption (Akrofi-Atitianti et al., 2018; Atta-Aidoo et al., 2022; Zakaria et al., 2020).

2.7.3 Effect of CSA Adoption on Maize Yield and Net Return

In low and middle-income nations, CSA is particularly essential to achieving the United Nations SDGs, which include eradicating hunger and combating climate change (FAO, 2018). One of CSA's objectives is to raise agricultural production and incomes to increase food security sustainably. Some studies have argued that risk management which involves techniques to reduce losses from various sources is one of the climate change adaptation strategies (Adger et al., 2018; Forino et al., 2017; Van Der Pol et al., 2017). The adoption of Climate-Smart Agriculture (CSA) technologies is influenced by several factors, including farmers' risk attitudes. CSA technologies are designed to help smallholder farmers manage climate-related risks in farming and increase farm-level output sustainably (Musyoki et al., 2022). Farmers use ex-ante and ex-post strategies to mitigate potential losses. Ex-ante strategies involve adopting climate-smart agriculture practices, investing in productive assets, and avoiding borrowing. Ex-post strategies, on the other hand, involve coping after losses. Farmers' risk attitudes influence their willingness to adopt climate-smart agricultural technologies, affecting their adoption of these practices.

Rigorous evidence on the effects of CSA practices on crop yields and net returns remains scanty generally, and specifically in sub-Saharan Africa. Understanding the effects of climate change adaptation measures by smallholder farm households in flood-prone areas is also underdeveloped, particularly in northern Ghana which is severely exposed to climate change risk and where the poverty level is high. Besides, CSA technologies are context-specific and the appropriateness of CSA technologies may differ by gender, region, age and cultural dimensions (Mwongera et al., 2017). Each of these play a role in determining the adoption of efficient CSA practices.

Understanding the factors shaping CSA adoption and impacts among smallholder farmers is especially important for promoting agricultural innovations in the face of climate change and essential for the development of climate policy targeting the northern parts of Ghana (Amadu et al., 2020). According to some studies, CSA adoption has a beneficial influence on crop output and revenue (Hasan et al., 2018; Karanja Ng'ang'a et al., 2017; Lan et al., 2018a; Ruales et al., 2020). Smallholder farmers sometimes seek assurances in addition to financial support before implementing any CSA practices that could affect their crop yield and income status (Kakraliya et al., 2022).

On a farm, there is a considerable likelihood that the short-term CSA benefits will surpass the long-term benefits, making smallholder farmers particularly dependent on short-term gains because they lack the financial means to take on significant financial risk(Abegunde et al., 2020). Due to the limited profit margins and high risk involved in agriculture, they opt for CSA practices that produce results right away (Sain et al., 2017). The need to assess the impact of CSA on maize yields across farms is also necessary given that measures for adapting to climate change must be adopted at the farm level, taking into consideration the variations in crop management techniques.

The analytical methodologies used to evaluate the impact of the CSA, however, lean toward a more rigorous economic analysis. Sardar et al. (2021) applied the two-stage least square estimation method. Agbenyo et al. (2021) used the endogenous switching regression framework, whereas the Cost Benefit Analysis (CBA) and Average Treatment Effect (ATE) are largely utilized by others (Anaman, 1996; Karanja Ng'ang'a et al., 2017; Mutenje et al., 2019). By using an augment production function that allows us to understand the complex relationships that drive economic productivity to assess the effect of CSA adoption on maize yield and net returns, this work adds a layer to the methodological discourse of CSA.

These analytical methodologies are likely chosen because they provide rigorous, data-driven approaches to evaluating the economic impacts of the CSA intervention. The combination of techniques, such as 2SLS, endogenous switching regression, CBA, and ATE, allows researchers to address potential econometric challenges, establish causal relationships, and obtain a comprehensive assessment of the economic implications of the CSA program. By using these analytical models, scholars aim to generate robust and reliable findings that can inform policymakers, practitioners, and stakeholders about the economic viability and effectiveness of the CSA intervention.

2.7.4 Determinants of Willingness to Invest in CSA Practices

Scholars and practitioners have given a great deal of attention to the adoption of technological innovations in agriculture because the vast majority of people in developing nations depend on agriculture for their livelihood and because new technology appears to provide the potential to significantly increase production and income (Glover et al., 2016; Pamuk et al., 2014; Senyolo et al., 2018). The introduction of several new technologies in agriculture including CSA however, has only been partially successful as seen by reported adoption rates (Feder et al., 1985; Feder & Umali, 1993; Senyolo et al., 2018). According to common knowledge, barriers to the quick adoption of innovations are mostly attributable to a lack of financing (Teye & Quarshie, 2022; Zerssa et al., 2021), restricted information availability (Shiferaw et al., 2015), aversion to risk, and insufficient farm size (Feder, 1980; Mwangi & Kariuki, 2015; Spiegel et al., 2021) among others.

Despite its promised benefits, CSA sometimes necessitates a large investment in agricultural inputs, which frequently prevents low-income nations from adopting it. However, major efforts have been made to provide funding for Climate-Smart Agriculture (CSA) and other associated climate challenges to enhance smallholder livelihoods and food security in poor nations (Mul et al., 2015; Mungai et al., 2020; Anderson et, al., 2022; Zougmoré et al., 2015).

A thorough impact assessment of climate funding in achieving CSA goals is required to enhance knowledge and guide future investment and development strategies. Yet such evaluations are still lacking because most of the literature is macro-focused and focuses on specific CSA components, such as integrated soil management techniques, conservation agricultural technology (Abdulai, 2016; Katengeza et al., 2019) and investments in physical infrastructure and actors (Totin et al., 2018). This contrasts with a wider range of farm-level CSA practices that are supported by mostly international development organizations. In addition, CSA practices, which are typically not commercialized, make it difficult to evaluate their financial viability at the micro level.

A wide range of factors affect farm-level investment in agricultural technology in general. The first little investments a farmer makes when he decides to experiment with the techniques are his own. If the desire and capacity to do so exist, steadily greater investments are made(Yigezu et al., 2018). resulting in the upscaling of the techniques to many smallholder farmers. Household willingness to invest in CSA is therefore not a simple binary concept that separates investors from non-investors. Farm household economics, socio-cultural and physical characteristics are all taken into account when analysing CSA investment decisions, and certainly, some farmers will invest more than others while others may not be willing to invest at all based on such factors.

The idea is that at least one substantial critical element at the farm household level positively influences CSA investments. What clever ways may this knowledge be put to use to convince farmers who aren't willing to invest in CSA? This information will aid in the development of a more effective CSA strategy and highlight additional initiatives, such as possible commercialization, that could be carried out to increase the number of households participating in CSA activities and also to give suppliers of such practices some financial returns.

2.8 Gaps in the Literature

The extensive literature on CSA practices provides evidence that a variety of individual socio-economic, environmental, and institutional factors, including policy initiatives, do influence their adoption. However, the extant literature is scanty concerning the influence of religion and religious practices on the adoption of CSA practices. Given the universal acceptance of the concept of the Supreme Being or God, throughout the non-Western World, especially in Africa, and the important role associated with how this Being influences decision-making and the outcomes of production processes, including the use of CSA practices, it is important to emphasize the unique role of religious preferences and associations in the choice of CSA practices. For example, from my review, gender and membership in farmer-based associations are cited much more in the CSA literature than religious preferences and beliefs. The study incorporates the important role of religion. The study incorporates the important role of religion in the analysis of the use and adoption of CSA practices.

A second gap in the existing literature is the limited role paid to political-economy factors in influencing the choice and use of CSA practices. While variables such as income, vulnerability and gender are widely reported in the literature to be influential in the uptake of CSA practices, other political-economy variables, which are normally linked to marginalization and social exclusion, such as ethnicity, tribe, lack of links to the political ruling class, inability or very limited role in governance mechanisms, are insufficiently addressed in terms of their influence of the degree of access to and uptake of CSA practices. Political-economy analysis used in this study enhances the role of various variables associated with marginalization and social exclusion to understand the underlying forces influencing the adoption and use of CSA practices.

Third, much of the existing literature deals with a single-analytical approach to evaluating and understanding the adoption and use of CSA practices, especially in Africa. The literature is heavy with analytical tools which tend to exclusively use econometric and regression procedures to evaluate CSA practices. Regression analytic procedures, which are used in the CSA and climate change adaptation literature, including the treatment and effects literature, tend to offer average-type responses to the influence of inputs; they are not ideal techniques when dealing with the appropriate optimal choice of CSA techniques for an individual or a group of individuals, for example, the optimal strategies for a group of highly-risk averse farmers in a particular area.

This study approaches the issue of adoption of CSA techniques by farmers through the use of a dual approach of investigation based on the widely used econometric analysis often involving surveys plus the approach of qualitative analysis involving in-depth interviews of 15 ordinary farmers 5 elites in climate change science and adaptation who were resident in the survey area. The overall methodological approach used in this study is further discussed in the next chapter, Chapter 3. It involves eliciting data from the masses through a survey of 566 households.

Finally, the literature reviewed does not fully address the concurrent use of different modes of production in the use of climate information and CSA strategies. Historically, throughout the 200,000-year known history of human beings, starting with the evolution of the human species in Africa, there have been four main modes of production. These are (1) the subsistence mode of production where the person produces the good or service for himself/herself or his/her family, (2) the market-based production where the producer produces a good that is exchanged for money or payment-in-kind with a consumer, (3) the hierarchical mode of production which involves production based on a ladder of structures where people in the higher-level structures give instructions to those in the lower-level structures for the production of goods, and (4) the slavery mode of production which involves human beings being treated as commodities to be used to produce goods and services for their owners.

This study approaches the use of climate information and the adoption of CSA techniques using three modes of production – (1) the subsistence mode, (2) the hierarchical mode, and (3) the market mode. The subsistence mode of production is covered in Chapter 4 where the production of climate information by farmers themselves for their use, based on indigenous knowledge and intuition, is discussed. The market-based mode of production is covered throughout Chapters 4 and 5. The hierarchical mode of production is tackled through the flow of climate information from elites (more influential farmers, experts and government extension officers) to the masses (ordinary farmers). This hierarchical mode of production is extensively covered in Chapter 6.

The literature review emphasizes the significance of CSA practices for achieving the United Nations SDGs, particularly in low- and middle-income countries, as well as the necessity of understanding the variables that influence the adoption of effective CSA practices, particularly among smallholder farmers in sub-Saharan Africa's flood-prone regions. The review suggests that the adoption of CSA practices varies by region of the world, with education being a primary driver in Latin America, the Caribbean, the Middle East, and North Africa while extension services, knowledge and expertise, and education are prioritized in East Asia and the Pacific. Other factors like ecological circumstances, accessibility to funding, expertise, extension services, agricultural inputs, social networks, and the experience and abilities of households are all important drivers of adoption in South Asia and Sub-Saharan Africa.

CHAPTER THREE

METHODOLOGY AND PROCEDURES USED FOR THE STUDY

3.1 Introduction

The research's methodology and procedures are presented in this chapter. The theoretical framework is first presented, highlighting the theoretical foundations of the objectives as well as the analysis techniques and implications associated with the data requirements. The conceptual framework that demonstrates how the research objectives fit together comes next. The theoretical framework and the study's techniques and processes are connected by the conceptual framework. The chapter also presents a section on data collecting techniques design, which includes a description of the study area and a summary of relevant information about the population, weather conditions, and agricultural activities. The Chapter concludes with a section on ethical concentrations in the research process.

3.2 Theoretical Framework

The science of neoclassical economics, beginning with the classical work of Professor Alfred Marshall in 1890, suggests that an economically-rational person maximizes his/her utility or satisfaction based on the consumption of the maximum possible material goods and services that are available given his/her budget limitations. This rational person therefore chooses the best or optimal amounts of goods and services guided by the limitations of his/her income and endowments (Borah & Kops, 2019; Schettkat, 2018). This utility maximization paradigm provides an underlying theoretical framework of the models used to predict the adoption and use of CSA strategies that were utilized in this study.

However, a human being is not a machine but a biological entity made up of several "psychological selves" with the dominant self-being the economically rational self (refer to a discussion of the multiple selves' theory from scholars such as Callahan et al. (2009) and Lester (2020). Cognizant of the multiple selves' paradigm, linked to the fact that an individual has limited cognitive abilities to process the numerous activities and actions involving the production, distribution, and exchange of material goods and services, the CSA adoption models used in this study, include other important variables, not normally captured by neoclassical economics science, but which are situated in the general area of political economy analysis.

Adopting climate-smart agricultural strategies and using inputs result from diverse agents' optimization (Jayne et al., 2016). This optimization occurs in the context of a limited budget, information, credit availability, the availability of technology and other inputs, influences of social and political mechanisms, and cognitive limitations of human beings. Starting from the neoclassical theory of human behaviour based on economic rationality, it is assumed that farm households make decisions about the choice of CSA practices through the lens of constrained optimization. This constrained optimization is directly linked to the available information, resources and existing technology. Adoption and use of CSA is predicated on the individual farmer or household assessing the expected costs and expected benefits and making the choice based on their risk preferences. The difference between the utility of adopting CSA and the utility of not adopting can be denoted as U_I^* , such that utility-maximizing farmer 'i', will choose to adopt the CSA if the utility gained from adopting is greater than the utility from not adopting:

Ui* = U_IAdopt – U_INonAdopt > 0) **Equation 3.1**

These utilities which are unobservable can be expressed as a function of observable elements in the latent variable and the adoption decision can be modelled as follows:

$$U_I^* = \text{Xi}'\beta + \mu_i \text{ with Ui} = \begin{cases} 1 \; if \text{ Ui}^* > 0 \\ 0 \; otherwise \end{cases} \qquad \textbf{Equation 3. 2}$$

Where U_I^* is a latent variable that measures the likelihood of farmers choosing a CSA strategy. It assigns the value ‘1' for adoption and ‘0' for non-adoption. Xi′ stands for explanatory variables for adoption by maize farmers, β is a vector of parameters to be estimated in the CSA adoption, and μ_i stands for an error term that is supposed to be independent and normally distributed as u_i N. (0, 1).

3.3 Conceptual Framework of Climate Information Use and CSA Adoption

The conceptual framework is presented in Figure 3.1. Climate change is commonly defined as significant changes in global temperature and measures of climate occurring over decades or it is a long-term shift in temperatures and weather patterns (Bodansky, 1993). As a result of their reliance on rain-fed agriculture, smallholder farmers in developing nations are particularly susceptible to weather variability resulting from climate change. The vulnerability of these farmers has increased due to changes in rainfall patterns, rising temperatures, frequent floods and droughts, crop diseases, and pest infestations.

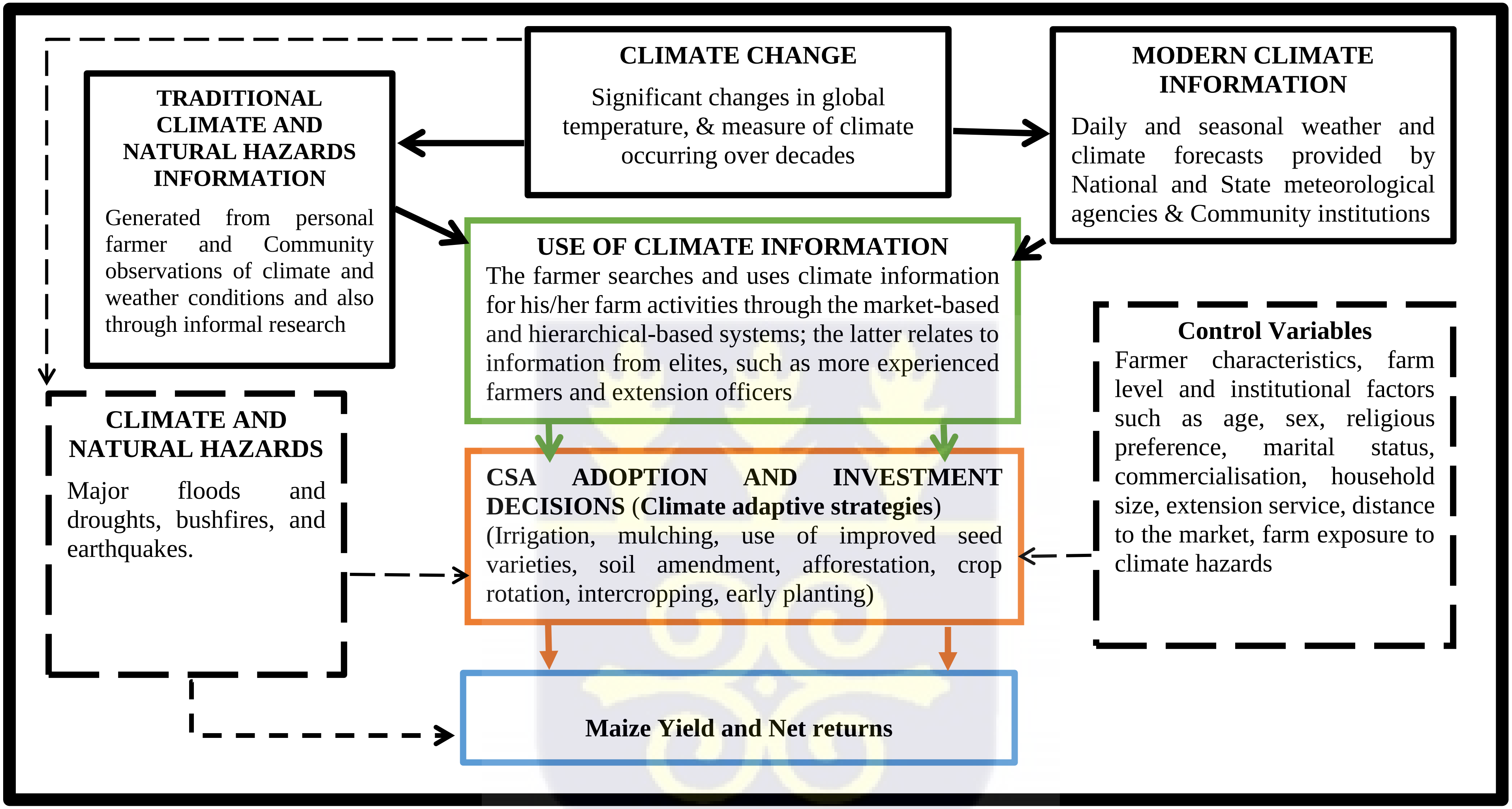
It provides context for understanding the requirement for accurate climate information to adjust to changing circumstances. There are two strands of getting climate information: The daily and seasonal weather forecasts offered by national meteorological agencies and other organisations are considered scientific or modern climatic information. It reflects the most recent developments in science and technology for gathering and disseminating climate data. Personal observations of the weather are included in traditional climatic information; these observations are frequently based on socio-cultural orientation and occasionally formalised through traditional knowledge. It symbolises traditional or earlier methods of interpreting the climate. In this study climate change, scientific or modern climate information and traditional climate information are considered independent variables while the use of climate information in farm-level decisions and adoption and investment in climate-smart agricultural practices are mediating variables.

The use of climate information is a key component linking climatic data (both traditional and contemporary) to agricultural practices. It affects choices made in a variety of farming-related decisions such as land preparation, water management, seed variety selection and planting schedules, fertiliser selection and application, weed, pest and disease control measures and harvesting. Using climate information to support decisions leads to the adoption and investment in climate-smart agricultural practices related to irrigation, mulching, use of improved seed varieties, soil amendment, afforestation, crop rotation, intercropping, and early planting. However other influencing factors which served as control may include farmer characteristics, farm level and institutional factors age, sex, religious preference, marital status, commercialisation, household size, extension service, distance to the market, and farm exposure to climate hazards. Increased maize productivity, measured by both yield (quantity of maize produced) and net return (profitability), is the central outcome of interest in this study.

In effect, the conceptual framework establishes the interrelated challenges of climate change, climate information sources (both traditional and modern), the use of climate information, adoption and investment in climate-smart agricultural practices, and the subsequent effect on maize production. The larger context of climate change emphasises the pressing need for adopting resilient farming practices. While traditional climate information represents indigenous knowledge, modern climate information offers exact data. The decision-making process for farming practices is influenced using climate data, which eventually affects the productivity of maize by encouraging the adoption of climate-smart practices.

The primary argument of the study contends that efficient use of climate data will encourage adoption and investment in climate-smart agricultural practices, thereby increasing maize production. This paradigm provides a methodical way to investigate how climate knowledge affects agricultural choices and raises production, especially in the context of coping with climate change. It emphasises how crucial it is to utilise both conventional wisdom and cutting-edge scientific information to advance sustainable agriculture in the context of changing weather and climate conditions.

FIGURE 3. 1: CONCEPTUAL FRAMEWORK OF CLIMATE INFORMATION USE AND ADOPTION



Source; Author's elaboration from literature 2023

3.4 Description of Researcher-Managed Survey of Maize Farmers in Northern Ghana

In this study, a researcher-led survey of 566 smallholder maize farm households in five districts of the Northern, Upper East and West Regions of Ghana was conducted. Following a brief pre-testing survey in May 2022, the survey was conducted from June to August 2022. The survey questionnaire can be found in Appendix 1 of the report.

3.4.1 Research Design

A mixed-methods research approach was used in this study to evaluate the adoption strategies of Climate-Smart Agriculture (CSA) in the Northern, Upper East and West regions of Ghana. The major goal was to collect quantitative data through a cross-sectional survey, digging into various CSA adoption strategies such as the use of enhanced maize seed, irrigation, soil fertility enhancement, and other relevant measures. A smaller qualitative analysis was also carried out, consisting of 25 in-depth interviews with prominent farmers and specialists in climate change and CSA practices within the study's geographical scope. The cross-sectional survey method allowed for direct data gathering from respondents from June to August 2022.

3.4.2 Sampling and Data Collection Techniques

To select the 566 maize-producing households, the study used a multi-stage random sampling technique. 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 the Ministry of Food and Agriculture (MoFA) Facts and Figures for 2020. The sample size was determined based on certain 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 the researcher does 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 an extract from the Ghana Agricultural Census data for 2018 obtained from MoFA (2020). The study calculated a sample of 1,113 smallholder maize or cereal staple farmers based on administrative regions and districts. However, due to time and resource constraints, only 50% of the estimated sample was used for the study, resulting in 566 cases chosen and the quota sampling technique was used to allocate the samples to the study communities based on their urban or rural nature.

The significance threshold was set at 0.05%, with a 95% confidence level, using the Yamane (1973) formula denoted in Equation 3.3. The Yamane, (1973) formula was used to estimate the sample distribution for the three study regions (Northern, Upper East, and West regions):

$$n = \frac{N}{1 + N(\propto^2)} \qquad \textbf{Equation 3.3}$$

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 In Table 3.1, the specifics of the sample size determination are shown. For example, the sample for Savelugu Municipality was estimated as follows in Equation 3.4

$$n = \frac{N}{1 + N(\propto^2)} = \frac{4{,}336}{1 + \ 4{,}336\,(0.05^2)} = \frac{4{,}336}{11.84} = 366 \qquad \textbf{Equation 3.4}$$

From Table 3.1 the quota sampling approach can be observed across the three regions presented. In the Northern region, which has a total of 86,732 cereal staple households, the selected sample of 186 households was distributed across three rural communities: Tibali, Kundonayili, and Duko, each receiving 62 households. These communities were identified as rural due to their relatively lower household numbers compared to the urban areas in the region.

Moving to the Upper East region, which has 54,936 cereal staple households, the selected sample of 191 households was divided between two communities: Nyariga with 95 households and Nankalkania with 96 households. While the table doesn't explicitly list all communities, these numbers suggest a balanced distribution between rural and urban areas, with the unlisted urban communities likely having higher household counts. In the Upper West region, which has the smallest number of cereal staple households at 28,675, the selected sample of 189 households was allocated between two communities: Busa receiving 89 households and Jirapa receiving 100 households. Similar to the other regions, these communities were identified as rural based on their relatively lower household counts compared to the urban areas in the region. This quota sampling approach ensured a representative sample across both rural and urban communities within each region, although the urban communities with higher household counts are not explicitly listed in the table. The method demonstrates a systematic approach to data collection that captures the diversity of household distributions across different community types within each region.

TABLE 3. 1 SAMPLING FRAME AND SAMPLE SIZE DETERMINATION

Region/Dist.	Community Name	Cereal Staple HH	Study District HH	Estimated sample	Selected Sample
Northern		86,732	4,336	366	**186**
	Tibali				62
	Kundonayili				62
Savelugu	Duko				62
Upper East		54,936	6,043[2]	375	**191**
Bolga	Nyariga				95
Kassena N	Nankalkania				96
Upper West		28,675	5,162[3]	371	189
Wa	Busa				89
Jirapa	Jirapa				100
TOTAL				**1,112**	**566**

Source: Author's elaboration from MoFA, (2021) and GSS (2021 & 2020) data

Then 10% was added to the selected sample to allow for under-sampling in case of non-responsiveness making a total sample size of 666 for the study. The study relied heavily on original data gathered through a survey. Where maize-producing households were the primary participants. The survey questionnaire is in the appendix section of this report.

3.5 Methods of Analysis of the Survey Data

The study used a combination of descriptive and econometric analysis for the data. Descriptive statistics were used to analyse farmers' access to and use of climate information products and

[2] Average HH for Bolga and Kassena Nankana
[3] Average HH for Wa and Jirapa

services. The multinomial logit was used to assess the factors influencing the adoption and use of Climate Smart Agriculture strategies among maize farm households in Northern Ghana. The Generalised Linear Model and Logit regression were used to analyse the effect of CSA adoption on maize yield and net returns and households' willingness to invest in CSA practices respectively.

3.5.1 Descriptive and Qualitative Analysis of Climate Information Access and Use

To achieve research objectives 1 and 2 a combination of qualitative techniques such as in-depth interviews descriptive and inferential analytical techniques was utilized. This involved the use of a correlation matrix and contingency tables, in addition to chi-squared tests, to gain further insight into district-specific trends observed in the study. Factor analysis was utilised 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. In this regard, various input variables, including the onset of rain, precipitation, temperature, wind direction/speed, sunshine, and humidity were considered. These factors were examined concerning farm-level decisions, such as land preparation, water conservation, seed variety selection, planting schedule, fertilizer application, pest and disease control, weed control, and harvesting.

Employing different methods has the advantage of obtaining detailed insights into the elements that increase the chance of a person being aware of, having access to, and utilizing a particular climate information service. Given that farmers engage with climate service products in various ways, this approach aligns with the complex systems concept on which this research is founded.

Thus, 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.

3.5.2 Multinomial Logit Analysis of CSA Adoption

Principal Component Analysis (PCA) and a multinomial logit regression model were used to assess factors influencing maize farm households' adoption of CSA practices. The PCA was used to determine the number of practice 'combinations' and the technologies that comprise them.

PCA is a Cluster analysis with statistical exploratory data analysis that compresses a large set of variables into a smaller set of representative variables. The original data in this analysis are binary dummies that record current CSA practices in northern Ghana. Based on 11 dummy variables representing the variety of CSA practices, the study divided farmers based on three CSA practice combinations using the K-means clustering approach. These include, the use of irrigation facilities, crop rotation, mulching, drought-tolerant maize, disease-pest tolerant maize, early planting, maize intercropping with other crops, landscaping, organic amendment, afforestation, and delayed weed control. The primary CSA methods adopted by maize-producing households were characterized by the PCA analysis as improving soil fertility, using improved maize varieties, and conventional crop rotation.

Second, the multinomial logistic regression model was used to explain the adoption of the CSA bundles that were created (improving soil fertility, using better maize varieties, and conventional crop rotation). Given the variety of CSA practice combinations, the appropriate econometric model is a multinomial probit (MNP) or multinomial logit (MNL) regression model, particularly when dealing with an unordered, categorical dependent variable. Technically, these models are identical: the only difference is in the distribution of the error terms (Kropko, 2007a).

The MNL model was used to estimate the effect of the explanatory variables on a dependent variable that included multiple combinations of unordered response categories; improved maize seed variety use, soil fertility enhancing option and the traditional crop rotation option. The MNL has the advantage of allowing the analysis of decisions across more than two categories (Wooldridge 2002). The MNL is also claimed to be superior to the MNP because it is computationally simpler, although it makes the frequently incorrect independence of irrelevant alternatives (IIA) assumption (Kropko, 2007b).

Empirical Model Specification

The multinomial logit is used to estimate how marginal changes in the independent variables will affect the likelihood of adoption of one set of CSA strategies relative to another The MNL model's theoretical foundation is centered on random utility theory, which emphasizes that consumer preference is primarily modelled using a discrete choice utility framework. Farmer utility is thus influenced by farmer socioeconomic characteristics and other institutional and macroeconomic factors. Therefore, for each CSA practice, a combination ‘j’ or ‘k’ for the i^{th} farmer, the Utility function can be expressed as: in Equation 3.5

$$U_{ij} = \beta_j X_I + \varepsilon_J \; and \; U_{ik} = \beta_k X_I + \varepsilon_k \qquad \textbf{Equation 3.5}$$

where: U_i and U_k are perceived utilities of practice bundles j and k, respectively. X_i is the vector of explanatory variables β_j and β_i are parameters to be estimated and ε_J and ε_k are error terms assumed to be independently and identically distributed with a mean equal to zero.

The probability that a maize farm household *i* with characteristics *x* chooses CSA practice adoption option j over k occurs when the utility from combination j is greater than the utility from combination *k* ceteris paribus is defined as follows in Equation 3.6:

$$U_{ij}\left(\beta_j X_I + \mu_I\right) > U_{ik}(\beta_k X_i + \mu_K),\ k \neq j$$ **Equation 3.6**

Following the works of Greene & Hensher, (2003) and Mujeyi et al., 2020) the probability of a farmer adopting a bundle of CSA practices is assumed to be a function of farmer attributes. In this study, such attributes are farmer socio-demographic, economic and institutional factors. Therefore, the probability of a maize farm household using a particular bundle *j* among the set of bundles available is expressed as indicated in Equations 3.7a, 3.7b and 3.7c.;

$$P\ (Y = 1/X) = \mathrm{P}\ (\cup_{ij} > \cup_{ik}\ |X)$$ **Equation 3.7a**

$$= P\ (\beta_j X_I + \mu_i - \beta_k X_i + \mu_k > 0|X)$$ **Equation 3.7c**

$$= P\ (\left(\beta_j - \beta_k\right) X_i + \mu_i - \mu_k > 0|X)$$ **Equation 3.7c**

Where P is a probability function, $\beta_j - \beta_k$ is a vector of unknown parameters which is a net influence of the vector of independent variables explaining CSA adoption, $\mu_i - \mu_k$ is a random disturbance term. The dependent variable P (Y=1/X) is the probability of adopting a CSA, where 1 denotes adoption, 0 denotes non-adoption, and X denotes a bundle of CSAs. Following a

Principal Component Analysis of all accessible CSA practices utilised by farmers, these bundles are divided into three groups in this study. The constructed bundles include soil fertility-enhancing practices, improved maize varieties, and conventional crop rotation. The description of the variables used is presented in Table 3.2 in the appendix section.

Assumptions:

The data was appropriate to use. All six fundamental assumptions of the MNL model were met.

1. Three categories were used to measure the dependent variable at the nominal level (use of improved maize seed varieties, soil fertility enhancing CSA and conventional crop rotation.
2. To guarantee the independence of the observations, the dependent variable categories were defined to be mutually exclusive and exhaustive.
3. There are continuous, ordinal, or nominal independent variables. All ordinal variables, however, were changed to either continuous or all categorical
4. Some of the variables were eliminated due to multicollinearity issues to assess how strongly each independent variable affected the dependent variable.
5. The continuous independent variables' linear relationships were examined.
6. All outliers, high-leverage values, or highly influential points were removed from the data

Assumptions 4, 5, and 6 were checked using SPSS Statistics.

3.5.3 Effect of CSA Adoption on Maize Yield and Net Returns

The utilization of innovative technologies, particularly climate-resilient practices, within contemporary agriculture plays a pivotal role in bolstering agricultural output and ensuring food security. Through the optimization of resource utilization and the enhancement of yield outcomes, the adoption of Climate-Smart Agriculture (CSA) practices, such as irrigation, early planting, utilization of improved seed varieties, afforestation, crop rotation, and soil fertility enhancement techniques, possesses the transformative potential to revolutionize the agricultural sector. With this objective in mind, this study employs the production function framework—an established analytical method widely utilized in agricultural economics and farm management. The primary aim is to investigate the effect of CSA adoption or investment decisions on farm productivity.

A production function is a fundamental concept in economics science; it is used to describe the relationship between inputs and outputs in the production process of a firm or economy. It provides a mathematical or functional representation of how various combinations of inputs are transformed into outputs, indicating the maximum amount of output that can be produced for a given set of inputs. The most common form of a normal production function is the Cobb-Douglas production function, which allows you to assess the impact of multiple input factors, on crop output or yield.

Following Varian & Varian, (1992) and Gujarati & Porter, (2009), this production function in its stochastic form can be expressed as follows:

$$Q = A{*}L^{\propto} * L^{\beta} * M^{\gamma} \ldots \qquad \textbf{Equation 3.8}$$

Where Q represents the quantity of output produced, A is a constant term representing total factor productivity or technology, L is labour input, K and M represent capital and material inputs respectively while $\propto, \beta$ and γ are the output elasticities of labour, capital and material.

To understand how changes in inputs impact output, researchers in practice estimate the values of the parameters A, $\propto, \beta$ and γ using empirical data and statistical approaches like Ordinary Least

Squares (OLS) regression (Boyd, 2008). In this regard and following the work of (Gujarati, 2022), the Cobb Douglas in its stochastic form can be expressed as follows:

$$Y_t = AX_1^{\beta 1} X_2^{\beta 2} \ldots . X_n^{\beta n\, e\, \varepsilon} \qquad \textbf{Equation 3.9}$$

Where Y_t represents the dependent variable yield or output, $X_1 \ldots . X_n$ are vectors of explanatory variables, $\beta_1 \ldots . \beta_n$ are parameter estimates, A is a constant term, e is the base of the natural logarithm and ε is the disturbance term

However, it has been established by studies such as Demirer, (2020) and Mishra, (2007) that an augmented production function incorporates extra variables or elements to offer a broader representation of the production process because the conventional production function normally takes into account only inputs of production like labour and capital. These extra variables may be connected to technology, human capital, natural resources, or other production-influencing variables such as CSA practices. As such the non-linear form of Cobb-Douglass in Equation 3.9 can be restated by taking the natural log of both sides of the equation to become log-linear to give direct elasticities of the variables:

$$lnY_t = \beta + \beta_i \sum_{i=1}^{n} lnX_i + \varepsilon_i \qquad \textbf{Equation 3.10}$$

This can be stated in a functional form as:

$$lnY_t = \beta_0 + \beta_1 lnX_1 + \beta_2 lnX_2 \ldots . . \beta_n lnX_b + \varepsilon_i \qquad \textbf{Equation 3.11}$$

Where lnY_t is the natural log of the dependent variable (yield or output). $lnX_1 \ldots . lnX_n$ is the natural log of the explanatory variables (factor inputs and other elements that impact production). Equation 3.11 is modified into a Generalised Least Squares (GLS) estimation to overcome the heteroscedasticity problem associated with OLS. This transformation entails subjecting each of the related variables to a proper mathematical transformation.

$$tralnY_t = \beta_0 + \beta_1 tralnX_1 + \beta_2 tralnX_2 \ldots . . \beta_n tralnX_b + \varepsilon_i \quad \textbf{Equation 3.12}$$

Where $tralnY_t$ is the transformed value of the dependent variable (yield), $tralnX_1 \ldots \ldots tralnX_N$ are the transformed values of the explanatory variables including factor inputs and other elements.

Empirical model

In this study, an augmented production function which is a modification of the traditional production function is used to model the relationship between CSA adoption and maize yield and net return measured on a per hector basis. The augmented production function includes other independent variables, beyond the traditional factors of production such as land, labour, capital and management. The additional variables are largely human capital inputs such as formal educational attainment, experience in crop farming, age of the farmer, reflecting his/her biological human capacity status, specialist vocational and educational training and investments in migration.

Yield Equation

$$tralnY_t = \beta_0 + \beta_1 tralnX_1 + \beta_2 tralnX_2 \ldots . . \beta_n tralnX_b + \varepsilon_i \quad \textbf{Equation 3.13}$$

Where $tralnY_t$ is the transformed log of yield per hector (measured in kg/ha) $tralnX_1 \dots \dots tralnX_n$ are transformed logs of the explanatory variable which include, age, sex, education, and farming experience. marital status, household size, climate information use, farm size, farm exposure to climate hazard, use of improved maize seed variety (CSA1), and use of soil fertility enhancing agronomic practices (CSA2).

Net Returns Equation

$$tralnNetR_t = \beta_0 + \beta_1 tralnX_1 + \beta_2 tralnX_2 \dots \dots \beta_n tralnX_b + \varepsilon_i \qquad \textbf{Equation 3.14}$$

Where $tralnNetR_t$ is the transformed log of Net Return per hectare (measured in Ghana cedis), $tralnX_1 \dots \dots tralnX_n$ are transformed logs of the explanatory variable which include, age, sex, education, and farming experience. marital status, household size, climate information use, farm size, farm exposure to climate hazard, CSA implementation cost, use of improved maize seed variety (CSA1), use of soil fertility enhancing agronomic practices (CSA -2).

Assumptions under CSA effect on Yield and Net Returns as measured on per hector basis:

1. Maize yield changes indicate indirect consequences of CSA practice adoption (Branca et al., 2021).
2. Yield changes would differ across the three alternative CSA combinations (improved seed variety use, soil fertility enhancing and crop rotation options) depending on how each of the combinations is implemented, soil quality, and other geophysical factors such as topography and slope (Liliane & Charles, 2020; Michler et al., 2019).

3. It is assumed also that a wide variety of factors, such as management and financial capabilities of farm households and the operation and quality of agricultural resources such as CSA, affect net returns or farm profitability, which is measured as revenue per hector less cost per hector in this study.

3.5.4 The Determinants of Households' Willingness to Invest in CSA Practices

The drivers of maize farmers' household annual willingness to invest (WTI) 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:

$$V(y - WTI,_{p,q1} : Z) = V(_{y,p,q0} : Z) \quad \textbf{Equation 3.18}$$

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:

$$meWTI = \frac{1}{n}\sum_{i=1}^{n} yi \qquad \textbf{Equation 3.19}$$

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 & 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 (Aldrich and Nelson, 1990): When using OLS regression with a binary dependent variable (0,1), the results show heteroscedastic error structure and inefficient parameter estimations. As a result, confidence interval creation and hypothesis testing become unreliable and possibly deceptive. 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 (Amemiya, 1981; Hills et al., 2018; 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:

Logit (P (Y = 1)) = $\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon$ **Equation 3.20**

Where P (Y=1) represents the probability that a maize-producing household is willing to invest an average amount of money they proposed to spend in climate-smart 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, $X_1 \ldots\ldots X_n$ 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.

3.5.5 Perceptions of Climate Change and CSA Practices among Experts and Smallholder Farmers:

The study employed interviews conducted with 15 farming households drawn from the five distinct districts located in the Northern, Upper East, and West regions of Ghana. It also included one-on-one discussions with five climate change research specialists. All of the responses from these interviews were painstakingly written down and then analysed using the following thematic categories: Attitudes towards formal and indigenous climate information, access to climate and utilising climate information, and coping with climate change challenges.

3.6 The Study Area

This study was undertaken in three regions of Northern Ghana. These are the Northern region, Upper East region, and Upper West region. It covered five districts and seven communities identified as climate-smart communities based on ongoing CSA projects.

3.6.1 Geographical Location

The Northern part of Ghana which consists of Northern, North East, Savannah, Upper East and West regions is bordered by the Bono region to the south, Volta region to the southeast, Republic of Togo to the East, La Cote d'Ivoire, and Burkina Faso to the West and North respectively. The surface of these regions is generally flat, except for Gambaga escarpment. Broad grassland in the area is dominated by trees including acacia, baobab, shea nut, dawadawa, mango, neem, and others. The annual rainfall is between 750 and 1050 millimetres, with maximum temperatures at the end of the dry season (March/April) and minimum temperatures in December and January.

3.6.2 Rainfall and Climatic Conditions

The northern part of Ghana has only one rainy season; this season occurs from May to October. The Upper East region has a hot and dry climate with yearly average temperatures ranging from 15^0 to 45^0 C in the dry season; relative humidity ranges from 30 percent to 80 percent in the wet season. Between May and October, the average yearly rainfall is between 950 and 1100 mm. The dry season, which lasts from November to April, is marked by chilly, dry, and dusty harmattan winds. An early to normal onset, usually late to near normal cessation, and a considerable probability of shorter dry spells are the characteristics of the rainfall season for Northern Ghana (Ansah et al., 2020; Ghana Meteorological Agency, 2016; Ghana Meteorological Agency, 2022).

3.6.3 Demographic Characteristics

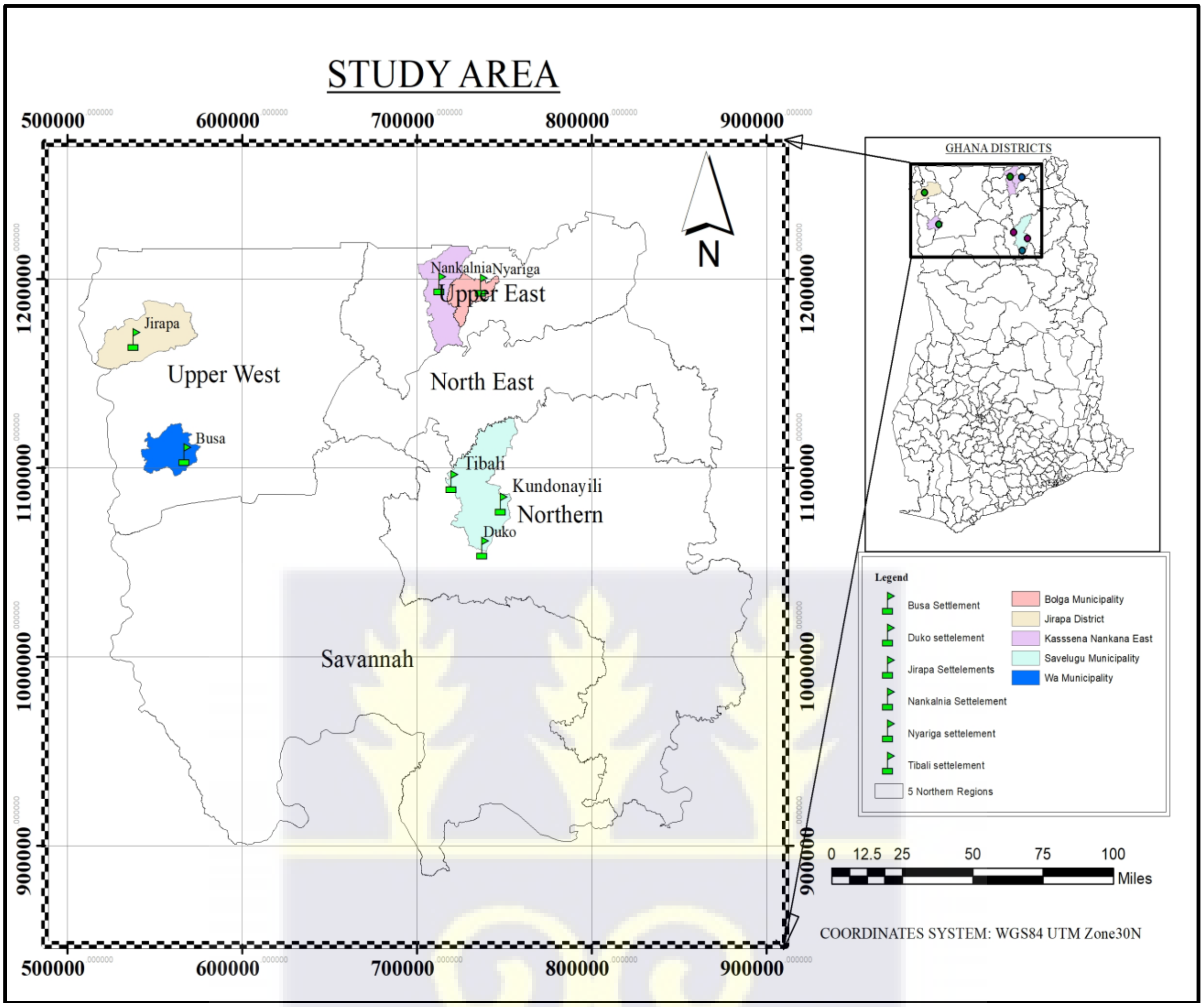
The 2021 Ghana Population and Housing Census (PHC) provisional report put the population of the Northern region at 2,310,939 (49.4 percent males 50.6 percent females and 53 percent youth), with 6.0 percent rural and 4.5 percent urban populations. Upper East region has a population of 1,301,226 (48.5 percent males, 51.5 percent females, and 56.1 percent are youth) with 5.1 percent rural and 4.2 percent urban populations while the Upper West region has a population of 901,502 (48.8 percent males and 51.2 percent females, 56.8 percent are the youth) with 5.1 percent rural and 3.6 percent urban population (GSS, 2021). The literacy level is 44.2 percent, 49.2 percent, and 52.4 percent in the Northern Region, and Upper West Region and 52.4 percent, respectively (GSS, 2021).

3.6.4 Agricultural Activities

Agriculture has always been an important and frequently leading source of livelihood in northern Ghana with the most prevalent crops being maize, sorghum, and millet which are sometimes intercropped with legumes and other crops (Darfour & Rosentrater, 2016b). These crops including rice are the major food crops grown in the area and are often intercropped with other crops and legumes. About 80% of families in Northern Ghana are engaged in the cultivation of cereal crops (GSS, 2021). Agricultural production is thus the main economic activity in the area, which is mostly done on a seasonal and subsistence basis. Farm holdings are small with an average size of less than two hectares (Bawa, 2019).

The main farming system is traditional with the hoe and cutlass being the primary farming tools. Little mechanized farming is undertaken in this area. However, bullock or animal traction-based farming is practiced in several parts of Northern Ghana, including the study areas of Northern, Upper East, and Upper West Regions. Based on information from the 2021 Census, the number of agricultural households in the Northern, Upper East and Upper West Regions were 297,743, 186,859 and 98,036, respectively (MoFA, 2021). The specific study areas and communities where the research study was undertaken are indicated in Figure 3.1.

FIGURE 3. 2: GEOGRAPHICAL LOCATION OF STUDY AREA



Source; Town and Country Planning Ghana 2023

3.7 Ethical Considerations

Because the study's aim and objectives were fully disclosed and explained to all participants, their identities, as well as their political and socio-cultural backgrounds, were kept private. In effect, the study considered the research participants' protected rights to improve research validity and maintain scientific integrity. In this regard, the research proposal, data collection tools, and protocol permission documents were submitted to the University of Ghana's Ethics Committee for

Basic and Applied Sciences for full board evaluation and approval was given before data collection was implemented in 2022.

3.8 Conclusion

An overview of the methodology used for the study has been discussed in this chapter. This overview consisted of the theoretical foundation, the conceptual framework, the theoretical framework, and the survey methods used to collect data from the randomly selected farmers.

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CHAPTER FOUR

RESULTS AND DISCUSSION

USE OF CLIMATE INFORMATION AND ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES

4.1 Introduction

In this chapter, the findings of research objectives 1 and 4, which investigate how maize-producing households utilise climate information and make investment decisions about CSA practices, are reported. First, the socio-economic characteristics of the respondents are summarized and described. Then, the results of the respondents' assessment of the availability of climate information services, including both science-based climate data and indigenous knowledge are reported. This is followed by the results of the analysis of the use of climate information services by the respondents. The fourth section of this chapter is devoted to the impacts derived from the use of climate information by the farmers. The fifth section deals with the impacts of climate information arising from the farmers' decisions to invest in CSA practices followed by the conclusions of the chapter.

4.2 Socioeconomic Characteristics of the Respondents

The socioeconomic characteristics of respondents, presented in Table 4.1, offer critical insights into the sociocultural diversity and demographic composition of northern Ghana. These characteristics align with existing studies that emphasize the need for climate adaptation strategies that reflect the varied sociocultural and economic landscapes of West African communities (Adger et al., 2009; Tschakert et al., 2014). Understanding these factors is essential for designing climate change interventions that address the specific needs and preferences of diverse subgroups within this population. The gender composition of the sample, with 80% of respondents being male, highlights a pronounced gender imbalance. Literature on gendered impacts of climate change in agrarian societies underscores that male-dominated samples may influence both economic activities and the effectiveness of gender-specific interventions (Bryan et al., 2018; Carr & Thompson, 2014).

This imbalance suggests the potential need for tailored approaches that engage both men and women in economic and climate adaptation activities in ways that resonate with local gender norms. Age distribution also varied significantly, with a majority of respondents aged 30 to 49, an observation consistent with studies indicating that age shapes both adaptive capacities and livelihood choices in agrarian societies (Wu et al., 2017). Given this concentration, it becomes crucial to consider age-specific needs and preferences in the design of programs, as younger or older populations may have different vulnerabilities and adaptive capacities in the face of climate change. A notable finding is the large proportion of married individuals, which aligns with research on family dynamics in rural African settings where marital status often influences resource access, labour availability, and livelihood choices (Deschênes et al., 2020; Hornby & Hull, 2023). This underscores the need to account for family structure and marital status when assessing the socioeconomic resilience of households in northern Ghana. Educational attainment within the sample was generally low, with many respondents lacking formal education. This is consistent with findings from studies on educational disparities in rural West Africa, where lower levels of literacy often limit access to information and adaptation resources (Abdul-Razak & Kruse, 2017; Dumenu & Obeng, 2016; Jolley et al., 2018). Educational programs aimed at enhancing literacy and skill levels, particularly for resilient agronomic practices like climate-smart agriculture, are thus crucial for strengthening adaptive capacity in the region. The religious composition of the sample, predominantly Muslim, reflects the religious diversity of the area and aligns with other studies that highlight the importance of religious identity in shaping community dynamics and values in West African rural areas (Salihu & Baidoo, 2024; Sheppard, 2021). Cultural sensitivity to these dynamics is essential in designing interventions that are socially acceptable and effective. Lastly, the predominance of the Mole-Dagbani ethnic group highlights the need for ethnically nuanced interventions. Studies suggest that understanding ethnic diversity in rural African settings can improve the cultural fit of policies and programs (Banks et al., 2023; Renzaho, 2020).

The socioeconomic profile of this study's sample reveals a complex and diverse community. Findings in gender, age, marital status, education, religion, and ethnicity provide a foundational understanding that can guide the planning of agricultural interventions and climate adaptation policies. These elements are vital for developing interventions that resonate with the unique needs of the various subgroups, ensuring that programs are both inclusive and effective in enhancing resilience within this population.

Table 4. 1 Summary of Socio-Economic Characteristics of Respondents

Characteristics of Farmer	Response	Percent
Sex	Female	20.0
	Male	**80.0**
	Total	100.0
Age Group	20 to 29	14.8
	30 to 39	**38.5**
	40 to 49	**29.5**
	50 to 59	14.3
	60 to 69	1.9
	70 to 79	0.9
	Total	100.0
Marital Status	Currently married	**82.2**
	Single	10.4
	Divorced	3.9
	Widowed	3.6
	Total	100.0
Level of Education	No schooling	31.1
	Incomplete primary school	**56.2**
	Complete primary	9.9
	Junior High	1.9
	Senior High	0.5
	Bachelor degree	0.4
	Total	100.0
Religion	African Traditional Religions Only	13.4
	African traditional religions and Christianity	1.6
	Christian only	32.3
	Muslim only	52.7
	Total	100.0
Broad Ethnic Group	Mole-Dagbani	**74.0**
	Grusi	21.0
	Gruma	1.2
	Guan	0.9
	Mande	0.2
	Akan	0.7
	Others	2.0
	Total	100.0

Source; Author's elaboration from survey 2023

4.3 Farmers' Perceptions of Trends in Climate Variables

The results of the analysis of maize-producing households' access to climate information services are predominantly presented through descriptive statistics accompanied by illustrations. Additionally, the study provides information on farmers' perceptions of trends in weather variables over the last five to 10 years in various regions, including Jirapa and Wa Municipality in the Upper West region, Kassena Nankana and Bolga Municipality in the Upper East region, and Savelugu Municipality in the Northern region. Furthermore, the study evaluates the meteorological climatic data, emphasizing the transmission sources, format, and usefulness of the information received from different sources. This analysis is important because farmers' perceptions of the value of climate information inform their choices or their farming practices.

To anticipate future climatic scenarios and expected changes, understanding Ghana's climatology is essential. However, rural farmers often find this information challenging to comprehend and use. Therefore, farmers resort to personal observations of rainfall and weather patterns, which are considered primary indicators of climate change. As part of the study, farmers were requested to give their perceptions of trends of four prominent climatic indicators based on their observations spanning the past five and ten years. Specifically, they were whether these indicators have been increasing or declining. The findings of this assessment are reported in Table 4.2.

Increasing irregular rainfall: Table 4.2 indicates that irregular rainfall has been increasing over time in all study districts Most of the respondents from Jirapa, Wa Municipality, Kassena Nankana, Savelugu, and Bolga municipal areas reported rising trends in irregular rainfall. This aligns with previous studies such as Abbam et al., (2018) and Klutse et al., (2021b) that have also reported changes in rainfall patterns, including increased variability and irregularity. These changes have significant implications for agriculture and food security in the region.

Increase in flood frequency*:* Respondents from most of the studied districts reported an increase in flood frequency over the previous five to ten years. Bolgatanga and Savelugu municipalities had the highest percentage of respondents (73 percent each) reporting an increase in floods, followed by Wa (72 percent) and Jirapa (69 percent) municipalities. However, respondents from the Kassena Nankana area stood out, as 57 percent reported a decrease in floods over the same period.

A decline in drought trend: It is interesting to note that 93 percent of respondents from the Kassena Nankana area noticed a decline in the drought trend. In contrast, respondents from other areas, including Jirapa, stated that the frequency of droughts has been increasing. This suggests that the Kassena Nankana area may have experienced some improvements, or a different climate trend compared to the other districts.

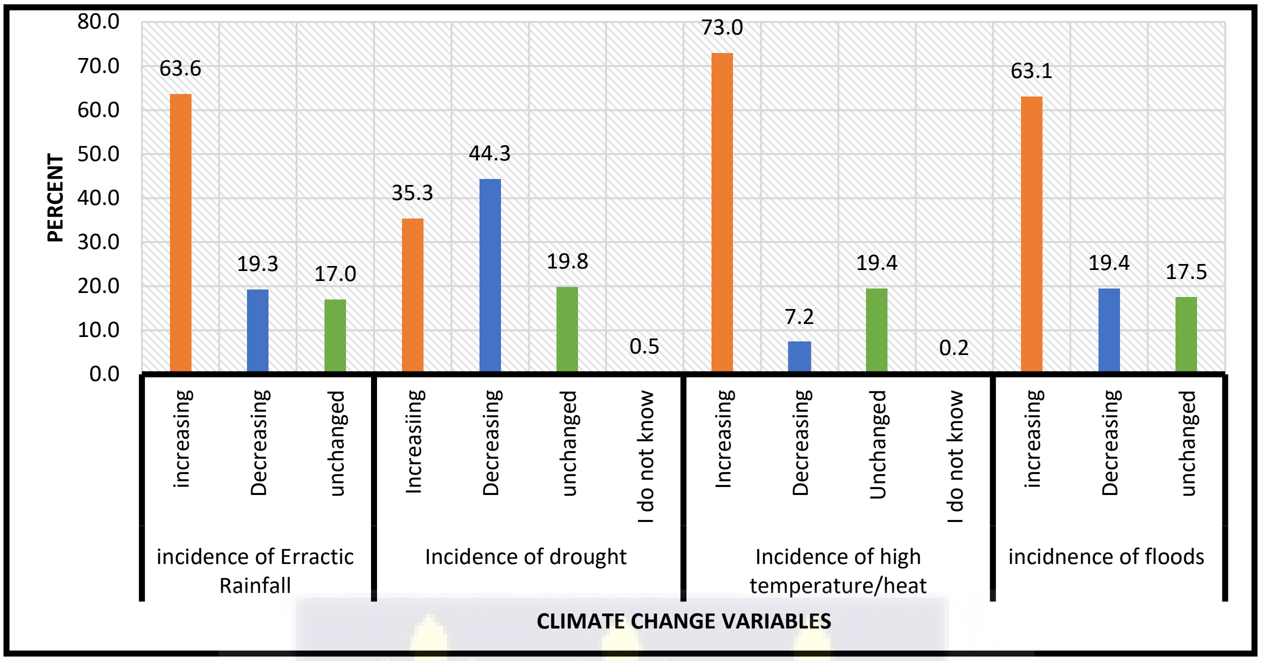
TABLE 4. 2 OBSERVATION OF CLIMATE VARIABLES BY DISTRICT (N=566)

		Study District				
Climate Variable	Observation	Savelugu %	Bolga %	Kassena Nankana %	Wa %	Jirapa %
Incidence of Erratic Rainfall	increasing	73	73.3	33.7	72.0	69.4
	Decreasing	9	9.2	57.0	13.0	1.2
	unchanged	17	17.4	9.3	15.0	29.4
	Total	100	100.0	100.0	100.0	100.0
Incidence of drought	Increasing	45	44.6	3.5	37.0	71.8
	Decreasing	37	37.4	93.0	33.0	0.0
	unchanged	17	17.4	3.5	30.0	28.2
	I do not know	1	0.5	0.0	0.0	0.0
	Total	100	100.0	100.0	100.0	100.0
Incidence of high temperature	Increasing	81	80.5	64.0	70.0	70.0
	Decreasing	5	4.6	7.0	10.0	10.0
	Unchanged	15	14.9	29.1	19.0	19.0
	I do not know	0	0.0	0.0	1.0	1.0
	Total	100	100.0	100.0	100.0	100.0
Incidence of floods	increasing	73	73.3	33.7	72.0	69.4
	Decreasing	9	9.2	57.0	13.0	1.2
	unchanged	17	17.4	9.3	15.0	29.4
	Total	100	100.0	100.0	100.0	100

Source: Author's elaboration from survey data 2023

Figure 4.1 presents the overall trends observed in the study districts. The findings reveal that there has been an increase in the frequency of unpredictable rainfall, extreme heat, and floods. Out of the 566 households surveyed, a significant majority of 73 percent of respondents reported a rise in high temperatures, while 63 percent observed an increase in both irregular rainfall and floods. Conversely, there was a general downward trend observed for droughts over the study period.

FIGURE 4. 1: OBSERVATION OF MAJOR CLIMATE VARIABLES FOR ALL DISTRICTS (N= 566)



Source: Author's elaboration from survey 2023

Statistical test

The crosstabulation analysis result reported in Table 4.3 shows the four categorical variables under study: erratic rainfall, drought, high temperatures, and frequency of floods. Each variable has four possible values: increasing, decreasing, unchanged, and not known. The null hypothesis assumes that these variables are independent and have no interaction. To test this hypothesis, the Pearson chi-square test was applied, and the results are presented in Table 4.3. The p-values of the climatic factors (0.067, 0.000, 0.007, and 0.000) indicate that they are statistically significant at probability levels between 1% to 5%. Therefore, it can be concluded that the four variables are not independent of each other, and hence the null hypothesis is rejected.

TABLE 4. 3: PEARSON CHI-SQUARE TEST FOR CROSS TABULATION

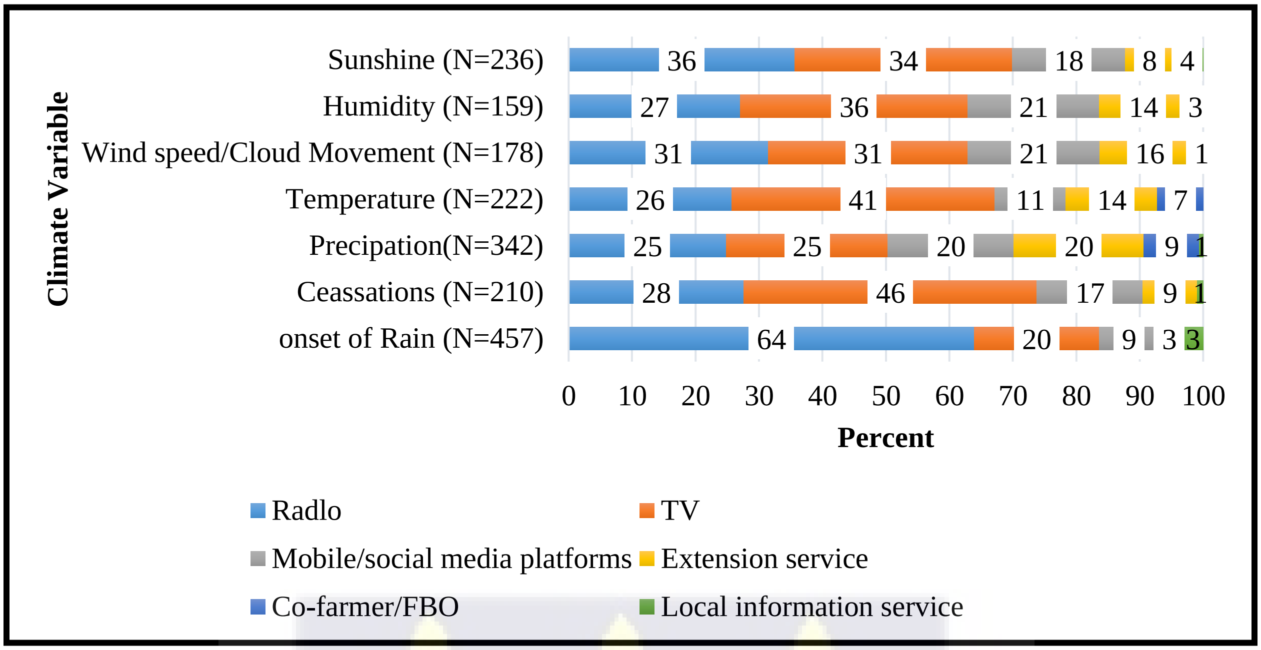
Climate variable	Value	df	Asymptotic Significance (2-sided)
Erratic Rainfall	20.010	12	0.067
Drought	201.131	12	0.000
high temperature	27.093	12	0.007
floods	122.916	8	0.000

Source: Author's elaboration from survey 2023

4.4 Assessment of Meteorological Services from Various Sources

Figure 4.2 shows the main sources of climate services, with radio and television being the primary sources of receiving these services. Most of the respondents (81 percent) reported receiving information about the onset of rain dates through radio, followed by precipitation (60 percent) which was mostly received through radio and TV (50 percent). Information about sunshine (42 percent) was mostly received from radio (36 percent), while temperature (39 percent) was mostly received through TV (41 percent). Cessation dates (37 percent) were mostly received through TV (46 percent), while information about wind speeds and cloud movement (31 percent), was mostly received through radio and TV (60 percent). Lastly, humidity (28 percent) was mostly received through TV broadcasts (36 percent).

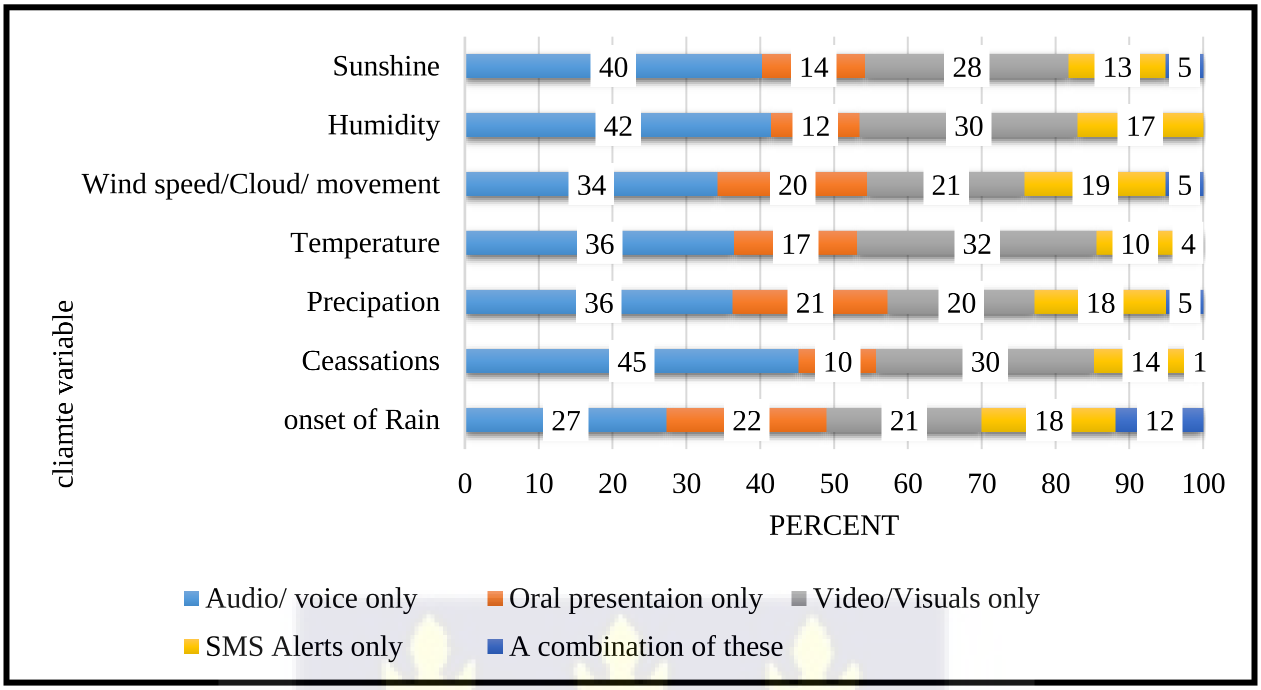
FIGURE 4. 2:MAIN SOURCES OF MODERN CLIMATE INFORMATION (N=566)



Source: Author's elaboration from survey 2023

Figure 4.3 analyzes and shows the format in which these climatic information services are transmitted. All seven of the key climatic information; sunlight, humidity, wind speed and direction, temperature, precipitation, cessations, and on-set of rain dates were largely received as audio or voice and audio-visual content. This is consistent with the fact that radio and television are the primary means of delivering climate information to households in northern Ghana which grow maize.

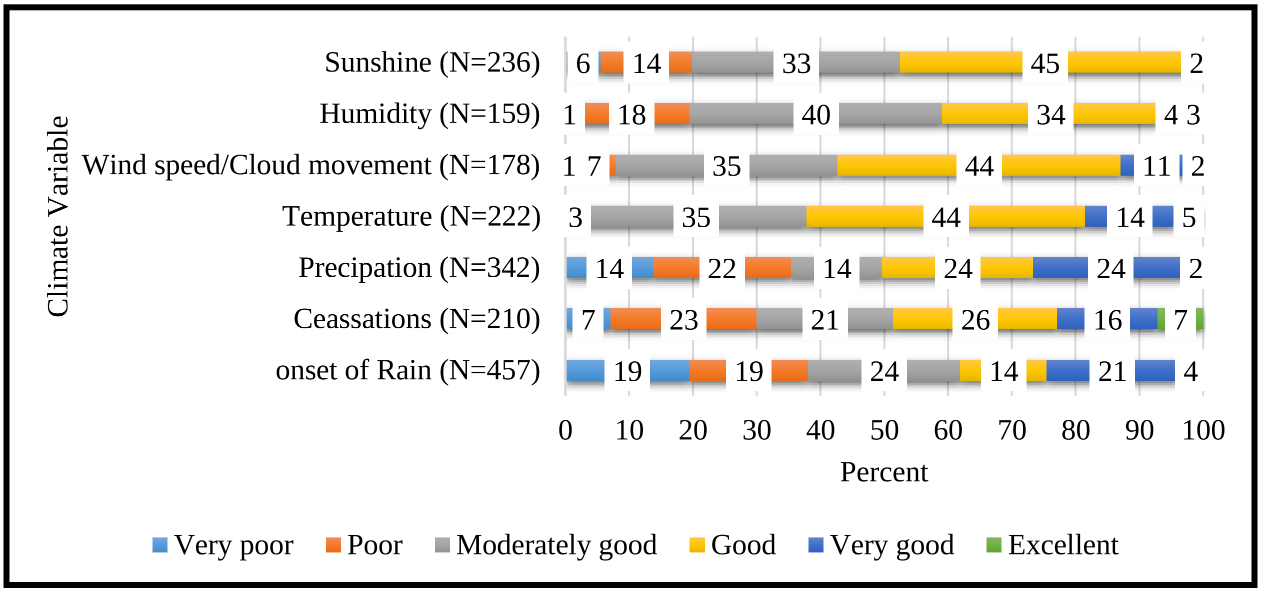
FIGURE 4. 3:MODERN CLIMATE INFORMATION TRANSMISSION (N= 566)



Source: Author's elaboration from survey 2023

The dependability, accuracy, and general applicability of the climate information services were evaluated by households using the following criteria: 1 = very poor, 2 = poor. 3 = moderately good, 4 = good, 5 = very good, and 6 = excellent. The findings as shown in Figure 4.4 indicate that in comparison to other climate services like precipitation, cessation, and on-set of rains supplied by Ghana meteorological services, information on sunlight, humidity, wind speed, and temperature obtained from all sources was either reasonably good or good.

FIGURE 4. 4: USEFULNESS OF CLIMATE INFORMATION RECEIVED (N=566)



Source: Author's elaboration from survey 2023

4.5 Indigenous Climate Knowledge of Farmers

From the concept of subsistence or own production mode of production, a farmer can produce climate information based on personal observations and Community knowledge for his/her use. This study assessed farmers' indigenous knowledge about climate trends based on their observations of seven different climatic indicators. These were selected based on literature, their independence and likelihood of occurrence were assessed using crosstabulations in the analysis across the study districts. The results are presented in Tables 4.4 and 4.5. Table 4.4 focuses on the emergence of armyworms, dark clouds amid high winds, and the singing of coucal birds. Table 4.5 assesses the behaviour of cows, the presence of fog, and ants moving their eggs uphill.

Earthworms as an indicator of rainfall: A significant majority of respondents across all five research districts believed that if there were a lot of earthworms on a particular day, it was rather likely that rain would fall in a day or a few hours. This belief was expressed by respondents from

Jirapa (61 percent), Bolgatanga (53 percent), Wa (41 percent), Savelugu (39 percent), and Kassena (37 percent). Overall, 45 percent of all respondents across the study districts considered it likely, while 13 percent considered it unlikely, 24 percent considered it highly likely, and 17 percent had no clue. This suggests that earthworm activity is perceived by many as a reliable indicator of imminent rainfall.

Dark clouds amidst strong winds as a rainfall signal: Respondents across all study districts, particularly in the Wa municipality, strongly believed that dark clouds amidst strong winds indicated that rain would occur in a few hours. Overall, 51 percent of all respondents maintained that it was highly probable to have rain in a few hours when they observed dark clouds amidst strong winds. This indicates that this traditional observation is widely recognized as a reliable signal of imminent rainfall.

Singing birds and flying insects as rainfall indicators: The perception regarding the likelihood of loud singing of birds and flying insects signalling rain in the next few days varied among the study districts. In Savelugu municipality. Many respondents (42 percent) considered it less probable to occur, while in Bolga municipality, 38 percent of respondents believed it was somewhat likely. On the other hand, respondents from Kassena Nankana, Wa, and Jirapa believed that this traditional climate observation was highly likely to be a signal of rainfall in the next few days.

TABLE 4. 4 ASSESSMENT OF INDIGENOUS CLIMATE KNOWLEDGE BY DISTRICT (N=566)

		Probability of occurrence (%)				Pearson χ^2 Test		
Climate Observation	**Study District**	**less probable**	**Somehow probable**	**highly probable**	**No idea**	**Value**	**df**	**sign**
The appearance of a large number of earthworms on the day is a sign of rain the next day or in a few hours	Savelugu	18.5	**39.5**	27.2	14.9	56.023	12	0.000
	Bolgatanga	16.0	**53.0**	12.0	19.0			
	Kassena	17.4	**37.2**	15.1	30.2			
	Wa	3.0	**41.0**	37.0	19.0			
	Jirapa	5.9	**61.2**	24.7	8.2			
Dark clouds amidst strong winds signal rain in a few hours	Savelugu	16.4	28.7	**45.6**	9.2	30.142	12	0.000
	Bolgatanga	10.0	35.0	**47.0**	8.0			
	Kassena	8.1	25.6	**54.7**	11.6			
	Wa	2.0	22.0	**71.0**	5.0			
	Jirapa	9.4	22.4	**57.6**	10.6			
The loud singing of coucal birds and flying insects is an indication of rain in the next few days.	Savelugu	**42.6**	39.5	10.3	7.7	260.015	12	0.000
	Bolga	12.0	**38.0**	24.0	26.0			
	Kassena	1.2	7.0	**74.4**	17.4			
	Wa	2.0	5.0	**66.0**	27.0			
	Jirapa	23.5	30.6	**43.5**	2.4			

Source: Author's elaboration from survey 2023

The results of the other indigenous climate variables are presented in Table 4.5.

***Cows flapping their ears and tails as a rainfall indicator*:** Respondents across the study districts believe that cows repeatedly flapping their ears and tails indicate rainfall in the next day or up to three days, with a probability of occurrence at 30 percent. However, there is no strong indication from any district regarding the exact probability of this indigenous climate information. This suggests that while respondents generally perceive this behaviour of cows as somewhat probable in predicting rainfall, there is variability in the degree of confidence across the districts.

The appearance of fog as a rainfall indicator: The majority of respondents (59 percent) across all study districts believed that the appearance of fog was highly probable as a sign of rainfall in the next few hours. Except for the Bolga municipal district, a significant number of respondents in each district maintained the same observation. This indicates a widespread belief in the correlation between fog and imminent rainfall, emphasizing the reliability of fog as a rainfall indicator.

Lepisiota ant carrying its eggs uphill as a rainfall indicator: The research results indicate that, for the overall assessment of the study area, the observation of a lepisiota ant carrying its eggs uphill during the rainy season is highly probable as a sign of rainfall in the next day or few hours. However, the district-specific analysis reveals that the Jirapa district is an outlier, as approximately 82 percent of respondents stated that this observation is less probable as a signal of rainfall. This suggests that there is a discrepancy in the perception of this indigenous climate information within the Jirapa district compared to the other districts.

TABLE 4. 5: ASSESSMENT OF INDIGENOUS CLIMATE KNOWLEDGE BY DISTRICT (N=566)

Climate Observation	Study District	Probability of occurrence (%)				Pearson χ^2 Test		
		less probable	**Somehow probable**	**highly probable**	**No idea**	**value**	**df**	**sig**
Cows repeatedly flapping their ears and tails indicate rainfall the next day or up to 3 days.	Savelugu	19.0	**33.8**	22.6	24.6	31.458	12	0.000
	Bolga	25.0	26.0	**30.0**	19.0			
	Kassena	**29.1**	20.9	16.3	33.7			
	Wa	30.0	**33.0**	9.0	28.0			
	Jirapa	25.9	**35.3**	9.4	29.4			
The appearance of fog indicates rain in the next few hours or the next day.	Savelugu	11.3	23.1	**56.9**	8.7	98.756	12	0.000
	Bolga	16.0	**40.0**	28.0	16.0			
	Kassena	0.0	22.1	**69.8**	8.1			
	Wa	0.0	6.0	**76.0**	18.0			
	Jirapa	0.0	18.8	**74.1**	7.1			
A lepisiota ant carrying its eggs uphill during the rainy season signals rain the next day or in a few hours	Savelugu	6.7	25.6	**51.8**	15.9	382.501	12	0.000
	Bolgatanga	22.0	**36.0**	17.0	25.0			
	Kassena	0.0	0.0	**75.6**	24.4			
	Wa	3.0	2.0	**69.0**	26.0			
	Jirapa	**82.4**	7.1	7.1	3.5			

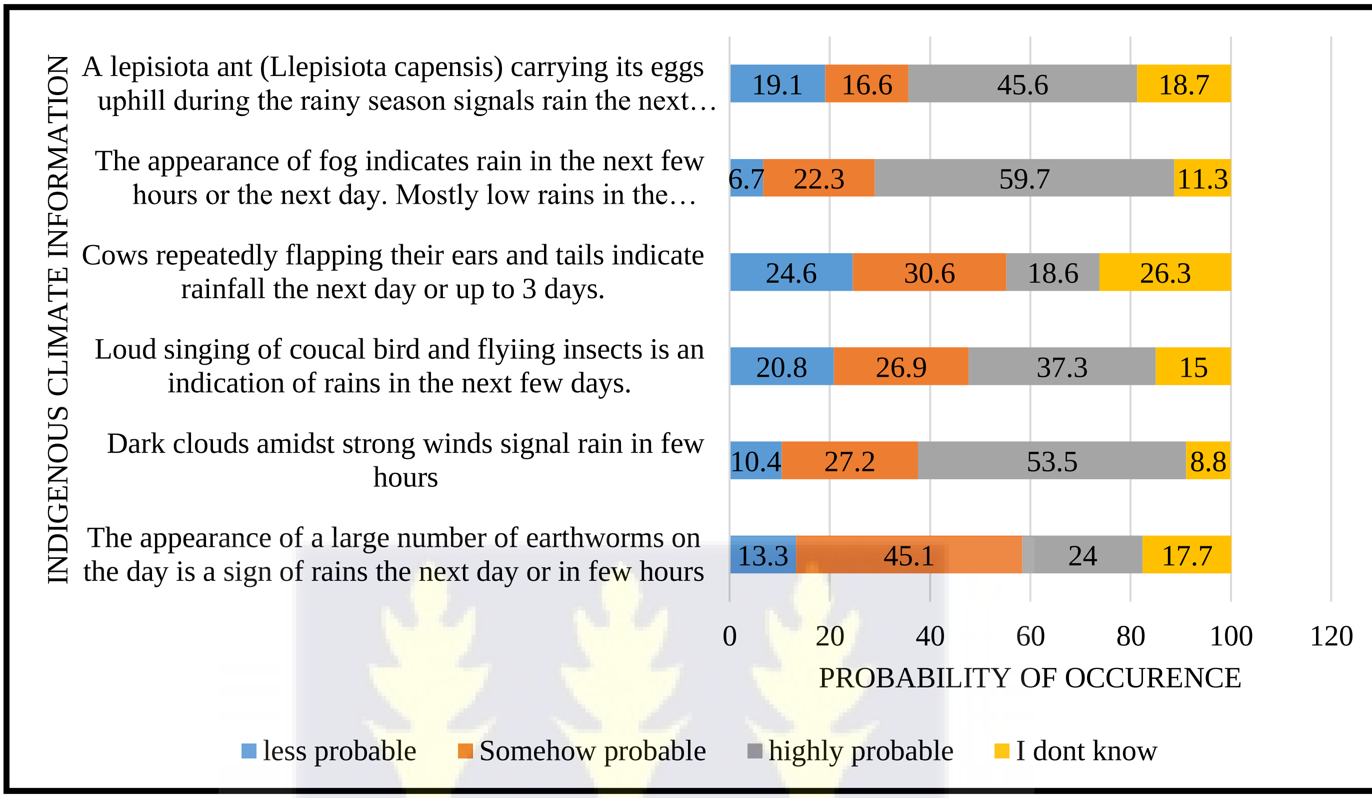
Source: Author's elaboration from survey 2023

Statistical Test

For each variable, the Pearson Chi-square test for the significance of independence of the variables and probability of occurrence was conducted. All six variables were significant at 1 percent. Therefore, the null hypothesis that the climate observation variables and their probability of occurrence were independent was rejected in all cases.

The total assessment of the local climate knowledge in the study area is shown in Figure 4.5. While 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 percent 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.

FIGURE 4. 5 ASSESSMENT OF INDIGENOUS CLIMATE KNOWLEDGE FOR ALL DISTRICTS (N=566)



Source: Author's elaboration from survey 2023

4.6 Use of Climate Information in Farm-Level Decisions

To identify the underlying dimensions or factors that are most relevant to the use of climate information in farm-level decisions, factor analysis was employed specifically the Principal Component Analysis (PCA) utilizing a Varimax rotation approach was used. It must be emphasised that Principal Component Analysis (PCA) is a dimensionality reduction technique that works by transforming the original variables into a new set of uncorrelated variables called principal components (PCs) (Jolliffe & Cadima, 2016). The aspects of dimensionality are that it captures the majority of the variance in the original data, determines the maximum variance directions in high-dimensional data, projects it onto a lower-dimensional space (Vasan &

Surendiran, 2016) and reduces the impact of original variables while maintaining model dimensionality, enabling efficient data capture by retaining the underlying structure (Gewers et al., 2022).

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 PCA 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 4.5 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.

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.

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 (A. Ajani & Van Der Geest, 2021; E. N. 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.

TABLE 4.5 PRINCIPAL COMPONENT ANALYSIS OF FARM-LEVEL DECISIONS

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	2.1360	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	2.7650	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	2.6360	0.828	
CI is easily accessible and less costly	2.6078	0.210	
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		0.000

Source; author's elaboration from survey 2023

The results of the factor analysis show that the climatic variables studied can be grouped into two underlying constructs. Factor 1, which includes factors that offer immediate farm-level decisions precise information effective crop management timely crop harvest, is likely measuring daily weather forecasts from meteorological agencies and other institutions. Factor 2, on the other hand, which is mainly comprised of factors of Climate information that allow for long-term planning mitigation planning against climate hazards and for water conservation or management plans appears to measure a distinct construct related to seasonal weather forecast.

Factor 3 which is made-up climate information that builds the trust of local knowledge, is easily accessed and less costly and provides supplementary information related to indigenous weather predictions. Overall, these findings highlight the importance of considering multiple climatic variables when analyzing their influence on farm-level decisions and suggest that the daily, seasonal and indigenous weather projections and predictions may be particularly relevant for such analyses.

In conclusion, the PCA results highlight the significance of different aspects of weather information for agricultural decision-making. To support farmers effectively, policies should focus on improving daily and seasonal weather forecasts while also recognizing the value of indigenous knowledge. This holistic approach can lead to more informed and resilient agricultural practices.

4.7 Determinants of Household Willingness to Invest in CSA

Table 4.11 summarizes the results of the binary logistic model explaining the willingness of maize-producing households to investment an averaged amount of money they propose to spend on CSA practices.

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 & 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, 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: 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, 2017b).

Age: 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 level 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 (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 Farming 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 the 1 percent level and it is estimated that for every additional visit of extension officers to armers, 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 & Sherzad, 2019).

Distance to the nearest market: This is a continuous variable measured in kilometers. 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 & 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., 2015b; C. 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, & Abaidoo, 2021; Djido et al., 2021; Ngigi & 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.

TABLE 4. 6: DETERMINANTS OF HOUSEHOLDS' WILLINGNESS TO INVEST IN CSA PRACTICES

Variables	Coefficient (B)	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
Climate Information Use	1.748	0.330	0.000***	5.741
Constant	-9.466	1.218	0.000***	0.000
Observations				566
-2 Log likelihood				274.424
Cox & Snell R Square				0.465
Nagelkerke R Square				0.694
Chi-square				354.333
p-value				0.000

Source: Author's elaboration from survey 2023

4.8 Conclusion

Overall, these variables can have different impacts on farmer's decisions to invest in climate-smart agriculture practices and technologies. To fully understand the relationship between these variables and farmers' decisions, it is important to consider the specific context in which farmers are operating. Nonetheless, the results of the binary logit model suggest that promoting increased maize commercialization, targeting female farmers and experienced farmers, and targeting large-scale farmers can be effective in promoting the investment in climate-smart agricultural practices

Specifically in northern Ghana, lack of access to key CSA inputs such as irrigation facilities is a major challenge in CSA investment decisions.

CHAPTER FIVE

RESULTS AND DISCUSSION

ADOPTION OF CLIMATE-SMART AGRICULTURAL PRACTICES AND ITS EFFECTS ON FARM YIELDS AND NET RETURNS

5.1 Introduction

The findings from the analysis of research objectives 2 and 3 are presented in this chapter. The adoption of climate-smart agriculture (CSA) practices and their effects on household maize farm net return and yield are the focus of these objectives. The first part examines farmers' adoption of CSA practices by estimating the determinants of adoption through a multinomial logistic regression. This approach sheds light on factors influencing farmers' decisions regarding the use of CSA practices in their farming operations. Subsequently, the chapter moves on to present and discuss the findings related to the effect of CSA adoption on yield and net returns.

The use of improved seed types, soil fertility enhancing practices, and traditional crop rotation are the three main categories of CSA practices that are the subject of the study. These three categorised practices serve as the main variables of interest. The Generalized Least Squares regression technique was used to examine these effects through the removal of the severe heteroscedasticity in the original OLS models. In general, the findings of this chapter provide insightful information on the factors that influence CSA adoption among households that produce maize. It also clarifies the specific effects of CSA practices on maize yield and net returns. These findings have the potential to be a catalyst for CSA technology adoption, eventually improving the sustainability and profitability of maize production in Northern Ghana.

5.2 Determinants of Adoption of Climate-Smart Agricultural Practices

The multinomial regression model is a statistical method for examining the relationship between one or more independent variables and a categorical dependent variable with more than two categories. Principal component analysis in this study identified two key Climate-Smart Agriculture practices: the use of improved maize seed varieties and soil fertility improvement methods. These methods were compared with the conventional crop rotation method which served as the reference category. Table 5.2 provides the results of this analysis.

Model Diagnostics

The Chi-square which is a test statistic for the likelihood ratio test, compares the fit of the full model (with predictors) to the fit of the null model (intercept-only). The high chi-square value of 176.969 indicates that the full model provides a significantly better fit than the null model. The p-value associated with the chi-square test is 0.000, which is less than the typical significance level of 0.05. This means the full model is significantly better than the null model at explaining the variation in the outcome variable This is McFadden's pseudo-R-squared, which is a goodness-of-fit measure for MNL regression is 0.419 suggesting the model explains about 41.9% of the variation in the outcome variable. The Log Pseudolikelihood is the log of the pseudo-likelihood function, which is used to estimate the model parameters. The value of -316.080 is the maximized log-pseudo-likelihood for the full model.

These results indicate that the MNL regression model has a good overall fit, with the full model being significantly better than the null model at explaining the adoption of the categorised CSA practice (*Use of improved maize variety and Soil fertility enhancing practices*). with crop rotation as the reference category. The relatively high pseudo-R-squared value further suggests the model is explaining a decent proportion of the variability in the data.

All the predictor variables of the model for improved maize variety except for FBO membership and off-farm income were statistically significant and the expected signs of their coefficients were met. With regards to the Soil fertility enhancing model, out of the 16 predictor variables, only 6 were statistically significant and their expected signs were also met. however, in the combined model, 10 of the variables were statistically significant. For Improved maize seed variety use CSA.

Based on Table 5.2 the odd ratios for the different predictor variables can be interpreted as follows:

Age: The results indicate that the log-odds of selecting "Improved maize variety use" over "Crop rotation" increase by 0.203 units for every year increase in "Age", assuming that all other factors remain constant. In the same vein holding all other factors constant, a year increase in the age of the farmer increases the log-odds of selecting "Soil fertility enhancing practices" over "Crop rotation" by 0.167 units. The coefficients for "Age" in both cases indicate that as people age, they are more likely to choose "Improved maize variety use" or "Soil fertility enhancing practices" over "Crop rotation. The findings suggest that age can play a role in the adoption of CSA practices. However, the relationship between age and adoption of climate-smart agricultural (CSA) practices is not consistent across studies. While some studies have found a positive relationship (Djido et al., 2021), others have found no relationship or even a negative relationship (Kangogo et al., 2021; Kurgat et al., 2020). More research is therefore needed to better understand the factors that influence CSA adoption, including the role of age. Nonetheless, policymakers can use this finding to design targeted interventions for specific age groups to encourage the adoption of these practices. Additionally, the findings may inform the development of educational campaigns aimed at increasing awareness of the benefits of these practices, particularly among farmers who are older and may be less likely to adopt them.

Sex: The odds ratio for sex is 2.204 for improved maize variety use and 2.438 for soil fertility enhancing CSA practices. These odds ratios indicate that all else being equal, being a male farmer is associated with a higher probability of adopting improved maize varieties and soil fertility enhancing CSA practices, compared to being female. The relationship between gender and the adoption of climate-smart agricultural (CSA) practices is another complex and context-dependent issue. The relationship may vary depending on factors such as cultural norms, access to resources, and the types of practices being adopted. For crop diversification, sol conversation and irrigations practices are dominated by males in some countries (Dhenge et al., 2016; Glemarec, 2017a) while more women tend to use more improved seeds, early planting to adapt to climate changes in other countries such as Malawi (Nchanji et al., 2022).

Gender-sensitive policy recommendations are crucial for promoting positive gender impacts and ensuring that both men and women can equally benefit from climate-smart agricultural practices. Among other things, there is the need to promote women's participation in decision-making. Women farmers face unequal access to land, credit, and other resources, which can limit their ability to adopt climate-smart agricultural practices. Policies should be put in place to provide women with equal access to land, credit, and other resources.

Farming experience: The odd ratios for improved variety use (0.144) and soil fertility enhancing practices (0.108) are both less than 1. As years of farming experience increase by one unit, the odds of adopting improved maize variety and soil fertility enhancing practices, reduce by 1.4%, and 1.08%, respectively. In other words, farmers with more years of farming experience are less likely to adopt these practices compared to farmers with less experience. The evidence to support this finding is scanty. While it was established that farmers in Zimbabwe with more years of farming experience were less likely to adopt conservation agriculture practices, a study in Nigeria found no significant difference in the adoption of soil conservation practices between experienced and inexperienced farmers (Ojo & Baiyegunhi, 2020). These studies largely attributed this phenomenon to experienced farmers' lack of awareness of and scepticism toward new agricultural practices. This finding suggests that targeted efforts may be needed to encourage farmers with more years of farming experience to adopt improved variety use, soil fertility enhancement, and both. For example, providing information and training on the benefits of these practices, as well as addressing any perceived barriers, such as cost or lack of information, may help to increase adoption rates among experienced farmers.

Married: The results show that keeping all other factors equal, the coefficient of 0.579 shows the difference in the log-odds of married farmers choosing soil fertility-enhancing CSA practices compared to farmers who aren't married over crop rotation. This variable's and the independent variable's interaction term is statistically significant at the 10% level, which is less than the usual 5% threshold. The results suggest that adoption of CSA can be impacted by gender roles in homes. Married couples' decisions about CSA practices may be influenced by the different roles and duties they each have on the farm. Additionally, household dynamics and societal norms can be quite important. According to some studies for example, when married couples make decisions together about farming methods, the results may differ from those of single people who make separate choices. As opposed to single farmers, married farmers may be more or less impacted by their social networks (Anderson et al., 2017; Bjornlund et al., 2019; Michalscheck et al., 2020).

Access to climate information: The odds ratios for the predictor variable "access to climate information" are 1.980 for improved maize variety use and 1.675 for soil fertility-enhancing practices. This implies that individuals with access to climate information are 1.980 times more likely to choose improved maize varieties and 1.675 times more likely to adopt soil fertility-enhancing practices in comparison to farmers who practice crop rotation. These odds ratios imply a greater likelihood of choosing these practices compared to crop rotation. Therefore, there should be efforts to strengthen the capacity of climate information systems in the region to provide timely, accurate and relevant climate information to farmers. This can be achieved through the provision of modern technologies such as weather stations, remote sensing, and mobile-based platforms.

Farm size: The log-odds of selecting "Improved maize variety use" over "Crop rotation" rise by 0.797 units with every hector increase in farm size. Consequently, it appears that larger farms are more likely to select "Improved maize variety use" than "Crop. On the other hand, a one-unit increase in farm size leads to an increase in the log odds of choosing "Soil fertility enhancing practices" over "Crop rotation" by 0.687 units, holding all other variables constant. This implies adoption of both CSA practices is significantly influenced by farm size relative to crop rotation.

Smaller farms may have obstacles that larger farms do not, thus governments may think about giving specific support or incentives for them to adopt these practices. It can be advantageous to invest in research and innovation to create varieties of crops and agricultural techniques appropriate for small-scale farming.

Level of commercial farming: The coefficient of 0.548 shows the difference in the log odds of commercial farmers choosing soil fertility-enhancing CSA practices over conventional crop rotation practices compared to non-commercial farmers. The idea that higher adoption of climate-smart agricultural practices results from the commercialization of farming is being supported by some studies. In South Africa for example farmers who engaged in commercial farming were more likely to use sustainable land management techniques (Makate et al., 2018). Commercial farmers in Ghana, Tanzania, and Kenya were more likely to practice conservation agriculture and improved maize varieties use (Stevenson et al., 2014), whereas farmers in Zambia and Malawi who engaged in contract farming or received credit through commercial farming were more likely to adopt soil fertility management practice in Malawi (Fisher et al., 2018 & Persha et al., 2015). Access to training, input subsidies, or market connections are potential incentives for commercial farmers to adopt and promote soil fertility-enhancing CSA practices.

Yearly extension visits: For the predictor variable "seasonal of extension visits to the farmer," an odds ratio of 0.990 with a p-value of 1% suggests that for each additional visit from an extension worker, the odds of adopting an improved maize seed variety increase by a factor of 0.990, holding all other variables constant. Similarly, for the same predictor variable an odds ratio of 0.912 with a p-value of 1% suggests that for each additional visit from an extension worker, the odds of adopting soil fertility-enhancing CSA practices increase by 0.912. This suggests that encouraging extension visits can significantly boost the adoption of improved maize seed varieties and soil fertility-enhancing CSA practices. Research shows that farmers with extension support are 3.5 times more likely to adopt improved maize varieties, with economic benefits including 28% higher returns and 15% higher crop income (Merga et al., 2023). Farmers who receive extension support are more likely to embrace soil fertility enhancement techniques, especially in integrated soil fertility management and conservation agriculture ((Brown et al., 2018; NGAIWI et al., 2022).

Farmland exposure to climate hazards: This predictor variable is a continuous variable that is measured as the number of land conditions that may adversely affect crop output, soil fertility, and plant growth. Since most farmers had various land conditions, these factors were included as dummies and transformed into continuous variables in the model. These requirements included, among others, "if portions of the land are prone to erosion", "limited or no afforestation around the land", and "whether the land is waterlogged" The odds ratio associated with this variable is -0.277implying that holding all other variables constant, for every unit increase in the level of farm exposure to climate risk, the odds of using an improved maize seed variety decrease by 0.277. however, this association is not statistically significant, the odd ratio for the predictor variable on soil fertility enhancing CSA practice of -0.364 which indicates that for every unit increase in farmland exposure to climate risk, the odds of using a soil fertility enhancing CSA practice decreases by a factor 0.364. all other variables being constant. This relationship is statistically significant at a conventional level of 5 percent.

Overall, while there may be some variability in the extent to which farmers are affected by climate risks and their ability to adopt climate-smart practices, there is evidence to suggest that exposure to climate risk can be a barrier to the adoption of these practices. For example, studies have shown that climate variability and extreme weather events can have negative impacts on crop yields and farm productivity, which can, in turn, affect farmers' willingness and ability to adopt climate-smart agricultural practices (Fisher et al., 2017; Sharma et al., n.d.; Teklewold et al., 2013) Furthermore, some other studies specifically FAO & MoFA, (2018), Karanja Ng'ang'a et al., (2021), and World Bank & MoFA, (2020) have also reported that farmers who are already facing economic and social challenges may be less likely to invest in new technologies and practices, even if they are beneficial in the long run.

TABLE 5. 1 MULTINOMIAL LOGISTIC REGRESSION EXPLAINING CSA ADOPTION

Variety	CSA Bundle 1 (Improved Maize Variety)	CSA Bundle 2 (Soil Fertility Enhancing Practices)
CSA implementation cost	0.001	0.000
	(0.001)	(0.001)
Age	0.203***	0.167***
	(0.033)	(0.028)
Sex	2.204***	2.438***
	(0.639)	(0.481)
Farming experience	-0.144***	-0.108***
	(0.028)	(0.024)
Married	0.671	0.579*
	(0.417)	(0.340)
Household size	-0.032	-0.018
	(0.038)	(0.025)
Religion (Muslim)	0.259	-0.309
	(0.404)	(0.332)
FBO member	0.448	-0.525
	(0.467)	(0.428)
Family labour	0.022	0.095
	(0.080)	(0.071)
Access to climate information	1.980***	1.675***
	(0.473)	(0.353)
Farm size	0.797**	0.687**
	(0.311)	(0.304)
Climate hazards exposure	-0.277	-0.365**
	(0.232)	(0.183)
Seasonal extension visits	0.990***	0.912***
	(0.216)	(0.209)
Education	0.167	-0.021
	(0.109)	(0.096)
Farming is commercial	-0.003	0.548**
	(0.302)	(0.245)
Distance to the nearest market	0.170	0.229
	(0.147)	(0.145)
Constant	-12.735***	-10.086***
	(1.804)	(1.555)
Observations		566
Chi-square		176.969
p-value		0.000
Pseudo R-squared		0.419
Log Pseudolikelihood		-316.080

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Author's elaboration from survey 2023

5.3 Effect of CSA Adoption on Maize Yield and Net Returns

This section discusses the effects of CSA adoption on crop yield and farmers' net returns, with a focus on the utilisation of improved maize seed varieties and soil fertility-enhancing strategies. To thoroughly examine the connection between CSA adoption and maize productivity in terms of yield and net return outputs, the study uses a Generalised Linear Regression (GLS) model, specifically the augmented production function. In addition to contributing to the empirical knowledge of CSA's effects, the analysis informs policy and decision-makers about the potential benefits of these practices in light of the current weather challenges facing farmers in northern Ghana. By doing this, the practical implications of adopting CSA practices for long-term food production and the prosperity of the farming business are highlighted. The interest variables are the two bundles of CSA practices; CSA-1 Improved Maize Seed variety use and CSA-2 Soil fertility enhancing practices which were quantified as categorical variables generated from a Principal Component Analysis involving 11 CSA practices.

Robust regression models that take into account the intricacies included in agricultural data are essential for accurate and insightful analysis of farming outcomes, such as maize yield and net return. First, the study employed a comprehensive Ordinary Least Squares (OLS) regression model to assess the effect of numerous variables on maize yield and net return. But as we examined the data more closely, two major problems emerged- Heteroscedasticity and collinearity issues. The results of the OLS regressions for maize yield are presented in Tables 5.5 and 5.6 in the appendices section.

Recognising the importance of addressing these statistical challenges, the study used an improved approach in this analysis. To reduce the possibility of collinearity, some predictor variables were dropped and those that have the greatest effect on the variations in maize yield and net return were maintained. Furthermore, the study switched to a Generalised Least Squares (GLS) model, which takes heteroscedasticity into account and offers more accurate parameter estimates when the variance of the residuals is not constant. This methodological shift provides an opportunity to produce more reliable and interpretable results, unveiling the nuanced relationships between predictor variables and maize productivity outcomes while still maintaining the objective of gaining deeper insights into the effects of CSA practices on maize yield and net return.

The Variable Inflation Factor (VIF) measures how much the variance of the predicted coefficients is inflated as a result of multicollinearity, acting as an indicator for the degree of multicollinearity. A significant increase in the VIF, usually above 10, indicates multicollinearity which is of concern. Conversely, Tolerance is the reciprocal of the VIF for a specific variable. It measures the fraction of variance in an independent variable that remains unexplained by the other independent variables in the model. A low tolerance value, approaching 0, indicates a substantial degree of multicollinearity. The results show that most independent variables in the model have a relatively low level of multicollinearity in the case of the yield and net return estimations shown in Tables 5.2 and 5.3. The variables age and age squared, however, are an exception. Age has a tolerance value of 0.022 and a VIF of 44.48 in Table 5.2 which is quite high. Similarly, the tolerance and VIF values for age squared are 0.026 and 38.35, respectively in Table 5.3. These high VIF values for age and age squared indicate that multicollinearity is a significant factor in the model. However, once multicollinearity among variables is not the main focus of the study, it may not always be constraining or harmful, as suggested by certain studies (Fotheringham & Oshan, 2016; Gordinsky, 2016). The focus of the study is primarily on two important variables in this scenario: "CSA1 use of improved maize seed variety" and "CSA 2 use of soil fertility-enhancing practices." Additionally, the inclusion of a sizable sample comprising 566 households results in considerably reduced standard errors for the variables. This factor can enhance the model's resilience in the face of multicollinearity.

5.3.1 Effect of CSA Adoption on Maize Yield

The results of the effect of CSA adoption on maize yield are presented in Table 5.5. The model diagnostic test indicates that the observed and predicted values have a relatively significant positive correlation, as indicated by the R of 0.685. This shows that a sizeable percentage of the variation in the dependent variable may be explained by the model. The R-squared value of 0.469 indicates that approximately 46.9% of the variance in the dependent variable can be explained by the independent variables in the mode. The Adjusted R-squared value of 0.460 provides additional insight into the model's efficiency. The relatively small difference between the R-squared and Adjusted R-squared values (0.009 or 0.9 percentage points) is particularly telling. The combination of an R-squared value of 0.469 and an Adjusted R-squared of 0.460 generally indicates a statistically meaningful and practically significant model, particularly in fields dealing with complex real-world phenomena. The small difference between these values suggests efficient model specification and appropriate variable selection. While there might be room for improvement depending on the specific research context, these values typically represent a solid foundation for most analytical purposes, especially in social sciences and related fields where multiple external factors influence the variables of interest.

Finally, the standard error of the estimates which represents the standard error of the residuals is 24.37. This relatively smaller value indicates a better fit of the model to the data.

The results show that all the predictable variables including the two key interest variables Improved maize variety use and soil fertility enhancing practices were statically significant at 1% and 5% levels. However, the parameter estimates for Age Square and farm size which is measured on a per ha basis were negative suggesting an inverse relationship between these variables and maize yield. The potential nonlinear interactions between age and the dependent variable are modelled using the term "Age Square" in a regression equation. By using a basic linear relationship with "Age" alone, the model can account for variations in the effect of age on the dependent variable that may not be fully explained.

CSA 1-Improved maize variety: The results from Table indicate that, on average, using an improved maize variety is associated with a 1.027 kg increase in yield**.** With a 1 percent alpha level ($p < 0.01$), the statistical association between using improved maize varieties and increased yield is very strong. Breeding programmes are frequently used to create superior maize varieties that have attributes including increased yield potential, disease resistance, tolerance to environmental stressors, and improved agronomic properties (Ekpa et al., 2019; Glenn et al., 2017; Rauf et al., 2016). Access to improved varieties is not a major issue due to the presence of the Savana Agricultural Research Institute (SARI) in northern Ghana.

Breeding programmes represent a pivotal strategy in addressing agricultural challenges in developing regions. Ekpa et al., (2019) highlight the transformative potential of advanced maize varieties in creating cultivars with exceptional genetic characteristics. These varieties are meticulously engineered to overcome traditional agricultural limitations, offering farmers crops with remarkable capabilities.

Glenn et al., (2017) demonstrate that modern breeding approaches focus on developing varieties with multiple critical attributes. These include enhanced yield potential, superior disease resistance, and improved tolerance to environmental stressors. (Rauf et al., 2016) emphasize that such genetic improvements are not merely technical achievements but strategic interventions that directly address food security challenges.

The significance of improved varieties extends beyond immediate yield increases. By creating more resilient crop options, breeding programmes provide farmers with tools to navigate increasingly unpredictable agricultural landscapes. This approach is particularly crucial in regions vulnerable to climate change and environmental uncertainties (Tadele, 2017).

CSA 2 Soil fertility enhancing practices: The coefficient of 0.717 associated with this variable suggests that adopting soil fertility-enhancing practices is associated with a 0.717 kg increase in yield**,** on average. The effect of this variable on maize yield per hector is positive and significant at the 5 percent level. Higher crop yields and better crop quality can all result from improved soil fertility, which ultimately boosts farmers' yield and net returns.

Soil fertility management emerges as a critical component of agricultural sustainability. Vanlauwe et al., (2010) argue that comprehensive soil fertility strategies are essential for long-term agricultural productivity and ecosystem health. These practices go beyond traditional fertilisation methods, embracing a holistic approach to soil management. De Sousa & Grichar, (2024) highlight the multifaceted benefits of integrated soil fertility practices. Restoration of degraded agricultural lands including a reduction of chemical fertilizer dependency, promotion of long-term soil ecosystem health, and enhancement of crop yield and quality.

Vanlauwe et al., (2017) also emphasize that soil fertility management is not just a technical intervention but a comprehensive approach to agricultural development. By addressing nutrient deficiencies and promoting sustainable practices, farmers can create more resilient and productive agricultural systems.

Age: The coefficient for age is 0.071 with a standard error of 0.028, indicating a statistically significant positive relationship at the 5 percent level. This suggests that holding other factors constant, each additional year of age is associated with a 0.071 unit increase in maize yield. The relationship between the age of farmers and farm yield performance is influenced by a variety of factors, and the direction of changes in this relationship is mixed. Some studies claim that older farmers frequently have more experience and knowledge about local conditions, crop varieties, and traditional farming practices (Abdul Rahman et al., 2021; van Loon et al., 2019). This could help improve farm management and obtain higher yields given their expertise and experience However, according to other research like Bowley et al. 2020 and Harrison 2018, farming can be physically demanding and elderly farmers may experience physical limits (Gullifer & Thompson, 2006; Reed et al., 2012). The physical demands of farming may be easier for younger farmers to manage, which could affect productivity positively. Farmers of all ages can gain from encouraging knowledge sharing, technology adoption, and general well-being, which will enhance farm yield performance.

Age Square: The coefficient for age squared is -0.001 with a standard error of 0.000319, which is statistically significant at the 5 percent level. This negative coefficient suggests a diminishing or slightly negative effect of age on the dependent variable at higher ages, indicating a non-linear, quadratic relationship. Age square's effect on crop productivity might vary depending on several variables including the context of the study. In some instances, when compared to younger farmers, older farmers may occasionally be less productive arising from the economic principle of diminishing returns where the physical capabilities of farmers decline as they advance in age or are reluctant to adopt improved farming techniques. As a result, the coefficient for "Age" can be negative, suggesting that crop output declines with age. Similarly, a negative or positive of farm size on crop yield depends on the context of the study and other factors. Such as the economic principles of diminishing returns to scale associated with higher average cost as the farm size becomes larger and operates beyond the optimal scale, resource allocation issues, management complexity, and the economies of diversification among others. With the remaining variables, several research studies support the findings of the study.

Farming experience: The coefficient for farming experience is 0.378 with a standard error of 0.074, which is statistically significant at the 1 percent level. This indicates a strong positive association, meaning that each additional year of farming experience increases the dependent variable by 0.378 units. Farmers with greater experience typically have a better awareness of the local climate, use more effectively in crop or livestock management and are better able to make informed decisions. For example, farmers with more experience frequently have a better understanding of soil characteristics, weather patterns, and pest and disease control, which helps them decide when to plant, irrigate, and harvest crops (Altieri et al., 2015; Lammerts van Bueren et al., 2002; Wheeler & Lobley, 2021). Investment in extension programmes that give beginners and seasoned farmers alike access to training and knowledge-sharing opportunities. Workshops, field demonstrations, and access to agricultural experts are a few examples of these programmes.

FBO member: The coefficient for being a member of a Farmer-Based Organization (FBO) is 0.409, with a standard error of 0.094, which is also significant at the 1 percent level. This suggests that FBO membership is associated with a 0.409 unit increase in maize yield, indicating a substantial positive effect. Farmers' groups can benefit their members in several ways, including by giving them access to resources, exchange of information, collective bargaining power, and assistance with the adoption of modern agricultural practices. Promoting FBO membership can be particularly beneficial in Northern Ghana, where agriculture plays a significant role in the economy. Already several projects have targeted FBO development in northern Ghana including the one implemented by the Korean International Cooperation Agency (KOICA) from 2016 to 2021 to develop the capacities of FBO/FBCs[4]. That notwithstanding, access to resources like improved seeds, fertiliser, and agricultural equipment at affordable costs must still be made easier for FBOs. Through subsidies or specialised credit programmes, this can be accomplished.

Family labour: Family labour has a coefficient of 0.148 and a standard error of 0.071, which is statistically significant at the 5 percent level. This positive association implies that increased family labor contributes to a 0.148 unit increase in maize yield. The findings indicate that in Northern Ghana, where small-scale, subsistence farming is prevalent, family labour can be useful for increasing farm yield performance. Enhancing rural households' access to quality

[4] See https://www.koica.go.kr/sites/gha_en/index.do#n

education through formal and informal channels in Northern Ghana, where there is greater reliance on family labour for agricultural activities is a crucial policy proposal Individuals will be more prepared to engage in farm-level practices targeted at improving yield outcomes if they are given adequate and appropriate educational training.

Farm Size: The coefficient for farm size is -1.006, with a standard error of 0.089, significant at the 1% level. This negative relationship indicates that as farm size increases, the dependent variable decreases by 1.006 units. The relationship between farm size and agricultural productivity represents a critical area of inquiry in agricultural economics. Empirical research has consistently demonstrated a counterintuitive phenomenon: as farm size increases, productivity often declines. the concept of an inverse relationship between farm size and productivity has deep roots in agricultural economic theory. For example, Alexander Chayanov in the early 20th century first proposed that smaller farms might possess unique economic advantages and can achieve greater efficiency through more intensive use of labour, lower transaction costs, and heightened personal motivation (Chai͡anov & Chai͡anov, 1986). Other studies across diverse geographical contexts have substantiated this theoretical perspective (Foster & Rosenzweig, 2022; Jouzi et al., 2017; Ren et al., 2019).

Education: The coefficient for education is 0.048 with a standard error of 0.017, statistically significant at the 5 percent level This positive coefficient suggests that higher education is associated with a 0.048 unit increase in maize yield. The findings indicate that improved access to formal education can increase farm yield performance in the context of Northern Ghana. Higher-educated farmers typically have easier access to knowledge, use modern farming methods, and make more informed choices. Policy implications include expanding access to high-quality education, offering specialised training and extension services, and encouraging the use of ICT in farming activities.

TABLE 5. 2 EFFECT OF CSA ADOPTION ON MAIZ YIELD ESTIMATED BY THE GLS METHOD

Variable	Yield (kg)	t-stat	Collinearity Statistics	
			Tolerance	VIF
CSA 1-Improved maize variety	1.027*** (0.155)	6.616	0.442	2.262
CSA 2-Soil fertility enhancing	0.717** (0.121)	5.93	0.453	2.208
Age	0.071** (0.028)	2.556	0.022	44.48
Age Squared	-0.001** (0.000319)	-3.206	0.026	38.35
Farming experience	0.378*** (0.074)	5.140	0.583	1.714
FBO member	0.409*** (0.094)	4.338	0.754	1.326
Family labour	0.148** (0.071)	2.082	0.784	1.276
Farm size	-1.006*** (0.089)	11.338	0.494	2.025
Education	0.048** (0.017)	2.826	0.815	1.228
Constant	111.704*** (12.619)			
Observations				566
R				0.685
R-Square				0.469
Adjusted R Square				0.460
Std. Error of the Estimates				24.37

Standard errors in parentheses p < 0.1, ** $p < 0.05$, *** $p < 0.01$

Source; Author's elaboration from survey 2023

5.3.2 Effect of CSA Adoption on Net Returns

Table 5.6 shows the findings of the analysis evaluating the effect of CSA adoption on the net return from maize production. Six of the nine variables in the model produced significant findings at the conventional 1% and 5% significance levels. The (R) value in the GLS model for net return is 0.789, which demonstrates a reasonably strong positive correlation between the independent and dependent variables in the model. The independent variables in the model account for roughly 62.3% of the variation in net return, based on the R-square value. The model's explanatory power may not have been greatly enhanced by the addition of some independent variables, since the adjusted R-square value of 0.612 is marginally lower than the R-square. The variability of the observed net returns around the predicted values is measured by the estimates' standard error. A standard error of 0.663, which shows that the model's predictions are more accurate than the actual data points is desirable. Overall, these statistics show that the model fits the data reasonably well.

Two specific CSA practices which are the key interest variables in the study are highlighted in the model**.** They are Improved Maize Variety and Soil Fertility Enhancing Practices.

CSA 1-Improved maize variety: The variable has a coefficient of 0.359, and a p-value of 1 percent suggesting that using enhanced maize seed varieties can raise net returns among maize-producing households in Northern Ghana by 35.9 percent. The positive effect on net returns likely operates through multiple channels: the higher yield potential of improved crop varieties translates to increased output per unit area, while better drought and disease resistance reduces crop failure risks, stabilizing income (Hansen et al., 2019). Additionally, improved varieties often enjoy better market acceptance, potentially commanding premium prices, and enhanced grain quality can lead to reduced post-harvest losses (Ndirangu & Oyange, 2019; Neema, 2023; Neme et al., 2021).

Together, these factors contribute to stronger and more reliable net returns for farmers. A study by Bi et al., (2022), and Huang et al., (2016), showed that greater productivity, resistance to disease and pests and adaptation to regional conditions are all features of improved maize seed varieties. Contrary to conventional seeds, farmers that use these types often receive higher crop yields. Also, several modified maize varieties are selected for attributes such as enhanced flavour, improved texture, and higher nutritional value (Kumar et al., 2020). Consequently, this can lead to an increase in market prices, potentially resulting in higher revenue for farmers.

CSA 2-Soil fertility enhancing practice: This variable shows an even higher positive coefficient 0.423 and p-value of 0.001) suggesting a stronger effect on net returns. Higher crop yields, better crop quality, and lower production costs can all result from improved soil fertility, which ultimately boosts farmers' net returns. The stronger positive effects of soil fertility enhancement practices translate into increased net returns and profitability in maize farming through several key mechanisms. First, improved soil structure and fertility boost maize yields, lower production costs, and increase profitability (Mafongoya et al., 2016). Secondly, better nutrient availability reduces the need for costly inputs, resulting in wider profit margins (Adamtey et al., 2016), and reducing soil erosion and improving nutrient use efficiency may lower fertilizer costs, allowing farmers to allocate resources more effectively and maintain profitability (Wani et al., 2017).

Numerous research studies and study findings support this claim. Plants receive the key ingredients required for strong growth from nutrient-rich soils, resulting in healthier and more fruitful crops (Janmohammadi et al., 2018; Robinson et al., 2019). Furthermore, crops' flavour, texture, and nutritional value can be improved by maintaining adequate soil nutrient levels, pH, and organic matter content (Timsina, 2018).

Age: The analysis reveals a nuanced relationship between age and agricultural net returns. With a coefficient of 0.0 at 5 percent alpha level, each additional year of a farmer's age is associated with a 5.6% increase in net returns, indicating that older farmers tend to achieve better financial outcomes. The positive age effect likely captures various advantages that come with maturity, such as accumulated farming knowledge (Popescu, 2019), established networks, better access to resources, and refined decision-making abilities (Niu et al., 2021; Nuthall & Old, 2018; Phillips et al., 2018). Older farmers may have developed more effective risk management strategies and built stronger relationships with market participants over time (Heiman & Hildebrandt, 2018; Meraner & Finger, 2019). However, the negative quadratic term indicates that these benefits eventually plateau and potentially decline, perhaps due to physical limitations or reduced adoption of new farming technologies in later years (Austin et al., 2020; Frick & Sauer, 2021).

In essence, the findings suggest that older farmers frequently have more knowledge and experience of the regional climate conditions, crop variety, and traditional and modern farming techniques. This experience could result in better farm-level decision-making and higher net earnings. On the other hand, farming can involve physically demanding tasks that provide difficulties for older farmers. When compared to younger farmers, these physical restrictions may limit their capacity to engage in particular farming or marketing activities, which could harm their profitability.

Age Square; The age-square coefficient of -0.0005 highlights an important nonlinear aspect in the relationship between a farmer's age and net returns. This negative quadratic term indicates that while the benefits of age on returns are initially positive, they do not continue indefinitely; rather, they exhibit a diminishing returns pattern. The significance at the 5% level reinforces confidence in this curvilinear trend, suggesting that, after a certain point, each additional year provides a decreasing marginal benefit, eventually turning negative. In practical terms, this means that although returns increase with age initially (as reflected in the positive linear term for age), they eventually reach a peak and begin to decline, forming an inverted U-shape in the age-return relationship. The small magnitude of this coefficient (-0.0005) suggests that this decline occurs gradually, rather than abruptly, as age advances.

This finding is especially relevant for understanding the lifecycle of farming productivity, potentially informing policies related to succession planning and support services for ageing farmers. The quadratic effect of age underscores the need to consider both the opportunities and challenges presented by an ageing farmer population. Specifically, it suggests a need for targeted interventions to help older farmers maintain productivity, perhaps through labour-saving technologies or adaptive farming practices.

The use of an age-squared variable in regression analysis is common to capture potential nonlinear relationships, yet interpreting its effects can be complex. In this context, the influence of age on net returns can vary significantly depending on individual circumstances and farming contexts. Despite their experience, older farmers may face physical limitations that reduce their ability to carry out labour-intensive tasks, potentially impacting their net returns. For example, certain farming tasks may become increasingly challenging with age, as noted by (Corsi et al., 2021).

Furthermore, factors such as healthcare access and support for the well-being of older farmers can greatly influence their ability to sustain agricultural production and generate profits. This need is particularly pressing given the challenges posed by inadequate healthcare systems in northern Ghana (Awoonor-Williams et al., 2016).

Overall, the age-squared effect illustrates the complexities of ageing within the agricultural sector, indicating a need for policies that address the evolving needs of ageing farmers while supporting their long-term well-being and continued contributions to agriculture.

Farming experience: Farming experience emerges as another crucial factor, with a 36.6% increase in net returns associated with a strong statistical significance of 1 percent. The significant positive effect of experience, independent of age, suggests that practical farming knowledge plays a vital role in determining financial outcomes. Farmer experience, quantified as the number of years a farmer has been involved in maize farming, exhibits a statistically significant positive correlation with net returns. This finding underscores the crucial role of accumulated practical knowledge in agricultural success. The magnitude of this effect is particularly noteworthy, suggesting that experience may be one of the most valuable assets in farming operations. In general, there is evidence to support the idea that farmer experience may increase farm net revenue. Farmers with more experience typically have a better understanding of agricultural practices, such as crop selection, planting procedures, managing pests and diseases, and irrigation strategies (Islam et al., 2020). They are more inclined to embrace more effective farming techniques that can result in higher yields and, eventually, higher net income. (Ma & Abdulai, 2019; Maertens & Velde, 2017). Also experienced farmers often develop improved market timing, more efficient resource allocation, and stronger risk management capabilities. (Ullah et al., 2016).

Farm size: This variable has the most substantial effect on net returns, with a 66.2% increase associated with larger farm size. This finding suggests significant economies of scale in maize production in northern Ghana where larger farms can potentially benefit from improved resource utilization and operational efficiencies. The benefits of larger farms are strongly supported by the high statistical significance of 1 percent. It's important to note, however, that several factors, including the specific context, farming practices, and farm management efficiency, can influence the relationship between farm size and farm net revenue. Nonetheless, available literature suggests that, generally, larger farms may have the capacity to generate higher net revenue. Economies of scale, where the cost per unit of production falls as farm size increases, may be advantageous for larger farms. This may result in more effective resource use, cheaper cost of production, and eventually higher net revenue (Archer et al., 2018; Nayak, 2018). Larger farms may also have better access to resources including modern machinery, improved infrastructure, and irrigation systems (Mottaleb et al., 2016). These resources have the potential to boost output and expand the farm's total capability for generating income(Liao et al., 2022). Due to their size, larger farms may have easier access to markets and be in a better position to negotiate favourable prices for their crops (Aryal et al., 2021). This may have a favourable effect on net income.

However, some shreds of evidence highlight the complexities and caveats of the relationship between farm size and net return or farm profitability. The efficiency of farm management, including resource allocation, decision-making, application of modern techniques, and the quality of the land can have significant effects on a farm's financial success (Kryszak et al., 2021). The fertility and adaptability of the land are important considerations, and larger farms may not always have better land. Traditional practices, land tenure systems, and sociocultural factors can all have an impact on how farming is carried out. Households with smaller farms with strong community ties might occasionally be quite profitable (Heinrichs et al., 2021; Hu et al., 2022).

TABLE 5. 3EFFECT OF CSA ADOPTION ON NET RETURNS ESTIMATED BY THE GLS METHOD

Variable	Net Returns (Ghc)	t-stat	Collinearity Statistics	
			Tolerance	VIF
CSA 2-Improved maize variety	0.359*** (0.124)	2.892	0.373	2.684
CSA 2-Soil fertility enhancing	0.423*** (0.105)	4.045	0.392	2.551
Age	0.056** (0.022)	2.553	0.016	61.752
Age Square	-0.0005** (0.0003)	-2.228	0.019	51.353
Farming experience	0.366*** (0.063)	5.844	0.484	2.065
FBO member	.099 (.071)	1.403	0.807	1.239
Family labour	0.37 (0.055)	0.682	0.696	1.437
Farm size	0.662*** (.098)	6.763	0.359	2.783
Education	0.003 (.012)	0.233	0.769	1.301
Constant	1226.23*** (249.03)			
Observations				566
R				0.789
R-Square				0.623
Adjusted R Square				0.612
Std. Error of the Estimate				0.663

Standard errors in parentheses $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source; authors elaboration from survey 20223

5.4 Conclusion

The adoption of CSA practices and its effects on farmers' crop yields and net returns have been discussed in this chapter.

CHAPTER SIX

RESULTS AND DISCUSSION

QUALITATIVE ANALYSIS OF ACCESS TO CLIMATE INFORMATION SERVICES AND INDIGENOUS CLIMATE KNOWLEDGE

6.1 Introduction

The chapter deals with the results of the qualitative analysis of how farmers in Northern Ghana use climate information. It discusses the topic of climate information from the perspective of the hierarchical mode of production whereby farmers get relevant climate information from more experienced farmers, experts, and government extension officers (the elites). The views of these elites and their similar and different perceptions of climate information vis a-vis ordinary farmers (the masses) are addressed in this chapter. The analysis involves in-depth individual interviews with 15 relatively more experienced farming households selected from the five study districts of Northern, Upper East, and West regions of Ghana and detailed individual face-to-face consultations with five climate change science specialists.

The chapter also explores how combining formal climate information and indigenous climate knowledge influences CSA practices and adaptation strategies. It investigates households' perspectives, attitudes, and challenges in accessing and using climate information and traditional knowledge. It concludes with a discussion of the similarities and differences, ascertained from the 566 survey householders (the masses) and the 20 experts (elites), related to the use of climate information. Hence, the degree of symmetry of the information shared between elites (climate experts) and experienced smallholder farmers in terms of the quality of climate information is assessed.

6 Description of the Elites and Experienced Farmers in Northern Ghana Interviewed for this Study.

Table 6.1 presents demographic, occupational, and expertise information about two groups involved in farming and agricultural-related work: "Elite" professionals and "Experienced Farmers among smallholders" across three regions of northern Ghana: Northern, Upper East, and Upper West. This analysis explores the characteristics of each group, emphasizing age, education, occupation, language, and area of expertise.

6.2.1 Primary Occupation and Experience.

Elite Group: The elite members work in specialized roles, such as climate change experts, agricultural officers, NGO directors, and researchers. Their work is often focused on advisory, research, or educational aspects, aiming to improve farming methods, provide climate education, and enhance agricultural services. Their experience ranges from 15 to 20 years, demonstrating long-term involvement in their areas of expertise.

Experienced Farmers: The "experienced farmer" group comprises individuals involved directly in farming, with occupations like crop farming or mixed farming. Their years of experience are even higher, with many having 30 or more years in farming. This suggests that ordinary farmers bring extensive practical knowledge of farming practices. However, this experience may be more traditional due to lower formal education levels.

6.2.2 Regional Distribution and Language Proficiency

Regional Representation: Both groups are spread across the Northern, Upper East, and Upper West regions, reflecting a broad geographical coverage. However, there is no significant regional concentration within each category.

Languages Spoken*:* Language use is diverse and regionally oriented. Members of the elite group often speak English in addition to local languages (Dagbani, Gurune, and Dagaare), while experienced farmers predominantly communicate in their regional languages. This language diversity highlights the importance of multilingual communication strategies for agricultural outreach and information dissemination.

6.2.3 Main Areas of Expertise or Farming Focus

Elite Group*:* The elites' expertise spans fields critical to modern agricultural challenges—climate change, weather forecasting, climate research, extension services, and climate education. Their roles often address broad, systemic issues such as climate resilience, sustainable farming, and farmer education, aligning with national and global agricultural priorities.

Experienced Farmers*:* Ordinary farmers' expertise focuses on traditional farming areas, including specific crops like millet, maize, groundnuts, and sorghum, as well as conventional farming methods. Many are mixed or crop farmers, relying on indigenous practices and rain-fed agriculture. This reliance on traditional practices could pose challenges with the increasing need for climate adaptation, water conservation, and advanced agricultural techniques.

The findings imply that the "Elite" group's advanced education and focus on climate-related research could bridge the knowledge gap between traditional and modern farming practices. However, due to language and educational differences, effective communication and educational strategies will be essential. The wealth of practical experience among experienced farmers is invaluable emphasising the immense value of hands-on knowledge and skills gained through working directly with crops, livestock, and soil. However, the limited formal education and dependency on traditional methods highlight the potential need for training programs focusing on sustainable and climate-resilient practices to help them adapt to changing environmental conditions. Multilingual communication strategies and community-based workshops could facilitate knowledge transfer, given that ordinary farmers predominantly speak local languages.

TABLE 1.1 DESCRIPTION OF THE 20 IN-DEPTH INTERVIEWEES

ID	Category	Age	Gender	Level of Education	Primary occupation	Region	Years of Farming/Work	Languages Spoken	Main Farming/Expert Area
R1	Elite	52	M	Bachelor	Climate Change	Northern	20	English, Dagbani	Weather Forecasting
R2	Elite	48	F	Bachelor	Agric Officer	Upper East	15	English, Gurune	Extension Services
R3	Elite	55	M	Bachelor	NGO Director	Upper West	18	English, Dagaare	Climate Education
R4	Elite	50	M	PhD	Researcher	Northern	16	English, Dagbani	Climate Research
R5	Elite	51	F	Masters	Agric Officer	Upper East	17	English Gurune	Farming Systems
R6	Experienced Farmer	58	M	Primary	Crop Farmer	Northern	35	Dagbani	Millet & Maize
R7	Experienced Farmer	52	F	SHS	Mixed Farmer	Upper East	30	Gurune	Groundnuts & Vegetables
R8	Experienced Farmer	61	M	None	Crop Farmer	Upper West	40	Dagaare	Sorghum & Maize
R9	Experienced Farmer	49	M	Primary	Mixed Farmer	Northern	28	Dagbani	Mixed Cropping
R10	Experienced Farmer	55	F	None	Crop Farmer	Upper East	32	Gurune	Legumes & Cereals
R11	Experienced Farmer	63	M	None	Mixed Farmer	Upper West	42	Dagaare	Traditional Crops
R12	Experienced Farmer	47	F	Primary	Crop Farmer	Northern	25	Dagbani	Vegetables & Maize
R13	Experienced Farmer	59	M	None	Crop Farmer	Upper East	38	Gurune	Millet & Groundnuts
R14	Experienced Farmer	51	M	Primary	Mixed Farmer	Upper West	30	Dagaare	Mixed Farming
R15	Experienced Farmer	54	F	None	Crop Farmer	Northern	33	Dagbani	Cereals & Vegetables
R16	Experienced Farmer	57	M	None	Mixed Farmer	Upper East	35	Gurune	Traditional Methods
R17	Experienced Farmer	50	M	Primary	Crop Farmer	Upper West	28	Dagaare	Maize & Sorghum
R18	Experienced Farmer	62	F	None	Mixed Farmer	Northern	40	Dagbani	Indigenous Practices
R19	Experienced Farmer	53	M	None	Crop Farmer	Upper East	32	Gurune	Rain-fed Farming
R20	Experienced Farmer	56	M	Primary	Crop Farmer	Northern	23	English Dagbani	Maize & Rice

Source: author's elaboration from in-depth-interviews 2023

6.3 Access to Climate Information Services

The interviews revealed various sources through which respondents access climate information services. The most common sources include text messages, the internet, radio, and TV. Respondents also mentioned obtaining information from extension officers, although the frequency of interaction varied. Another significant source is indigenous climate knowledge. Additionally, some respondents highlighted the use of smartphones to access climate information. Overall, the primary sources of climate information reported by the participants are radio, TV, indigenous knowledge, and interactions with extension officers.

For example, according to a respondent from in Kassena Nankani district in Upper East regions …*"Both radio broadcasts and agricultural extension officers serve as the main channels for obtaining climate-related information. Additionally, the agricultural extension officers occasionally convene meetings with farmers, during which discussions encompass topics related to climate and agriculture"* …. *(Quoted verbatim from audio recording)*

The findings shed light on the diverse range of sources that respondents utilize to access climate information services. These sources play a crucial role in informing local communities about climate conditions and guiding their decision-making processes. The identified sources include text messages, the internet, radio, TV, extension officers, indigenous climate knowledge, and smartphones.

The prevalence of radio and TV as primary sources of climate information aligns with the established literature. Radio has been widely recognized as a vital tool for disseminating information, especially in remote areas where access to other forms of communication may be limited (Olajide, 2011). Additionally, TV broadcasts can effectively reach a larger audience, making them a significant channel for conveying weather forecasts and updates (Gavin, 2017).

The mention of extension officers as a source of climate information is consistent with previous studies highlighting the role of agricultural extension services in disseminating valuable information to farmers (Antwi-Agyei & Stringer, 2021b; Muhammad et al., 2018). However, the varying frequency of interactions with extension officers underscores the need for consistent and accessible support services, as sporadic interactions may hinder the timely receipt of crucial climate information.

The inclusion of indigenous climate knowledge as a significant source of information aligns with the growing recognition of the value of local knowledge in enhancing adaptive capacity to climate variability (Granderson, 2017). Indigenous climate knowledge reflects the accumulated wisdom of communities, built upon generations of experience with local weather patterns and ecological indicators (Apraku et al., 2021). The emerging role of smartphones as a means of accessing climate information reflects the increasing penetration of mobile technology even in remote regions (Jankowski & de Sousa, 2016). Mobile phones offer a convenient and personal platform for receiving updates and alerts, particularly for individuals who might have limited access to traditional media.

The findings from the study highlight the multi-faceted approach that respondents in northern Ghana adopt to access climate information services. These approaches draw from a mix of modern technological platforms, established media channels, local knowledge systems, and direct interactions with extension officers. Acknowledging and supporting this diverse array of information sources can contribute to better-informed decision-making and enhanced adaptive capacity within the context of climate variability.

6.4 Perception and Attitudes Towards Formal Climate Information Services

Some respondents highlight the occasional unreliability of formal climate information, suggesting potential inaccuracies. Some others acknowledged the significance of formal climate information but adopted a cautious approach due to perceived inaccuracies. They combine formal information with personal farming experience and indigenous climate knowledge to make informed decisions. Farmers' perceptions and attitudes toward formal climate information services encompass a spectrum of viewpoints. Concerns about reliability and accuracy are juxtaposed with recognition of their importance. Some farmers choose to supplement formal information with personal experience and indigenous knowledge, while others express a higher level of trust in official sources. Overall, while the usefulness of formal climate information is acknowledged, its potential limitations are also recognized by the interviewed farmers.

In the view of a respondent from Jirapa in the Upper East Regions*; Formal climate information holds significant importance, yet I maintain a cautious approach due to occasional inaccuracies in the provided data. Therefore, I harmonize this formal information with my extensive years of farming experience and traditional climate wisdom"* …. (Quoted verbatim from audio recording)

These findings underscore the diverse perspectives that farmers hold regarding formal climate information services. The range of viewpoints reflects a complex interplay between different factors that influence how farmers perceive and engage with these services. The study reveals a dynamic landscape where concerns, recognition of importance, trust in sources, and the integration of various knowledge systems coexist. This variation in perception aligns with existing literature, which acknowledges that farmers' attitudes toward climate information services are shaped by a combination of factors including the quality and reliability of the information provided, previous experiences with climate forecasts, and the compatibility of formal information with local knowledge (J. W. Jones et al., 2000; Ricart et al., 2022)

The study's findings align with previous research showing that farmers both recognize the importance of formal climate information but have reservations about its reliability. These mixed feelings often stem from instances where formal forecasts have not aligned with actual weather outcomes, leading to scepticism (Deressa et al., 2009). This duality highlights the complex interplay between the value of formal information and the need to assess its accuracy in the local context.

The phenomenon of some farmers integrating formal information with their personal experience and indigenous knowledge reflects an adaptive approach, aligning with the notion of "knowledge blending." This blending is recognized as an effective strategy to enhance the accuracy of decision-making by combining formal information with localized insights (Roncoli et al., 2009).

In conclusion, the findings of the study in northern Ghana reveal a complex landscape of perceptions and attitudes toward formal climate information services among farmers. These attitudes are influenced by various factors including past experiences, the perceived reliability of forecasts, and the integration of different knowledge systems. Acknowledging and addressing the diverse viewpoints of farmers can contribute to the development of more effective climate communication strategies that align with local contexts and enhance the resilience of agricultural communities.

6.5 Indigenous Knowledge and its Role in Climate Decisions

The results from the in-depth interviews indicate the growing importance of indigenous climate knowledge in farm-level decisions. The Major finding is that this knowledge aids them in predicting weather patterns, especially rainfall. These predictions inform crucial decisions like land preparation, planting dates, and fertilization schedules. The respondents' reliance on this knowledge underscores its practical relevance in improving the resilience and productivity of their farming endeavours.

The following observations were made regarding the relevance of Indigenous climate knowledge in farm-level decisions by respondents from Wa and Savelugu municipalities:

"*My indigenous climate knowledge helps me to study the weather to be able to make informed decisions right from planting to. harvesting….* (Quoted verbatim from the transcribed audio recording).

"I use indigenous knowledge in farm level decisions such as water conservation, land preparation planting dates, draw a calendar for fertiliser application and weed control"….. (Quoted verbatim from the transcribed audio recording).

The findings also indicate seasonal signifiers and agricultural farm-level decisions. Respondents mention specific indicators from nature that are used to predict weather conditions, such as the formation of dark clouds, the presence of earthworms, and the croaking of frogs. These observations align with traditional ecological knowledge, where certain natural phenomena are considered reliable indicators of impending weather changes. Such information aids in making informed decisions about agricultural practices, including land preparation and cultivation.

Another dimension of the results points to the variability in climate information awareness. Lack of awareness regarding indigenous climate knowledge highlights an important aspect of this study. It suggests that the transmission of this knowledge might not be uniform across all members of the community. This variation could be due to generational differences, cultural shifts, or other factors. Acknowledging such differences helps in understanding the complex dynamics of how traditional knowledge is transferred and maintained within a community.

The results also focused on local ecological knowledge for weather predictions. Respondents drew attention to their use of natural cues, such as the position of the moon, the flowering and fruiting of certain trees, and the direction of winds, to predict weather patterns. These practices align with the concept of phenology, which studies the timing of recurring natural events about climate and environmental changes (Song, 2023). Such local ecological knowledge forms the basis of a community's ability to anticipate and adapt to climatic shifts.

Finally, the results highlight the integration of traditional and scientific climate knowledge in promoting farm-level decisions. The findings from all respondents underscore the integration of indigenous climate knowledge with modern agricultural practices. Respondents specifically mention combining traditional weather forecasting methods with contemporary decision-making processes. For example, according to a respondent in Nankalnia in the Kassan Nankana District of Upper East regions…

"*While I recognize the value of formal climate information, I remain sceptical of its accuracy. That's why I combine it with my years of farming experience and traditional knowledge when making agricultural decisions.*". (Quoted verbatim from the transcribed audio recording).

This blending of traditional and scientific approaches reflects the potential for synergies between local knowledge and externally derived information. These findings align with the broader understanding of traditional ecological knowledge and its role in sustainable resource management and climate adaptation. Scholars like Bohensky & Maru, (2011) and Inaotombi & Mahanta, (2018) have highlighted the importance of indigenous knowledge in maintaining ecological resilience. Additionally, the integration of traditional and scientific knowledge is a topic of interest in the field of participatory research and community-based natural resource management (Armitage, 2005; Phuthego & Chanda, 2004).

Overall, the interview findings illustrate how indigenous climate knowledge serves as a valuable resource for making informed decisions in various agricultural activities. This knowledge, deeply rooted in local observations and experiences, contributes to the resilience and adaptability of communities facing climate variability. The integration of traditional and scientific knowledge systems highlights the dynamic nature of decision-making processes in response to environmental changes.

6.6 Challenges of Accessing and Utilizing Formal Climate Information Services and Indigenous Climate Knowledge

The findings from the interviews highlight several important barriers that communities in northern Ghana face in their efforts to gather and apply relevant information for climate adaptation and decision-making. These challenges encompass issues related to technological access, accuracy of information, language barriers, and traditional knowledge transmission. Respondents highlight concerns about the consistency and reliability of formal climate projections provided by Ghana Meteorological Agency (GMet) and other organizations. For example, according to a respondent.

"Formal climate information services can provide seasonal weather forecasts but they are sometimes inadequate or inaccurate which does not help us in planning.".

These parallel concerns about the precision and relevance of climate projections, which are vital for empowering communities to make informed choices, might arise due to systemic errors. (Ebert & McBride, 2000). Developing trust in climate services and encouraging their use within adaption strategies need accurate climatic information.

Another issue that was reported from the interviews is language and literacy barriers. Respondents account underscores the importance of language accessibility for effective communication of climate information. For instance, according to a respondent from Tibali in the Savelugu District in the northern region…

"*As I mentioned before the start of this interview. I am illiterate and unable to understand climate information when it is transmitted in English unless it is translated into the local language….. As with radio, I am unable to see the visuals or presentation for clear understanding.*"

The inability to understand English, the language in which some information is transmitted, hinders meaningful engagement with climate data. This aligns with studies emphasizing the need for information to be communicated in local languages and tailored to the literacy levels of the target audience (Dowse et al., 2010).

Respondents mentioned that indigenous climate knowledge is often passed down through oral tradition, primarily from older to younger generations. However, the absence of older individuals within households to transmit this knowledge poses a challenge. This echoes discussions on the erosion of traditional knowledge due to generational shifts and changing societal dynamics (Berkes, 2008). The loss of such knowledge could limit the community's resilience to climate variability.

Respondents also noted network and technical problems affecting the receipt of climate information via modern communication methods, revealing challenges in information delivery.

Connectivity issues can hinder timely communication, reducing channel effectiveness. These observations align with literature emphasizing user-centred design and context-specific climate services (Gladwin et al., 2001). Participatory communication research (Sultana et al., 2015) underscores involving communities in shaping strategies and tools to overcome barriers to accessing and utilizing climate information.

In conclusion, the challenges identified in the interviews reflect the complex interplay of technological, linguistic, cultural, and infrastructural factors in accessing and utilizing climate information services and indigenous climate knowledge. Addressing these challenges requires context-specific solutions that prioritize inclusive and participatory communication strategies, improved infrastructure, and the preservation of traditional knowledge systems.

6.7 Coping Strategies and Practices Based on Indigenous Climate Knowledge

The interviews revealed a range of responses to the challenges posed by climate change and variability. These practices reflect the maize-producing households' reliance on traditional wisdom to navigate the changing climatic conditions and enhance their resilience. These coping strategies as reported by respondents include early planting and irrigation, indigenous climate knowledge and adaptive practice, adaptive and coping strategies combination, adjustments in farming practices due to unpredictable weather and application of fertilisers and afforestation.

Respondents highlight the significance of traditional coping strategies such as early planting and irrigation. These strategies enable communities to anticipate climate threats and mitigate potential impacts. Early planting aligns with the concept of shifting planting dates to align with changing climatic patterns, as discussed in studies emphasizing the role of traditional knowledge in adapting to climate change (Ford et al., 2013).

The integration of indigenous climate knowledge into adaptive practices like mulching, irrigation, and proper storage is also emphasized. This reflects the value of combining traditional wisdom with contemporary approaches to enhance resilience. This aligns with research advocating for the integration of indigenous knowledge systems into modern adaptive strategies to improve climate resilience (Adger et al., 2011). Respondents also underscore the importance of combining adaptive and coping strategies. This holistic approach recognizes that both short-term coping mechanisms and long-term adaptive practices are necessary for effective climate resilience. The integration of adaptive strategies like drought-resistant crop varieties aligns with research advocating for a mix of strategies to address varying temporal scales of climate impacts (Hill et al., 2019).

Additionally, respondents discussed adjustments made to cope with unpredictable weather, including planting at recommended schedules, reducing farm size, and using compost and inorganic fertilizers. These responses reflect the adaptive capacity of farmers in northern Ghana to modify farming practices in response to changing weather patterns, aligning with literature on flexible farming strategies as an adaptive response (Mertz et al., 2012). They also indicated afforestation and the use of organic fertilizers as coping strategies. Afforestation aligns with studies highlighting the importance of ecosystem-based approaches, such as reforestation, for climate adaptation (Dawson et al., 2019). The use of organic fertilizers reflects a sustainable approach to soil management in the face of climate variability (Vanlauwe et al., 2015).

6.8 Discussion of the Similarities and Differences Between the Views of Survey Respondents and Those Derived from the Qualitative Analysis of the Elites

The results from the study suggest that maize-producing households who constitute the masses and experts (the elites) may use climate knowledge and implement different Climate-Smart Agriculture (CSA) practices. Three main similarities and six differences emerged from the in-depth interviews of respondents.

6.8.1 Similarities

Climate change awareness: Both the masses (farmers) and the elites (experts) are aware of the difficulties presented by climate change. They understand that varying weather conditions, rising temperatures, and severe weather can affect agricultural output and food security. This awareness indicates that informational campaigns, educational activities, and media coverage have been effective in educating a variety of stakeholders about this worldwide issue. This emphasises how crucial it is for everyone to contribute to the mitigation and adaptation of these challenges. It emphasises the importance of working together, exchanging information, and creating workable solutions that will protect agricultural output and food security in the face of a changing environment.

Access to climate information: Both groups have access to climate information, though there may be differences in the sources and accuracy of this data. While experts have access to more advanced climate models and data, farmers may rely on regional weather forecasts, extension services, or traditional wisdom. Professionals can give expertise in climate science and sustainable agricultural methods, while farmers can offer insightful information about the regional effects of climate change. Together, they can create and put into action efficient plans to deal with the effects of climate change on agriculture.

Sustainable agriculture; This is something that both farmers and specialists are interested in. They are aware of how crucial it is to modify agricultural methods to reduce their negative effects on the environment and guarantee continued food production. The shared interest in sustainable agriculture as well as understanding of its importance for preserving the environment, ensuring food security and sustainable livelihood demonstrate a common commitment to addressing the challenges facing modern agriculture particularly maize production in northern Ghana. These findings imply that there is a basis for farmers and experts to collaborate on the development and use of sustainable agricultural practices including CSA practices that are favourable to both food production and the environment. In effect, the findings imply that both elite and ordinary farmers, along seed the need for agriculture to be sustainable. They acknowledge the need for sustainable practices that benefit food production and the environment, fostering a collaborative approach to tackle the challenges facing agriculture in their region.

6.8.2 Differences

***Knowledge and expertise*: ** Experts are more knowledgeable about the science of climate change and how it affects agriculture. They can decipher intricate climatic data and give farmers personalised advice. Farmers, on the other hand, could rely on simplified information and have inadequate scientific expertise. The results show that experts, who probably have training in climate science or similar subjects, have the abilities and knowledge required to analyse complex climate data. To understand how climate change can affect particular locations and farming systems, they can analyse climate models, historical weather patterns, and other scientific data. They can provide specialised guidance on issues like crop options, planting dates, irrigation plans, and risk management techniques that are particularly created to lessen the effects of climate change on agriculture in specific regions. Contrarily, farmers might only be somewhat familiar with the scientific aspects of climate change and its effects. Instead of relying on scientific research, their expertise frequently comes from practical farming experience. The intricacies of climate change and how it affects their farming practices can be difficult for them to fully understand given their limited scientific expertise.

Resource accessibility: Resources such as financing, technology, and research assistance are frequently more readily available to experts. This enables them to put into practice cutting-edge CSA techniques and technology that may be out of the price range of many farmers. Due to their links with institutions, research networks, and professional affiliations, experts frequently have easier access to advanced agricultural technologies. Research support for experts includes working with agricultural scientists, having access to research facilities, and receiving financing for research initiatives. Experts are more likely to use cutting-edge CSA approaches since they have access to research and equipment. On the other hand, farmers frequently lack the financial resources to invest in costly CSA technologies and research, particularly smallholder farmers and farmers in resource-constrained locations. Farmers may be discouraged from implementing modern agricultural solutions due to high upfront costs, restricted financial availability, and uncertain return on investment.

***Autonomy in decision-making**:* Farmers have the freedom to choose what to do based on a variety of factors, including the climate, customs, and the economy. Experts may advocate certain CSA practices based on their knowledge in a more top-down manner. Depending on their particular needs and local circumstances, farmers may choose to adopt or reject these ideas. The results illustrate the complicated decision-making environment in agriculture, where farmers exercise autonomy influenced by climate, tradition, and economics while experts contribute scientific information and top-down suggestions. The difficulty lies in establishing connections between different strategies, encouraging cooperation, knowledge exchange, and a shared appreciation of the advantages of CSA for both smallholder farmers and the environment.

Adoption barriers: Farmers may encounter adoption challenges, such as limited access to financing, a lack of infrastructure, or cultural considerations. Experts could be more concerned with developing and supporting CSA practices and policies than they are with understanding the difficulties smallholder farmers encounter at the local or grassroots level. The results show that CSA adoption has to take a more inclusive and context-specific approach. While specialists play an important role in the development and support of CSA practices and policies, sustainable agriculture practices must be successfully implemented at the grassroots level to recognise the difficulties experienced by smallholder farmers. Overcoming adoption barriers requires bridging the knowledge gap between experts and farmers through participatory approaches, policy adaptation, and capacity building.

Local knowledge: Farmers frequently have access to important local information and customs that experts may not completely understand. Having this knowledge can be essential for adjusting to the changing climate. The findings underline how crucial it is to take into account and incorporate regional expertise and practices into attempts to adapt to climate change. The distinct perspectives of farmers, influenced by their close ties to the land and the regional environment, are crucial for creating climate-resilient agricultural practices. The secret to effective climate adaptation in agriculture is collaboration and cultural sensitivity, as well as the use of both local and scientific knowledge.

Risk Tolerance: Because they directly depend on their agricultural activities for their livelihood smallholders, frequently have a higher tolerance for risk. Experts might approach risk management with a greater degree of caution. The findings highlight how smallholders and agricultural experts have varied opinions on risk. Because of their direct reliance on farming for a living, smallholders frequently have a higher risk tolerance than specialists, who place a larger priority on agricultural stability and sustainability as a whole. Achieving a balance that assures both short-term economic viability and long-term resilience in agriculture requires effective risk management techniques that include the viewpoints of both groups.

In conclusion, the findings imply that solving climate change concerns and promoting sustainable agriculture are shared goals of smallholder farmers (the masses) and professionals (the elites). However, there may be considerable differences in their expertise, resources, decision-making, and adoption hurdles. To ensure that climatic knowledge is converted into applicable and context-specific CSA practices that benefit farmers and the environment, effective collaboration and communication between these two groups are crucial.

CHAPTER SEVEN

SUMMARY OF STUDY, CONCLUSIONS AND RECOMMENDATIONS

7. 1 Introduction

The research is summarised in three different sections in this final chapter of the thesis report. It starts by giving a broad overview of the problem statement, study objectives, and research design. The adoption of climate-smart agricultural practices by households producing maize in Ghana's Northern, Upper East, and Upper West Regions is examined using statistical and econometric models, which are described in the second section. The final component of the study delves into its findings and draws conclusions based on the information gathered. This chapter concludes with a summary of the key policy recommendations derived from the research, followed by a section that discusses the study's limitations and makes recommendations for future research projects.

7.2 Overview of the Study Problem and Objectives

This study was motivated by the pressing reality of significant risks and shocks that farmers in Northern Ghana face due to climate change and variability. Although climate science has made strides in forecasting weather and climate information, there are still barriers preventing agrarian households in Northern Ghana from accessing this information due to socioeconomic and cultural differences. Climate-smart agriculture (CSA) is an integrated technique of managing landscapes, including crops, livestock, forests, and fisheries, to address the interconnected problems of food security and increasing climate change, contributing to the achievement of sustainable development goals. Despite the extensive body of research on the impact of CSA practices, few studies have sought to increase our understanding of the role of climate information access on adoption and investment decision-making. There is a disconnect between the climatic information offered by meteorological agencies and what farmers need to make timely and efficient decisions about climate change, an issue that is lacking in traditional extension service delivery. To address these issues, the study purposely targeted three regions, five districts, and seven communities in Northern Ghana, which were earmarked as climate communities by ongoing climate projects. According to much of the literature, an effective way to reduce declining farm productivity and incomes among smallholder farmers who mostly rely on rain-fed agriculture is for policies and actions to promote the adoption and investment in climate-smart agriculture. This requires evidence-based analysis of the problems in Northern Ghana using appropriate techniques, theories, and methods.

Therefore, this study was driven by five objectives. The first was to evaluate the utilization of climate information in farm-level decisions among maize-producing households in the study area. The second was to examine the determinants of CSA adoption. The third objective was to analyze the effect of CSA practices on crop yield and net returns. The fourth objective was to assess the willingness to invest in CSA among maize-producing households in the Northern, Upper East, and Upper West regions of Ghana and the fifth was to examine the elites' and ordinary farmers' views and perceptions about climate change and climate-smart agricultural practices in northern Ghana.

7.3 Statistical and Econometric Models Used for the Study

The study had five objectives, and the utility maximization theory guided the use of three main tools for statistical and econometric modelling. The initial tool employed simple descriptive statistics, including frequencies and percentages, to analyze the socioeconomic characteristics of the sampled households. The tool also evaluated the measures of climate information access and use by employing cross-tabulation, inferential statistics, and factor analysis. The second objective used multinomial logistic regression to investigate the determinants of CSA adoption. The regression model constructed for the study out of eleven CSA practices included improved maize variety use, soil fertility enhancing practices, and conventional crop rotation CSA practices as categorical dependent variables using Principal Component Analysis. The third objective employed a Generalised Least Squares model, specifically an augment production function, to examine the effect of climate-smart agricultural practices on maize yield and net returns. Finally, the study used the binary logit model to assess maize-producing households' willingness to invest in climate-smart agricultural practices.

7.4 Summary of Research Findings

7.4.1 Objective 1: Use of Climate Information in Farm-level Decisions

This section consists of two components. The first component entails a qualitative analysis of access to climate information. The second component focuses on the examination of how climate information variables are utilized in making farm-level decisions. The research findings revealed several important points related to climate patterns and information access in northern Ghana. Firstly, there is a growing irregularity of rainfall in all study districts. Additionally, there is a general increase in flood frequency across the majority of the surveyed areas, further exacerbating the challenges faced by farmers and communities. In terms of accessing climate information, radio emerges as the dominant source for obtaining rainfall-related updates, while television plays a crucial role in providing information on other climate variables. This highlights the importance of these traditional media platforms in disseminating crucial weather information to the local population.

The Ghana Meteorological Agency has demonstrated success in delivering accurate and reliable climate information, particularly regarding general weather conditions. This speaks to the effectiveness of their services and the value they provide to users in making informed decisions. Indigenous climatic knowledge among respondents is evident through their belief in the correlation between earthworm activity and rainfall, as well as the reliability of dark clouds amidst strong winds as indicators of imminent rainfall. However, it is worth noting that there is variation in the perception of singing birds and flying insects as indicators of rainfall across the study districts.

In examining the use of climate information in farm-level decisions, three underlying constructs are important in explaining the variance in the data. These are the daily weather forecasts (represented by factor 1) seasonal weather forecast (represented by factor 2) and indigenous weather predictions (represented by factor 3).

Strong factor loadings connected to features related to daily weather forecasts define factor 1. The essential variables in this component are "Climate information that allows effective crop management" and "Climate information that offers quick decisions at the farm level." This emphasises the critical role that reliable, timely daily weather forecasts play in influencing decisions made at the farm level and facilitating effective crop management.

The statements "Climate information allows for long-term planning and "Climate information allows mitigation planning" both of which are related to seasonal weather forecasts, are notable for having significant factor loadings in factor 2. This point emphasises how important seasonal weather forecasts are in assisting farmers with long-term agricultural planning and risk management techniques.

A significant factor loading for the statement "Climate information allows for trust in local knowledge" dominates factor 3. This aspect emphasises how important local indigenous weather knowledge is in farm-level decision-making. It suggests that local knowledge which is mainly used in predicting rainfall is important for many elements of farming and gives farmers access to climate data for free or at low costs.

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7.4.2 Objective 2: Determinants of Adoption of CSA Practices

The results of the multinomial logit analysis shed important light on how maize farmers in Northern Ghana are implementing Climate-Smart Agricultural (CSA) practices. The adoption of enhanced maize varieties and practices that increase soil fertility were two main areas of focus of the study with crop rotation serving as the reference category. Several important predictive variables for the adoption of improved maize varieties emerged. Age, sex, farming experience, access to climatic information, farm size, and seasonal extension visits are a few of these. These elements generally had a favourable impact on adoption. It's interesting to observe that farming expertise had an unexpected impact and may have prevented the farmers from using enhanced maize seed variety as a CSA practice relative to conventional crop rotation. The results also showed that similar elements, including marital status and maize commercialization, had a significant impact on whether maize producers employ practices meant to improve soil fertility. All of these variables were discovered to positively affect adoption, highlighting their significance in promoting sustainable agriculture practices.

7.4.3 Objective 3: Effect of the use of CSA practices on Maize Yield and Net returns

Analysis of the effects of adopting Climate-Smart Agriculture (CSA) practices on maize yield and net return provided important insights into the variables affecting these two. While net return denotes allocative efficiency, maize yield represents production efficiency. The study evaluated the effects of several variables, including the adoption of improved maize varieties, soil fertility enhancement methods, farmer age, farming experience, membership in farmer-based organisations (FBOs), use of family labour, years of farmer education, and some other significant socioeconomic characteristics. The findings demonstrate that many of these factors exhibit significant and positive effects on both maize yield and net return, underscoring their vital role in enhancing maize production. It's interesting to note that the analysis also reveals a negative effect linked to the age squared and farm size factors, indicating the need for focused initiatives to solve this problem.

7.4.4 Objective 4: Determinants of Farmer's Willingness to Invest in CSA Practices

The binary logistic analysis results show that the sex variable shows a positive coefficient, indicating that, when all other variables are kept constant, being labelled as "Male" is connected with a greater likelihood of farmers' willingness to invest in climate-smart agricultural practices. These variations may be explained by sex and access to resources like financing and land. In terms of years, the "Age" variable has a statistically significant impact on farmers' willingness to spend resources on climate-smart farming practices. Due to their established credit and financial stability or because of government efforts that target particular age groups, older farmers are more likely to be willing to invest in such practices. The likelihood of being willing to invest in climate-smart farming is inversely correlated with the number of years of farming. Experienced farmers may be less likely to invest in CSA practices or new agricultural technologies since the relationship between expertise and investment decisions can be complicated and context-specific.

The results also suggest that farmers are more likely to invest in climate-smart agriculture when Extension workers visit them more frequently. This implies that farmers who receive more frequent extension visits may be more likely to invest, presumably as a result of the fact that individual counselling and advising increases their awareness of various climate-smart agricultural practices and their related benefits. Additionally, Greater market accessibility is positively correlated with the willingness to invest in climate-smart agriculture practices. Farmers that are closer to markets may have better access to agricultural inputs and may be more likely to embrace techniques and technology that increase productivity and resilience.

Farmers who are more inclined to commercial farming have a larger predisposition to invest in climate-smart technologies. Increased resource access, greater information flow, and improved revenue streams can result from the commercialization of investments in climate-smart agriculture. Farmers who have access to climate information, such as through TV, radio, or mobile phones, are more likely to invest in climate-smart agriculture. Their awareness of climate-related hazards is increased by this accessibility, which also makes it easier for them to make well-informed decisions on crop management techniques. Overall, these findings show that a variety of socioeconomic and contextual factors have an impact on farmers' desire to invest in climate-smart agricultural practices. As a result, targeted interventions may be required to encourage such investments in specific farming communities and geographical areas in northern Ghana.

7.4.5 Objective 5: Perceptions of Elites and Ordinary Farmers Derived Through Qualitative Analysis

The study in northern Ghana sheds insight into the complex landscape of farmer opinions and perspectives towards formal climate information services. These views are influenced by factors including past experiences, the perceived accuracy of forecasts, and the incorporation of various information systems. The study also emphasises the value of using local knowledge of the climate when making decisions about various agricultural practices. Based on observations and experiences, this locally embedded knowledge improves community resilience and flexibility in the face of climatic change. The combination of conventional and scientific knowledge systems highlights how decisions are made in response to environmental changes in a dynamic way.

The findings also revealed that accessing and efficiently using indigenous climate knowledge and climate information requires overcoming numerous interconnected barriers that span technological, cultural, and infrastructure issues. However, farmers have cleverly used a wide range of coping mechanisms to deal with weather inconsistencies, such as following advised planting schedules, simplifying their agricultural operations, and using both organic compost and inorganic fertilisers.

7.5 Conclusions

- The findings suggest that three different factors; quick decision support, long-term planning and mitigation, and faith in local knowledge, influence how climate information affects farm-level decisions. Each element emphasises a certain quality of climate data that is particularly important for farmers to efficiently manage their farming practices.

- The study revealed two significant issues. First, adoption efforts are severely hampered by the detrimental effects of farm exposure to climate hazards, where farmland shows unfavourable features such as soil erosion, lack of afforestation upland and others, especially in areas susceptible to these issues. Second, the unanticipated role that farming experience plays in preventing the adoption of improved maize varieties points to the need for subtle strategies that promote CSA practices.

- The research findings emphasize the positive effect of CSA practices on maize yield and net return, as well as the significance of various variables in influencing these outcomes. Additionally, the results highlight the need for tailored interventions to address challenges related to farmer age and farm size.

- Gender, age, access to resources, extension services, market proximity, commercialization, and access to climate information all have a role in farmers' desire to invest in climate-smart agricultural practices. These findings can be used to build personalised interventions to promote sustainable agriculture practices in various locations of northern Ghana.

- The results of the qualitative study point to the fact that both climate change experts elite and experienced smallholder farmers share concerns about climate change and the promotion of sustainable agriculture. They differ significantly, though, in terms of their expertise, access to resources, ability to make decisions, and the challenges they encounter when putting ideas into practice.

7.6 Policy Recommendations

These policy recommendations are meant to assist in promoting resilient and sustainable agriculture in northern Ghana amid climate change by addressing the specific issues and opportunities shown by the research findings. Collaboration between government organisations, non-governmental organisations, local communities, and development partners is necessary for effective policy implementation.

Objective 1: Climate information access and use

Policymakers should strengthen traditional media platforms like radio and television to provide rainfall-related information and climate updates. This can be achieved through infrastructure investments, capacity building for meteorological services, and collaboration with broadcasters.

Climate information services should be tailored to meet farmers' unique needs, involving collaboration between traditional knowledge providers and modern meteorological agencies. Increasing the availability and accuracy of daily and seasonal weather forecasts is crucial for farming decisions. This can be achieved by investing in reliable location-specific weather data in real-time, with user-friendly platforms or mobile applications for easy by smallholder farmers.

Objective 2: Determinants of CSA adoption

Promote access to climatic information*:* To promote the adoption of Climate-Smart Agricultural (CSA) practices there is a need to improve farmers' access to weather and climate information in Northern Ghana through a variety of channels, including mobile apps, radio broadcasts, and community events. This can be accomplished by evaluating the present sources of climate information available to farmers, creating a localized weather information system that gathers data unique to various regions in Northern Ghana, and offering forecasts tailored to certain districts or farming communities. Create systems for feedback so that farmers can report weather abnormalities in their area or offer opinions on the value of the climate information they receive. The importance of the information can be enhanced by this two-way communication through local channels like meetings, community radio, and extension programmes.

Joint household decision-making**:** Relevant stakeholders should showcase the benefits of joint decision-making and resource sharing within households to encourage marital involvement in farming operations. Make awareness-creation efforts to encourage the adoption of CSA practices by all members of the household.

Encourage maize commercialisation; Support farmers in transitioning to commercial maize farming by offering training on market access and value addition. Create incentives for farmers to engage in commercial agriculture, which has been shown to positively influence CSA adoption. For example, improving the rural communication and road networks can facilitate less costly transportation and market linkages in northern Ghana the population of whom is faced with severe infrastructural challenges.

Tailor-made CSA practices: Tailor CSA adoption strategies to the specific climate and environmental conditions of different regions within Northern Ghana. This can be achieved through the promotion of localised and context-specific CSA practices that are effective in mitigating climate risks. In this regard, farmers and other members of the local community should be included in the process of defining and developing CSA practices. Their traditional knowledge and expertise are valuable assets. A proposal to develop tailored training programs and extension services that cater to the diverse needs of farmers, regardless of their age or level of experience is critical. In this process, the specific benefits of new maize varieties and soil fertility-enhancing techniques can be highlighted making them more contextually relevant to each farmer's unique circumstances.

Encourage seasoned farmers to adopt CSA farmers: Government and stakeholder organisations should develop educational initiatives to inform seasoned farmers of the benefits of integrating enhanced maize varieties into their Climate-Smart Agricultural (CSA) practices. These strategies ought to be created to eliminate any obstacles and misconceptions that may be present among the farmers. To learn more about the attitudes and beliefs of farmers, further investigation such as focus group discussion, the creation of demonstration farms, and peer-to-peer learning events should be used to effectively dispel misconceptions and encourage the adoption of CSA practices. These strategies can be effective instruments for changing attitudes and promoting the use of CSA practices by seasoned farmers in northern Ghana.

Reduce farmers' exposure to climate risk*:* The need for the government and its partners to implement strategies to lessen the effects of climatic risks on farms, particularly in vulnerable places is critical. Firstly, there is the need to assess vulnerable areas and engage stakeholders to develop climate-resilient farming practices. Work with agricultural experts to design and promote techniques like crop diversification, drought-resistant varieties, rainwater harvesting, and sustainable soil management. Implement early warning systems to provide timely information to farmers in vulnerable areas. Conduct training and capacity-building programs to empower farmers with knowledge and skills to implement climate-resilient practices. Support sustainable irrigation by investing in infrastructure to mitigate drought and water scarcity. The introduction of insurance schemes for extreme weather occurrences to the most vulnerable farmers is also essential.

Overall policies and initiatives can be created to offer specialised assistance to disadvantaged populations, including women, younger, and less experienced farmers. Create interventions that are tailored to their requirements and difficulties to encourage the adoption of better maize varieties. Increase farmers' access to climate information, especially in regions vulnerable to climate hazards. To help farmers respond to climate-related concerns, this may entail increasing communication channels, expanding weather forecasting services, and offering training. Recognise the advantages of characteristics like marital status and the commercialization of maize on the implementation of soil fertility improvement practices. These elements could be promoted among maize farmers to advance sustainable agricultural practices. Implement measures to lessen the impact of climatic hazards on agriculture. This could entail creating climate-resilient communities.

Objective 3 Effect of CSA on yields and net returns

Access to improved maize seed varieties: Through numerous methods, such as financial aid, seed distribution programmes, and extension services, it is easier to facilitate access to high-yielding maize varieties. Governmental bodies and agricultural organisations can use a variety of strategies to make these improved maize varieties more widely available. For instance, they can decide to offer discounts on high-yield maize seeds in the form of coupons or vouchers, helping smallholders and farmers with limited incomes. As an alternative, they may create seed credit programmes that would give farmers flexible repayment options while allowing them to acquire high-yield maize seeds on credit. Another strategy is to establish community seed banks where farmers can purchase top-quality maize seeds suitable for planting during the season.

Adoption and promotion of sustainable soil fertility enhancement techniques: such as crop rotation, the incorporation of organic matter, and the application of the proper fertilisers. The government can work with agricultural extension agencies, NGOs, and the Savanah Agricultural Research Institute in particular to set up demonstration plots to highlight the advantages of sustainable soil fertility practices. Firstly, the need to assess soil quality and farming practices in Northern Ghana to improve soil fertility is required. Also, the a need to launch farmer education programs to introduce sustainable techniques like crop rotation and organic farming. Collaborate with research institutions to develop region-specific knowledge. Ensure farmers have access to quality seeds, fertilizers, and organic inputs. Implement subsidies or financial support programs for smallholder farmers and scale up programmes for broader impact.

***Empowering senior farmers through specialized agricultural support*:** To mitigate the adverse impacts of ageing on farmers, the government, in collaboration with relevant ministries and agencies, can establish specialized assistance programs tailored for elderly farmers. These initiatives should focus on promoting less physically demanding, contemporary farming techniques such as no-till farming, precision agriculture, and drip irrigation. Additionally, partnering with agricultural extension services can facilitate the organization of hands-on training sessions. These efforts should encompass providing financial support, incentives, and healthcare and wellness services to support the well-being of senior farmers.

Encourage the creation of active engagement of farmers in farmer-based organisations. Through FBOs, the government can offer opportunities for resource sharing and capacity building and develop cross-learning and collaboration by hosting networking events or conferences so farmers can acquire knowledge from successful FBOs in other regions or nations. The provision of subsidies or financial assistance through the Ghana Cooperative Council and the Department of Cooperatives to help farmers develop and sustain their organisations.

Promoting the use of Family Labour*;* Family labour should be used as productively as possible on farms, and both the government and other stakeholders have an important role to play in this regard. This can be done by acknowledging and respecting the labour-related traditions and customs that are established in the agricultural environment of northern Ghana. It is possible to easily integrate family labour optimisation into the accepted social norms by involving community members and local authorities. Activities such as protecting land tenure rights for farming families, among other measures, will encourage long-lasting commitments to family labour-efficient practices.

Objective 4 Determinants of Household Willingness to Invest in CSA

Develop and implement policies that support gender equality: This policy aims to ensure equal access to agricultural resources for both male and female farmers, facilitate women's access to credit and financial services, address gender disparities in land ownership and tenure, and address specific challenges faced by female farmers. for example, measures to develop community seed banks where farmers of both sexes can obtain premium seeds at reasonable costs can be adopted. The need to offer rural women training programmes on resource management and sustainable farming methods is also crucial in this regard. Implement land reform measures that guarantee equal land inheritance rights for male and female heirs. To assist women in managing their farm labour while making sure their children are cared for, community-based childcare centres should be established. Offer training sessions at convenient times and locations, as well as extension services that are sensitive to the requirements and limitations of female farmers.

***Develop programmes that address the needs of elderly farmers*;** By addressing their unique needs, such as financial support, education, and access to climate-smart agricultural practices, this policy will ensure the creation of programmes to aid elderly farmers. In addition, it is meant to promote generational knowledge exchange to tap into the invaluable experience of seasoned farmers. The following are practical examples of applying policy; The government might offer payments to older farmers so they can buy new equipment or adopt more environmentally friendly farming methods. Workshops and seminars could be held on issues like agricultural diversification, effective water management and other agronomic practices that are resilient to climate change. These sessions would aid ageing farmers in adjusting to modern farming methods. A programme might offer resources for adopting drought-resistant crop varieties, training in organic farming, and access to weather forecasting systems. Create mentoring programmes where seasoned farmers teach younger people about sustainable farming techniques. Apprenticeship programmes or events to share expertise could be involved.

Encourage the creation of value chains that improve the sale of maize: Both commercial and subsistence farmers can gain a lot from promoting the development of value chains that increase the sale of maize as well as market accessibility. This policy objective could be achieved if the government encouraged the creation of cooperative processing and storage facilities close to farmers' maize-growing areas. Together, farmers can store and process maize, minimising post-harvest losses and guaranteeing a constant level of quality. raising the overall worth of products made from maize. To link locations that produce maize with important markets, expenditure on transport networks and road infrastructure is important. By doing so, farmers' competitiveness can be boosted because transportation and other related cost will be lowered facilitating easier access to urban markets. Additionally, the creation of online resources or mobile apps can offer farmers real-time market data, empowering them to freely decide when and where to sell their maize to maximise revenues. Promoting contract farming is also necessary to increase farmers' access to markets, provide price guarantees, and reduce the risks and uncertainties associated with their agricultural endeavours.

***Improve dissemination of climatic information to farmers*:** In this policy proposal, it is suggested that a multi-platform strategy, including radio, television, and mobile apps, be used to improve the dissemination of climatic information to farmers. This information dissemination should not only encompass general weather updates but also include region-specific climate forecasts and risk assessment tools. It's essential to make use of a variety of media platforms to effectively reach a diverse farming community. Information about the climate can be accessed through radio, television, and mobile apps. By making this information available through a variety of channels, it has a much better chance of getting to a larger audience, including people who live in rural locations with poor internet access. For their agricultural activities, farmers greatly rely on precise and current meteorological information. They can get crucial weather updates that affect their daily decisions, like planting, harvesting, or irrigation, by using radio and television broadcasts. Mobile apps are a useful tool for delivering personalised, real-time weather information. Farmers can use interactive tools, real-time data, alerts, and real-time data to plan their actions.

Objective 5: Perceptions of elites derived through qualitative analysis

***Climate Information Dissemination and Access*:** There is a need to create and put into place tailored programmes to increase smallholder farmers' access to and usability of formal climate information services. To deliver fast and reliable climatic information at the local level, investment in weather forecasting infrastructure and technology is key. In this regard, there is a need to encourage the use of digital and mobile platforms to provide farmers with climatic information in their local languages and dialects. Telecommunication networks can facilitate these by improving connectivity and network challenges, especially in rural areas.

***Integrating indigenous knowledge into climate services**:* Numerous practical advantages can be derived by combining indigenous knowledge with current climatic information in the context of resilient farming practices in Northern Ghana. Indigenous farmers in Northern Ghana are an invaluable source of information on traditional crop varieties that are suitable for the area's climate. This information can be used in conjunction with current climate data to plan the timing of planting and harvesting particular crops, resulting in improved yields and fewer crop failure risks. Therefore, the government can create regulations that formally include indigenous climate knowledge in the climate information services funded by the government. To improve the precision and applicability of climate forecasts, this may entail building mechanisms for cooperation between traditional knowledge holders and meteorological organisations.

Capacity development/ community-based climate workshops*:* Give farmers training and capacity-building opportunities to improve their comprehension of climate information and its use. To encourage cooperation between farmers and climate specialists, provide workshops and opportunities for knowledge-sharing. through these workshops and trainings, subject-matter experts and meteorologists can exchange knowledge and experiences. Such workshops can help bridge the gap between local expertise and scientific knowledge.

Communication and extension services: To help farmers and climate scientists communicate more effectively and close the informational gap, strengthen extension services. Encourage neighbourhood-based groups and networks for information exchange and peer education.

Policy coherence: To support climate-resilient farming practices, and ensure coherence and alignment between national climate policies and agricultural policies. This can be achieved by encouraging cooperation between appropriate governmental organisations, NGOs, and other stakeholders interested in agriculture and the effects of climate change.

Equity and Inclusivity: To meet the unique requirements of vulnerable populations, we must ensure that policies and programmes are equitable and take into account factors such as gender, age, and socioeconomic of individuals at the household level.

These policy suggestions are intended to provide an atmosphere that will allow smallholder farmers and specialists to work together to address the problems caused by climate change and advance sustainable farming practices. To customise these recommendations to the unique needs and contexts of the studied regions and districts in northern Ghana, policy officials must interact with local communities and stakeholders regularly.

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APPENDICES

Appendix 1a: Variables Description and Measurement for CSA Adoption

variable Category	Variable Name	Measurement	Expected Sign
Dependent Variable (categorical)			
Drought-Disease-Pest Tolerant CSA strategies	option 1	Dummy (1=yes, 0=no)	
Soil fertility enhancing CSA strategies	option 2	Dummy (1=yes, 0=no)	
Crop Rotation	option 0	Dummy (1=yes, 0=no)	
Explanatory Variable			
Farmer characteristics			
Age of farmer in years	Age	continuous	+
Gender of farmer	Gender	Dummy (1=male 0=female)	+
Years of education of farmer	Edu	Continuous	+
Years of farming experience	Experience	Continuous	+
Market Access			
Distance to the nearest maize market	KMmarket	Continuous	-
Maize farming is mainly Commercial	CommMaize	Dummy (1=yes, 0=no)	+
Net returns	NetR	Continuous	+
Social Capital and Information Access			
Membership to FBOs	FBOmember	Dummy (1=yes, 0=no)	+

Family labour	FamLab	Continuous	+
Access to climate/weather information	CI	Dummy (1=yes, 0=no)	+
Knowledge of CSA practices	KnowCSA	Dummy (1=yes, 0=no)	+
Access to Mass Media	AccMM	Dummy (1=yes, 0=no)	+
Farm Level Characteristics			
Land size used for Maize cultivation	LandSize	Continuous	+
Land exposure to climate risk	LandRisk	Continuous	+
Maize Yield	MaizeYield	Continuous	+
Institutional Factors			
Access to Credit	AccCredit	Dummy (1=yes, 0=no)	+
Number of extension visits per season	EXTvisits	Dummy (1=yes, 0=no)	+
Access to farm input subsidy	InputSibsidy	Dummy (1=yes, 0=no)	+
CSA training received	CSATrainin	Dummy (1=yes, 0=no)	+

Source; authors compilation from literature (May 2022)

Appendix 1b: OLS Estimates of Yield Effect of CSA Adoption

Variable	Coefficient Estimates				Collinearity Statistics	
	B	Std. Error	t	Sig.	Tolerance	VIF
(Constant)	17.722	8.298	2.136	0.033		
Farm size	-3.274	1.908	-1.716	0.087	0.001	953.463
Family labour	0.514	0.307	1.671	0.095	0.045	22.062
CSA 1-Improved maize variety	3.342	1.953	1.712	0.088	0.003	328.367
CSA 2-Soil Fertility practice	2.311	1.351	1.711	0.088	0.004	261.245
Age	0.218	0.130	1.672	0.095	0.001	879.841
Age Squared	-0.003	0.002	-1.688	0.092	0.001	1328.097
Education	0.144	0.086	1.678	0.094	0.036	27.948
Farming Experience	1.214	0.711	1.708	0.088	0.008	124.671
FBO Member	1.228	0.720	1.706	0.089	0.014	70.488

Source; author's elaboration from survey 2023

Appendix 1c: OLS Estimation of Net Return Effect of CSA Adoption

	Coefficients Estimates				Collinearity Statistics	
Variable	B	Std. Error	t	Sig.	Tolerance	VIF

(Constant)	6.545	0.401	16.330	0.000		
Farm size	-0.123	0.044	-2.808	0.005	0.769	1.301
Family labour	-0.015	0.045	-0.334	0.738	0.822	1.216
CSA 1-Improved maize variety	0.346	0.094	3.678	0.000	0.505	1.978
CSA 2-Soil Fertility enhancing	0.416	0.071	5.890	0.000	0.540	1.852
Age	-0.004	0.019	-0.217	0.828	0.020	50.944
Age Squared	9.137E-05	0.000	0.396	0.693	0.020	50.607
Education	0.011	0.011	1.036	0.301	0.851	1.175
Farming Experience	0.099	0.047	2.110	0.035	0.717	1.395
FBO Member	-0.039	0.059	-0.659	0.510	0.826	1.211

Source: author's elaboration from survey data

TABLE 2.3: ANALYSIS OF MAIZE YIELD BY DISTRICT

Region	District	2018 Yield (MT/HA)	2019 Yield (MT/HA)	2020 Yield (MT/HA)	3-Year Avg. Yield (MT/HA)	Rank	3-Year Avg. Yield as % of National Average	3-Year Avg. Yield as % of Potential Yield
Ashanti	Amansie West	3.4	3.98	4.38	3.92	1	158.03	71.26
Central	Gomoa East	3.7	3.8	4.22	3.91	2	157.46	71
Eastern	West Akim	4.1	4.1	3.46	3.89	3	156.67	70.65
Eastern	Upper West Akim	4.08	4.1	3	3.73	4	150.3	67.77
Ashanti	Bekwai (Amansie East)	3.38	3.67	4.02	3.69	5	148.8	67.1
Ashanti	Atwima Mponua	3.04	3.68	4.06	3.59	6	144.95	65.36
Central	Twifo Atti Morkwa	N/A	-	3.5	3.53	7	142.48	64.24
Central	Abura-Asebu-Kwamankese	3.4	3.4	3.78	3.53	8	142.24	64.14
Ashanti	Ejura Sekyedumase	3.3	3.37	3.91	3.53	9	142.24	64.14
Ashanti	Obuasi East	N/A	-	3.26	3.45	10	138.95	62.65

Source MoFA 2021 Statistics Research, and Information Directorate (SRID)

APPENDIX 2

SURVEY QUESTIONNAIRE

STRICTLY CONFIDENTIAL

DEPARTMENT OF AGRICULTURAL ECONOMICS AND AGRIBUSINESS
COLLEGE OF BASIC AND APPLIED SCIENCES
UNIVERSITY OF GHANA, LEGON, ACCRA, GHANA

MAIZE-PRODUCING HOUSEHOLDS USE OF CLIMATE INFORMATION AND ADOPTION

OF CLIMATE-SMART AGRICULTURE PRACTICES IN NORTHERN GHANA

INVESTIGATOR'S INTRODUCTION AND STATEMENT OF INFORMED CONSENT

My name is **Mr Abdul-Fatawu Shaibu,** PhD candidate of the Department of Agricultural Economics and Agribusiness, University of Ghana, Legon, Accra. My phone number is 0245735525 Email address: fatash75@gmail.com
The study's overall goal is to examine the use of climate information and adoption of climate-smart agricultural practices among maize-producing households in northern Ghana targeting three regions, five districts, and seven communities that are designated as climate villages by active climate programmes. Five objectives are the driving forces behind this investigation. The first is to evaluate the utilisation of climate information services in farm-level decisions among maize-producing households. The second is to examine the determinants of CSA adoption. The third objective is to examine the impact of CSA Adoption on maize yield and net returns. The fourth is to assess the willingness of maize-producing households to invest in climate-smart Agricultural practices and the fifth is to ascertain the level of agreement between maize-producing householders and elites (influential farmers and climate change and meteorological science experts) concerning the effect of climate information on the adoption of CSA practices and the impact of CSA practices on the productivity of maize farmers.

Consent: The purpose of the study has been explained to you. After learning about the study's goals and giving your approval for voice, photo, and video recording where necessary during the survey, you agree to take part in it. You also agree that your responses will only be used and/or shared as needed for research purposes only and that the identities of persons you identify will remain anonymous. You also understand that your participation is completely voluntary and that you can answer any question and/or leave the interview at any time. You recognize, however, that the information, knowledge, and viewpoints you'd contribute would be extremely valuable to agricultural research and development. All information gathered is kept strictly confidential.

If you consent, please continue to participate as required

SECTION 1: QUESTIONNAIRE IDENTIFIER

1.1 REGION:	Northern [1]	Upper East [2]	Upper West [3]		
1.2 DISTRICT:	Savelugu [1]	Bolga [2]	Kassena Nankana [3]	Wa [4]	Jirapa [5]
1.3 COMMUNITY1	Tibali []	Kundanayili [ ]	Duko [] Nyariga [ ]	Nankalkania []	
	Busa []	Jirapa []			

1.4 GPS ADDRESS OF RESPONDENT……………………………………………………………………………..

1.5 TELEPHONE NUMBER OF RESPONDENT…………………………………………………………………..

1.6 DATE OF SURVEY………………………………………………………………………………………………

1.7 START TIME OF INTERVIEW……………………………………………………………………………….

1.8 END TIME; ……………………………………………………………………………………………………..

1.9 SURVEY QUESTIONNAIRE ID………………………………………………………………………….

1.10 NAME OF ENUMERATOR……………………………………………………………………………………

1.11 CONTACT NUMBER

SECTION 2: FARM LEVEL CHARACTERISTICS

1. What is your maize farm size? ………………………………. (Hectors) or ………………………….. (Acres)

2. Maize farm land exposure to climate risk: *Please select all that apply*

   Portions of the land are sloppy [ ]

   The land has moderate to severe erosion [ ]

   Poor land drainage system [ ]

   Poor soil quality [ ]

   The land is not suitable for other crops [ ]

3. What was your total output of maize during the 2021 crop season? …………………. (Maxi bags) or ……………… (kg)

4. What was your total maize yield during the 2021 crop season ……………….. (maxi bags/acre) or ……………..… (kg/ha)

5. Total family labour during the 2021 crop season ……………………………………………………………………………..

6. Total hired labour during the 2021 crop season …………………………………………………………………………….

SECTION 3 CLIMATE INFORMATION ACCESS AND USE AND FARM LEVEL DECISIONS

3.1 Perception/observation of weather/climate change

7. Climate change is generally considered by scientists to mean significant increases in temperatures, reductions in the amounts of rainfall and increased occurrences of severe weather events for about 30 years. Do you agree with this statement? Yes [ ] No [ ]

8. Given this definition of climate change, in your view, how important is it for you as a farmer to prepare to deal with the negative aspects of Climate Change?

not important	[1]
somewhat important	[2]
moderately important	[3]
important	[4]
very important	[5]

9. What is your observation of the following major climate change variables in the last 5-10 years in your area?

Incidence of erratic rainfall? *please select only one*

Increasing	[2]
Decreasing	[1]
Unchanged	[0]

Incidence drought? *please select only one*

Increasing	[2]

Decreasing [1]

Unchanged [0]

Incidence of high temperature/heat? *please select only one*

Increasing [2]

Decreasing [1]

Unchanged [0]

Incidence of floods *please select only one*

Increasing [2]

Decreasing [1]

Unchanged [0]

3.2 Assessment of meteorological services from various sources

10. Do you have access to any climate information and products? Yes [1] No [0]

11. If yes, what types of climate information?

Sunshine: Yes [1] No [0]

Humidity: Yes [1] No [0]

Wind speed/Cloud movement: Yes [1] No [0]

Temperature: Yes [1] No [0]

Precipitation: Yes [1] No [0]

Cessations: Yes [1] No [0]

Onset of rain Yes [1] No [0]

12. What is your main source of climate information variables? *Please select as applicable*

Sunshine: Radio [ ] TV [ ] Mobile [ ] Extension Visits [ ] Co-Farmer/FBO [ ]
Local Information Service [ ]

Humidity: Radio [ ] TV [ ] Mobile [ ] Extension Visits [ ] Co-Farmer/FBO [ ]
Local Information Service [ ]

Wind speed/Cloud movement: Radio [ ] TV [ ] Mobile [ ] Extension Visits [ ] Co-Farmer/FBO [ ]
Local Information Service [ ]

Temperature: Radio [ ] TV [ ] Mobile [ ] Extension Visits [ ] Co-Farmer/FBO [ ]
Local Information Service [ ]

Precipitation: Radio [ ] TV [ ] Mobile [ ] Extension Visits [ ] Co-Farmer/FBO [ ]
Local Information Service [ ]

Cessations: Radio [ ] TV [ ] Mobile [ ] Extension Visits [ ] Co-Farmer/FBO [ ]
Local Information Service [ ]

Onset of rain Radio [ ] TV [ ] Mobile [ ] Extension Visits [ ] Co-Farmer/FBO []
Local Information Service [ ]

13. What is the form of transmitting these climate information services?

Sunshine: Audio/voice only [1] Oral [2] Audio/visual [3] SMS alert [4]

	A combination of these [5]				
Humidity:	Audio/voice only [1]	Oral [2]	Audio/visual [3]	SMS alert [4]	
	A combination of these [5]				
Wind speed/Cloud movement:	Audio/voice only [1]	Oral [2]	Audio/visual [3]	SMS alert [4]	
	A combination of these [5]				
Temperature:	Audio/voice only [1]	Oral [2]	Audio/visual [3]	SMS alert [4]	
	A combination of these [5]				
Precipitation:	Audio/voice only [1]	Oral [2]	Audio/visual [3]	SMS alert [4]	
	A combination of these [5]				
Cessations:	Audio/voice only [1]	Oral [2]	Audio/visual [3]	SMS alert [4]	
	A combination of these [5]				
Onset of rain	Audio/voice only [1]	Oral [2]	Audio/visual [3]	SMS alert [4]	
	A combination of these [5]				

14. What is the overall usefulness of these climate information services to you?

Sunshine:	Very Poor [1]	Poor [2]	Moderately Good [3]	Very Good [4]	Excellent [ ]
Humidity:	Very Poor [1]	Poor [2]	Moderately Good [3]	Very Good [4]	Excellent [ ]
Wind speed/Cloud movement:	Very Poor [1]	Poor [2]	Moderately Good [3]	Very Good [4]	Excellent [5]
Temperature:	Very Poor [1]	Poor [2]	Moderately Good [3]	Very Good [4]	Excellent [5]
Precipitation:	Very Poor [1]	Poor [2]	Moderately Good [3]	Very Good [4]	Excellent [5]
Cessations:	Very Poor [1]	Poor [2]	Moderately Good [3]	Very Good [4]	Excellent [5]
Onset of rain	Very Poor [1]	Poor [2]	Moderately Good [3]	Very Good [4]	Excellent [5]

15. Do you pay for receiving any of the climate information services received Yes [ ] No [ ]

16. If yes how much do pay for any of the climate information received for a cropping season? …………………….(Ghc)

3.3 Assessment of Indigenous Climate Knowledge

17. How probable is the occurrence of the following observation about rainfall in your area?

The appearance of a large number of earthworms on the day is a sign of rain the next day or in a few hours;

Less probable [1] somewhat probable [2] highly probable [3] I don't have any idea [0]

Dark clouds amidst strong winds signal rain in a few hours

Less probable [1] somewhat probable [2] highly probable [3] I don't have any idea [0]

The loud singing of coucal birds and flying insects is an indication of rain in the next few days.

Less probable [1] somewhat probable [2] highly probable [3] I don't have any idea [0]

Cows repeatedly flapping their ears and tails indicate rainfall the next day or up to 3 days.

Less probable [1] somewhat probable [2] highly probable [3] I don't have any idea [0]

The appearance of fog indicates rain in the next few hours or the next day. Mostly low rains in the form of drizzle

Less probable [1] somewhat probable [2] highly probable [3] I don't have any idea [0]

A lepisiota ant carrying its eggs uphill during the rainy season signals rain the next day or in a few hours

Less probable [1]   somewhat probable [2]   highly probable [3]   I don't have any idea [0]

3.4 Use of climate information in farm-level decisions (questions that focus on farmers' current practices and preferences)

Direct Usage Questions:

Which sources of climate information do you currently rely on for your farming decisions? Please select all that apply."
Daily Weather Conditions provided by Meteorological agencies [1]
Seasonal Weather Conditions provided by Meteorological Agencies [2]
Indigenous weather predictions through personal observation [3]
Other (please specify) …………………………………………………………..

Frequency and Importance*:*
How frequently do you consult each of the following sources for climate information in your farming activities?
Daily Weather Conditions provided by Meteorological agencies Seasonal

Daily [1],   Weekly [2],   Monthly [3],   Rarely [4]   Never) [5]

Weather Conditions provided by Meteorological Agencies

Daily [1],   Weekly [2],   Monthly [3],   Rarely [4]   Never) [5]

Indigenous weather predictions through personal observation

Daily [1],   Weekly [2],   Monthly [3],   Rarely [4]   Never) [5]

Reasons for Usage:
What are the main reasons you rely on the following types of climate information?

Daily Weather Conditions provided by Meteorological agencies

It offers an opportunity for quick decisions   [1] It provides precision information [2] crop management   [3]

Timely harvesting [4]

Seasonal Weather Conditions provided by Meteorological Agencies

Long-term planning [1] Risk mitigation Planning [2] Water Conservation [3]

Indigenous weather predictions through personal observation

Trust in local knowledge [1] Ease of access and cost-effective [2] supplementary information [3]

Satisfaction and Reliability:

If you had to choose only one source of climate information for your farming decisions, which one would you prefer?"

Daily Weather Conditions provided by Meteorological agencies [1]

Seasonal Weather Conditions provided by Meteorological Agencies [2]

Indigenous weather predictions through personal observation [3]

SECTION 4 ADOPTION OF CLIMATE SMART AGRICULTURAL (CSA) PRACTICES

4.1 Preferences of CSA Practices

18. The table below provides alternative climate-smart strategies commonly practiced in northern Ghana as reported by experts.

Kindly indicate how well you know about these practices and their usage in your maize farming

Table 4.1 Choice of Climate Smart Agricultural Practices

SN		CSA/Farm practice	Awareness and use of practice			
			Awareness of practice (1=Yes.0=No)	Do you use the practice? (1=Yes.0=No)	How long have been using practice in years?	Why do you prefer this practice? (Refer to code)
1		Early planting				
2		Drought-tolerant maize varieties use				
3		Disease and pest-tolerant maize varieties use				
4		Mulching				
5		Delayed weed control				
6		Landscaping				
7		Organic amendment for improved soil health/leguminous crops				
8		Crop rotation				
9		Agro-forestry				
10.		Irrigation				
11		Maize intercropped with other crops				
Code		1= adaptability, 2= mitigation and 3= resilient effects				

4.2 Willingness to invest in CSA practices

19. Based on your assessment of the practices are you willing to invest in your preferred CSA practices? Yes [1] No [0]

20. Assuming that information, training and other resources to use these practices are made available to you at a fee what is the maximum amount of money that you would be willing to pay for CSA practice options for one production season? (open-ended bidding)

1. Early planting

______________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

______________ **Ghana Cedis per season (highest bid)**

2. Drought-tolerant maize varieties use

________________**Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

_______ ________**Ghana Cedis per season (highest bid)**

3. Disease and pest-tolerant maize varieties use

_______________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

_______________ **Ghana Cedis per season (highest bid)**

4. Mulching

______________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

______________**Ghana Cedis per season (highest bid)**

5. Delayed weed control

____________**Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

____________**Ghana Cedis per season (highest bid)**

6. Landscaping to ensure zero or minimal rainfall-run offs and soil erosion

____________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

____________**Ghana Cedis per season (highest bid)**

7. Organic amendment for improving soil health/leguminous crops as the previous crop

____________**Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

___________ **Ghana Cedis per season (highest bid)**

8. Crop rotation

___________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

___________**Ghana Cedis per season (highest bid)**

9. Agro-forestry

___________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

___________**Ghana Cedis per season (lighest bid)**

10. Irrigation

___________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

___________**Ghana Cedis per season (lighest bid)**

11. Maize intercropped with other crops

___________ **Ghana Cedis per season (lowest bid)**

Increase the initial bid by one Ghana cedi per season till the respondent finally refuses to accept any more increases *(iterative bidding method).*

___________**Ghana Cedis per season (lighest bid)**

SECTION 5: MAIZE PROFITABILITY ANALYSIS OF 2021 FARMING SEASON

21. Please provide information regarding your expenditure on land, labour services and other physical inputs during the 2021 farming season. *Please write 0 if no expenditure was inured*

INPUT	TOTAL COST(GH¢)
Services	

Land preparation (Clearing and demarcation)	
Tractor and other machine Services (ploughing and harrowing)	
Labour services (Fertiliser application)	
Labour services (insecticide application)	
Labour services (Harvesting)	
Cost of transportation	
Physical Inputs	
Weedicides	
Pesticide	
Fertilizers	
Cutlass	
Plastic Sheets/Tarpaulin	
Sacks	
Baskets	
Rope (Line)	
Gloves	

Knapsack	
Hoe	
Wellington boot	
Maize Seeds	

22. Please provide information regarding the revenue earned from maize production during the 2022 cropping season{

Maize output maize harvested ………………………….(bags) or …………………………………………………. (Kg)

Maize output sold …………………………………….(bags) or …………………………………………………. (kg)

The average weight of a bag: *please select as applicable* 100kg [3] 50 kg [2] 25kg [1]

Price per bag …………………………………………………………………. Ghc

SECTION 6 BACKGROUND INFORMATION OF RESPONDENTS

6.1 Farmer-level characteristics

23. What is your Age? ……………………………………(Years)

24. What is your Gender? Male [1] Female [0]

25. What is your marital status? Single [1] Married [2] Divorced [3] Widowed [4] Engaged [5] Separated [6] Consensus [7]

26. Ethnicity (see appendix A for classification): Mole-Dabani [1] Grusi [2] Gruma [3] Guan [4] Mande [5]

Akan [6] Ewe [7] Ga/Dangbe {8] Ewe [9] All others [10]

27. Please indicate your religious affiliation;

African Traditional Religions Only	[1]	
African Traditional Religions and Christianity	[2]	Mixed religious preferences
African Traditional Religions and Muslim	[3]	Mixed religious preferences
Christian Only	[4]	
Muslim Only	[5]	

Other Religions (Please specify)…………………………………………………………………………

28. Are you the head of your household (HH)? Yes [1] No [0]

29. If you are not what is your relationship with the HH head? Wife [1] Husband, [2] Son, [3] Daughter, [4]

Brother [5] sister [6] farm labour [7] other relatives, [8] Other (specify……………………………

30. Ownership of livestock units: Cattle: ……….. Sheep ……………goats ………………pigs…………..poulty ……………

These will be converted to Tropical Livestock Units (TLU)

31. Farming experience ………………………………………. (Years)

32. Level of Education (current level of education)

Level of Education	**Length (Years)**
No Schooling	
Up to Primary	
Up to Junior High	
Up to Senior High and Technical institute	
Tertiary	
Other non-formal/apprenticeship	

33. What is your estimated average monthly off-farm income? ……………………………. (GHc)

6.2 Social Capital and information access

34. Membership of farmer-based organization: Yes [1] No [0]

35. Membership of community organizations, such as Mosque groups, Church associations and others: Yes [1] No [0]

36. Membership of secret or quasi-secret societies; Yes [1] No [0]

37. Number of extension visits during the last year……………………………………

38. Knowledge of CSA practices: Yes [0] No [1]

39. Access to mass media Yes [0] No [1]

6.3 Access to Market

40. Distance to the main road ……………………………………………(km)

41. Distance to the district capital …………………………………….(km)

42. Distance to the nearest maize market …………………………….(km)

6.4 Institutional factors

43. Access to credit facilities: Yes [0] No [1]

44. Access to irrigation facilities: Yes [0] No [1]

45. Access to fertiliser subsidy: Yes [0] No [1]

46. CSA training received over last 5 years …………………. (times)

APPENDIX 2: FORMAL GHANA STATISTICAL SERVICE ETHNICITY CLASSIFICATION OF CITIZENS

ETHNIC GROUP	CLASSIFICATION	ETHNIC GROUP	CLASSIFICATION
AKAN	Agona	**GRUMA**	Bimoba
	Ahafo		Kokomba
	Ahanta		Basare(Kyamba)
	Akuapem		Pilapila
	Akwamu		Salfalba (Sabulaba)
	Akyem		Kotokoli
	Aowin		Other Gurma
	Asante	**MOLE-DAGBANI**	Builsa (Kangyaga or Kanjaga)
	Asen (Assin)		Dagarte (Dagaba), Lobi , Wali (Wala)
	Bono (Banda)		Dagomba
	Bawle		Kusasi
	Chokosi (Anufor)		Mamprusi
	Denkyira/Twifo		Namnam (Nabdom)
	Evalue		Nankansi, Talensi & Gurense (Frafra)
	Fante		Nanumba
	Kwahu		Mosi
	Nzema		Other Mole-Dagbani
	Sefwi	**GRUSI**	Kasena (Paga)
	Wasa		Mo
	Other Akan (Bawle)		Sissala
			Vagala
GA/DANGBE	Ga		Other Grusi (e.g. Lela, Templensi, Birifor, Yangala, Miwo)
	Dangbe	**MANDE**	Busanga
	Other Ga-Dangbe		Wangara

EWE	Ewe		**OTHER GROUPS ORIGINATING OUTSIDE GHANA**
GUAN	Akpafu, Lolobi, Likpe, Bowiri, Buem, Santrokofi, Akposo	**All Others**	Fulani
	Avatime, Nyongbo, Tafi, Logba		Hausa
	Awutu, Efutu, Senya, Breku		
	Cherepong, Larteh, Anum-Boso		
	Gonja		
	Nkonya		
	Yeji, Nchumuru, Krachi, Nawuri, Bassa Achode		
	Nkomi, Wiase, Dwan		
	Other Guan		

END OF SURVEY

THANK YOU FOR PARTICIPATING IN THE SURVEY

Interview Guide for the 20 In-depth Interviews

SECTION A Demographic Characteristics of Respondent

1. Respondent's group:

   [1] Elites

   [2] ordinary farmer

2. Age of Respondent ………………(years)

3. Gender:

   [1] Male

   [2] Female

4. Level of Education

   [1] PhD

   [2] Masters

   [3] Bachelor

   [4] Diploma

   [5] SHS

   [6] Primary

   [7] No formal education

5. Region:

   [1] Northern

   [2] Upper East

   [3] Upper West

6. Languages Spoken (select all that apply)

   [1] English

[2] Dagbani

[3] Gurune

[4] Dagaare

[5] Others (please specify) …………………………………

SECTION B; ***Climate Change and Climate Information Perceptions of Elites and Ordinary Farmers***

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7. What is your area of expertise in farming or climate change?........................
8. How do farmers currently access climate information services, and what are the primary sources of this information?
9. What are the perceptions and attitudes of farmers towards formal climate information services provided by government agencies, NGOs, or other institutions?
10. How do farmers use indigenous climate knowledge in their agricultural practices, and what role does it play in decision-making?
11. What are the challenges and barriers faced by farmers in accessing and utilizing climate information services and indigenous climate knowledge?
12. What are the potential benefits and limitations of integrating indigenous climate knowledge with formal climate information services to improve maize production?
13. What are the communication preferences and information need of maize-producing households concerning climate-related issues?
14. How do traditional coping strategies and adaptive practices based on indigenous climate knowledge contribute to climate resilience among maize-producing households?